Volume 21, Number 4 October 2025

IJCB
INTERNATIONAL JOURNAL OF CENTRAL BANKING
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Macroeconomic Policy, Product Market Competition, and Growth: The Intangible Investment Channel 1
JaeBin Ahn, Romain Duval, and Can Sever

Public Funding of Banks and Firms in a Time of Crisis 39
Markus Haavio, Antti Ripatti, and Tuomas Takalo

Monetary Policy Shocks and Inflation Inequality 135
Christoph Lauper and Giacomo Mangiante

A Financial Stress Index for a Small Open Economy: The Australian Case 191
Pedro Gomis-Porqueras, Xiaoyang Li, Romina Ruprecht, and Xuan Zhou

Macroprudential Policy and Income Inequality: The Trade-Off Between Crisis Prevention and Credit Redistribution 249
Simona Malovaná, Jan Janků, and Martin Hodula

Forecasting Core Inflation and Its Goods, Housing, and Supercore Components 351
Todd E. Clark, Matthew V. Gordon, and Saeed Zaman

The Resilience of the U.S. Corporate Bond Market during Financial Crises 405
Bo Becker and Efraim Benmelech

Central Bank Credibility and Institutional Resilience 465
Christopher A. Hartwell and Pierre L. Siklos

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The *International Journal of Central Banking* is published bimonthly (ISSN: 1815-4654). Online access to the publication is available free of charge at **www.ijcb.org**.

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International Journal of Central Banking
Printing & Fulfillment K1-120
Federal Reserve Board
Washington, DC 20551

Phone: 202-452-3425
Fax: 202-728-5886
E-mail: editor@ijcb.org

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ISSN: 1815-4654

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Macroeconomic Policy, Product Market Competition, and Growth: The Intangible Investment Channel*

JaeBin Ahn, Romain Duval, and Can Sever
International Monetary Fund

While there is growing evidence of persistent or even permanent output losses from financial crises, the causes remain unclear. One candidate is intangible capital—a rising driver of economic growth that, being nonpledgeable as collateral, is also vulnerable to financial frictions. By sheltering intangible investment from financial shocks, countercyclical macroeconomic policy could strengthen longer-term growth, particularly so where strong product market competition prevents firms from self-financing their investments through rents. Using a rich cross-country firm-level data set and exploiting heterogeneity in firm-level exposure to the sharp and unforeseen tightening of credit conditions around September 2008, we find strong support for these theoretical predictions. The quantitative implications are large, highlighting a powerful stabilizing role for macroeconomic policy through the intangible investment channel, and its complementarity with pro-competitive product market deregulation.

JEL Codes: E52, E62, O30.

*The authors would like to thank Philippe Aghion, Alejandro Cunat, Sebnem Kalemli-Özcan, William Maloney, and participants of the ASSA 2019 session on "Financial Constraints, Interest Rates and Productivity Growth," Banque de France-Bocconi University conference on "Alternative Datasets for Macro Analysis and Monetary Policy," 7th COMPNET Annual Conference, 2019 European Network for Research on Investment, and 2019 Conference of the Italian Economic Association. The views expressed in this paper are those of the authors and do not necessarily represent the views of the International Monetary Fund, its Executive Board, or management. Author emails: jahn@imf.org, rduval@imf.org, csever@imf.org.

1. Introduction

There is growing evidence that recessions accompanied by financial crises are associated with large permanent output losses, although the magnitude of these is still being debated (Cerra and Saxena 2008; Jordà, Schularick, and Taylor 2013; Reinhart and Rogoff 2009; Romer and Romer 2017). Even more puzzling, some have argued that even "plain-vanilla" recessions are followed by permanently lower output (Blanchard, Cerutti, and Summers 2015). The causes of such large and persistent output losses remain to be determined, but the potential implications for economic theory and policy are daunting—in particular, this gives rise to the possibility that countercyclical macroeconomic policy persistently or even permanently affects growth. This paper focuses on the role of intangible investment as a transmission channel. Using cross-country firm-level data and focusing on the 2008–09 Global Financial Crisis (henceforth, GFC), we show that countercyclical macroeconomic policy alleviates intangible investment cuts by credit-constrained firms when financial conditions tighten. We also find that product market competition has the opposite effect, pointing to a complementarity between market deregulation and countercyclical macroeconomic policy for growth.

Intangible asset investment is an increasingly important driver of economic growth in advanced economies (Corrado, Hulten, and Sichel 2005, 2009).[1] Even focusing only on those intangible assets currently captured in national accounts, and leaving aside other possible sources of undermeasurement—such as inaccurate deflators—simple growth accounting suggests that intangible capital accumulation contributed about a third to overall labor productivity growth in the European Union and the United States over the 2000–13 period (Corrado et al. 2018).[2]

[1] At the firm level, structural estimation of various dynamic models of research and development (R&D) also point to a significant role of R&D in determining the evolution of productivity over time (e.g., Aw, Roberts, and Xu 2011; Doraszelski and Jaumandreu 2013).

[2] According to the latest version of the System of National Accounts (2008), only a few intangible assets are currently capitalized in national accounts, namely R&D, mineral exploration, computer software and databases, as well as entertainment, literary, and artistic originals. Expenditures for design, branding, new

However, intangible investment is also a potentially vulnerable growth driver. Because—unlike tangible investment—it cannot generally be pledged against collateral or liquidated quickly, it is likely to be particularly vulnerable to continued availability of external or internal sources of finance. Moreover, the inherent uncertainty regarding the outcome of intangible investment magnifies asymmetric information and moral hazard problems would prevail (Hall and Lerner 2010). For example, building on the work of Holmstrom and Tirole (1997), Aghion et al. (2010) show theoretically that credit constraints can lead firms to cut R&D spending—and long-term illiquid investments more broadly—during recessions. In turn, more volatile R&D spending can undermine long-term growth if research projects need continuity to bear fruit.

Countercyclical macroeconomic policy and product market reform policy should have a bearing on the availability and/or cost of internal and external finance, and thereby on the resilience of intangible investment to sudden shifts in credit conditions. Monetary and fiscal policies have an indirect impact on firms' credit constraints through their effect on output, while monetary policy also influences the cost and availability of bank and nonbank credit (Aghion et al. 2010; Aghion, Hemous, and Kharroubi 2014; Correa-Caro et al. 2021). Likewise, product market competition drives down product market rents and, thereby, the amount of internal funds available for investment projects. For these reasons, there should also be some complementarity between product market reforms and active countercyclical monetary policy. The argument runs as follows. Product market deregulation can boost growth,[3] and, as such,

financial products, organizational capital, and firm-provided training are instead currently treated as intermediate costs.

[3]The existence of gains from easing barriers to entry in product markets has gradually become consensual since at least Blanchard and Giavazzi (2003) (e.g., Ebell and Haefke 2009; Fang and Rogerson 2011; Felbermayr and Prat 2011). A strand of studies using country-time or country-time-industry panel data documents a significant positive effect of product market reform on productivity, investment, employment, and/or output (e.g., Aghion, Askenazy, et al. 2009; Alesina et al. 2005; Bassanini and Duval 2009; Bourlès et al. 2013; Bouis, Duval, and Eugster 2019; Conway et al. 2006; Fiori et al. 2012; Inklaar, Timmer, and Van Ark 2008; Nicoletti and Scarpetta 2003). A related firm-level literature provides evidence on the impact of competitive pressures on innovation, technology

features high on the policy agenda in many advanced economies,[4] but it also reduces product market rents. As a result, monetary policy—and, more broadly, countercyclical macroeconomic policy—can be more powerful in stabilizing intangible asset investment and thereby in fostering longer-term growth in a more deregulated economy. Aghion, Farhi, and Kharroubi (2019) build up a model that delivers these predictions, and provide some preliminary evidence using industry- and firm-level data. In particular, using data for over 2,000 listed firms in selected European economies, they find that the European Central Bank's Outright Monetary Transactions Program announced in 2012 had a larger positive impact on firms' sales and employment growth in industries where market concentration measures (Herfindahl indices) were low than in more concentrated industries.

In this paper, we use a large cross-country firm-level data set of several million firm-year observations, mostly covering small and medium enterprises (SMEs) on top of large listed firms, to test directly for the impact of the countercyclicality of monetary (and fiscal) policy on intangible asset investment, and whether this impact varies depending on direct measures of product market competition as predicted by the theory developed by Aghion, Farhi, and Kharroubi (2019).

Our empirical approach is a differences-in-differences strategy that exploits the sharp and unforeseen tightening of credit conditions that took place in the immediate aftermath of the collapse of Lehman Brothers on September 15, 2008. Using an extensive cross-country firm-level data set put together by merging different waves of ORBIS, we start by showing that firms with greater precrisis balance sheet vulnerabilities—higher leverage or, alternatively and as a robustness check, a higher interest expense burden—reduced their intangible investment rate more than their less vulnerable counterparts in the aftermath of the crisis. This holds within narrowly defined (four-digit NACE) country-industry cells—that is, controlling for any country-industry (supply or demand) shocks, and then

adoption, and productivity (e.g., Aghion et al. 2004, 2005; Aghion, Blundell, et al. 2009; Arnold et al. 2016; Gal and Hijzen 2016).

[4]See, for example, Draghi (2015), International Monetary Fund (2015, 2016), or Organisation for Economic Co-operation and Development (2016).

comparing firms with strong versus weak balance sheet vulnerabilities within each cell. This finding is not driven by more vulnerable firms having experienced slower intangible investment growth already before the crisis—more and less vulnerable firms do not differ significantly along these or other relevant dimensions. Instead, the results are consistent with the view that when credit markets froze after September 15, 2008, more exposed firms were forced to reduce expenditure, particularly on items such as intangible investment, that could not be pledged as collateral or translate quickly into sales. Indeed, we also find that firms with greater precrisis balance sheet vulnerabilities cut intangible asset investment more than they cut tangible asset investment.

Having established that financial frictions mattered for firm-level intangible investment after the crisis, we then explore the role of monetary (and fiscal) policy in mitigating their impact. Using various measures of the response of monetary (and fiscal) policy to the Lehman shock, we find a strong and statistically significant interaction with our measures of firm-level balance sheet vulnerabilities; monetary policy easing dampened the adverse impact of financial frictions on firms' intangible asset investment.

Finally, using various measures of product market competition at the country or country-industry-level, including Lerner indices and markups (following De Loecker and Warzynski 2012), we find that monetary policy was more powerful at stabilizing intangible investment after the collapse of Lehman Brothers where product market competition was stronger, that is, where product market rents were lower. This key finding confirms the theoretical argument laid out in Aghion, Farhi, and Kharroubi (2019) and highlights the complementarity between product market reforms and monetary policy. Our results also have significant policy implications. In particular, they suggest that product market deregulation should come hand in hand with aggressive countercyclical monetary policy—and countercyclical macroeconomic policy more broadly—to shelter intangible asset investment from macroeconomic shocks. Otherwise, there is a risk that the well-documented growth benefits from deregulation might be undermined by their side effect on intangible investment stability.

This paper relates to the existing studies on the permanent output costs of financial crises we mentioned above, but also to a

related literature on macroeconomic volatility and long-term growth. Ramey and Ramey (1995) point to a negative cross-country correlation between volatility and growth. Aghion et al. (2010) focus on intangible investment as one channel through which such link may arise. They show theoretically that in the presence of credit constraints, adverse macroeconomic shocks will lead firms to cut spending on intangible and other forms of long-term, illiquid, but high-return forms of investment. Using cross-country-industry panel data, Aghion, Hemous, and Kharroubi (2014) find that countercyclical fiscal policy mitigates the impact of credit constraints on country-industry-level output growth. Aghion, Farhi, and Kharroubi (2019) focus instead on monetary policy, introduce the interaction between monetary policy and product market competition, and explore industry-level variation drawn from firm-level data. Both papers focus only on output growth without investigating the possible channel(s) at play, including whether the intangible investment channel highlighted by theory is indeed operating. Also, competition is measured indirectly through broad indices of market concentration among a small set of listed firms, with well-known practical and conceptual limitations; in particular, competing non-listed domestic firms and—even more importantly in the case of highly open European economies—foreign firms are ignored in the calculations, market contestability cannot be accounted for (Baumol 1982), and, more broadly, the relevant markets cannot be identified at such an aggregate level. In this paper, we address both issues. We explore how intangible investment at the firm level is affected by monetary (and fiscal) policy and its interplay with direct measures of product market competition at the four-digit industry level, including (firm-level-based) Lerner indices and markups à la De Loecker and Warzynski (2012).

Also related to this paper is the recent literature on how the 2008–09 GFC affected firms. Using firm-level data for the U.S., several papers find that financial frictions amplified the adverse impact of the GFC on employment; those firms with weaker corporate balance sheets (Dinlersoz et al. 2018; Giroud and Mueller 2017), that had a relationship with weak banks (Chodorow-Reich 2014), faced greater refinancing risk (Benmelech, Bergman, and Seru 2021), or were smaller and younger (Siemer 2019) experienced greater job losses, all else equal. Other papers focus on the productivity losses

from such financial frictions, such as de Ridder (2016) for U.S. firms, Huber (2018) for German firms and counties, or Duval, Hong, and Timmer (2020) for a cross-country panel of firms. The latter paper also explores the effect of financial frictions on the response of firm-level intangible investment to the GFC. We extend their analysis to the role of countercyclical monetary (and fiscal) policy and its interplay with product market competition.

The remainder of this paper is structured as follows. Section 2 outlines our empirical strategy and the data set employed in this study. Section 3 presents our econometric results, while Section 4 provides extensions and robustness checks. Section 5 concludes.

2. Empirical Strategy and Data

2.1 Empirical Strategy

The baseline empirical strategy is set on a differences-in-differences framework, thereby comparing the difference in investment in intangible assets between firms with different levels of financial vulnerabilities, before and after the drastic unforeseen credit tightening that followed the collapse of Lehman Brothers.

Our methodology bears similarities with Giroud and Mueller (2017), who investigate the impact of this credit supply shock on firm-level employment in the U.S. by regressing the change in firm-level employment around the GFC on the precrisis leverage ratio which is the measure of firm-level credit constraint. A similar approach is employed in Kalemli-Özcan, Laeven, and Moreno (2022) to study the effect of financial factors on the slowdown in tangible investment in European countries. Duval, Hong, and Timmer (2020) apply this methodology to investigate the role of firm-level financial constraints in the productivity slowdown in advanced countries following the GFC. In a first stage, we start by estimating

$$\Delta\ Intangible\ Investment_{isc} = \beta_1 Financial\ Vulnerability_{isc} + \delta_{sc} + \gamma \mathbf{X}_{isc} + \epsilon_{isc}, \quad (1)$$

where $\Delta\ Intangible\ Investment_{isc}$ is the difference in the average investment in intangible assets (scaled by total assets) of firm i, in industry s and country c between the precrisis (2002–07) and

postcrisis (2008–13) periods. $Financial\ Vulnerability_{isc}$ is a measure of precrisis balance sheet vulnerability, details of which are discussed below. δ_{sc} denotes country-sector fixed effects, absorbing all the country-sector-level characteristics that might commonly affect firm-level changes in intangible investment between the two periods in a given country-sector where sectors are highly disaggregated at the four-digit NACE level.[5] In effect, this implies that we will be comparing the impact of the Lehman shock on intangible investment between firms with strong balance sheets and firms with weak balance sheets within a given country sector. Finally, $\mathbf{X}_{isc}$ is a set of firm-level controls including age, total assets, and cash flows (ratio of cash flows to assets) in the precrisis period. Our rich set of country-sector fixed effects and firm-level controls addresses key sources of omitted variable bias. Reverse causality is not a concern in our setup since the Lehman shock to credit conditions was unforeseen. Moreover, firms' debt structure prior to this event is unlikely to be correlated with other unobserved firm-level characteristics that may be correlated with the change in intangible investment after the crisis.

In a second stage, once β_1 is tested to be negative, implying that firm-level financial vulnerabilities had an adverse effect on intangible investment, we turn to the counteracting effect of countercyclical macroeconomic policy. To do so, we exploit the cross-country heterogeneity in the response of monetary conditions to the GFC and estimate

$$\begin{aligned}\Delta\ Intangible\ Investment_{isc} = {} & \beta_1 Financial\ Vulnerability_{isc} \\ & + \beta_2 Financial\ Vulnerability_{isc} \\ & \times Expansionary\ Conditions_c \\ & + \delta_{sc} + \gamma \mathbf{X}_{isc} + \epsilon_{isc}, \end{aligned} \tag{2}$$

[5]For instance, intangible investment in some sectors relying more heavily on external finance than others may have been on average more affected by the GFC. Similarly, export-intensive industries in a more export-oriented country may have been affected differently following the great trade collapse. All such potential channels that are specific at the country-industry level but common across firms in that specific country industry will be controlled by country-sector fixed effects.

where $Expansionary\ Conditions_c$ is a measure—discussed in detail further below—of the extent to which monetary conditions eased after the GFC due to countercyclical macroeconomic policies. In this specification, together with $\beta_1 < 0$, $\beta_2 > 0$ would imply that expansionary monetary conditions dampen and—depending on its magnitude and the estimated values of β_1 and β_2—even possibly offset the negative impact of financial vulnerabilities on the response of intangible investment to the credit supply shock. Since firm-level developments within each four-digit country sector are highly unlikely to influence monetary policy, reverse causality is not a concern here too.

In a third and final stage, we explore the complementarities between countercyclical macroeconomic policies and product market deregulation. The theoretical underpinnings are laid out in Aghion, Farhi, and Kharroubi (2019). They develop a model in which firms decide on the amount of investment in a growth-enhancing form of capital in the presence of profitability and liquidity shocks. In their setup, strong product market competition reduces profits, the ability of firms to weather liquidity shocks, and, thereby, investment. They also show that by mitigating the impact of liquidity shocks, countercyclical monetary policy incentivizes firms to invest more, particularly so where strong product market competition depresses profits.

In our empirical setup, these considerations yield two testable implications that can be checked by estimating the following specification:

$$\begin{aligned}\Delta\, Intangible\ Investment_{isc} &= \beta_1 Financial\ Vulnerability_{isc} \\ &+ \beta_2 Financial\ Vulnerability_{isc} \times Expansionary\ Conditions_c \\ &+ \beta_3 Financial\ Vulnerability_{isc} \times Weak\ Competition_{sc} \\ &+ \beta_4 Financial\ Vulnerability_{isc} \times Expansionary\ Conditions_c \\ &\times Weak\ Competition_{sc} \\ &+ \delta_{sc} + \gamma \mathbf{X}_{isc} + \epsilon_{isc}, \end{aligned} \tag{3}$$

where $Weak\ Competition_{sc}$ is a proxy measure for the degree of product market competition, which will be discussed in detail below. First, the adverse effect of corporate balance sheet weakness on intangible investment in the aftermath of the Lehman collapse

should be greater for firms facing higher competition; this implies $\beta_3 > 0$. Second, the beneficial impact of expansionary monetary conditions should be greater for firms facing higher competition, that is, $\beta_4 < 0$ should hold. Standard errors will be clustered at the country-sector level.

2.2 Data

2.2.1 Firm-Level Variables

Our firm-level variables are constructed using ORBIS, a cross-country longitudinal data set of both listed and unlisted firms provided by Bureau van Dijk. The data set features rich information on firms' activities and financial variables based on balance sheets and income statements. We refer the reader to Diez, Fan, and Villegas-Sanchez (2021) for a more detailed description of the data set and the approach taken to clean the data, which essentially follows similar steps as in Gopinath et al. (2017) and Kalemli-Özcan et al. (2024).[6]

We focus on 17 OECD countries for which we have data on both firm-level and country-level macroeconomic variables over this period, namely Austria, Belgium, Czech Republic, Germany, Finland, France, Greece, Hungary, Ireland, Italy, Korea, Norway, Poland, Portugal, Slovakia, Spain, and the United Kingdom.[7] We study firms in the nonfarm, nonfinancial business sector, which corresponds to the two-digit industry codes 5–82 in NACE Revision 2, covering both manufacturing and a number of service sectors (e.g., real estate and profession/scientific/technical activities). Basic firm-level summary statistics are provided in Table 1.

[6] To ensure consistency and comparability of monetary variables across countries and over time, time-industry varying value-added or gross output deflators are applied to convert nominal monetary variables to real variables in 2010 constant USD for noncapital variables, while the country-level investment deflators from the World Development Indicators database are applied for capital variables. Importantly, any heterogenous changes in country-industry-level capital price deflators will be absorbed by the country-sector fixed effects included in specifications (1)–(3). In addition, observations with likely reporting errors due to concerns related to the reliability of the data as well as the consistency of variables over time are excluded.

[7] Although a majority of our sample consists of firms from euro-area (EA) countries, these do not appear to be driving our results; when running our baseline regression separately for the full sample and the euro-area sample, we obtain qualitatively identical results.

Table 1. Summary Statistics

	Mean	Median	25th Percentile	75th Percentile	Standard Deviation
Firm-Level Variables					
Δ Intangible Investment	–0.001	0.000	0.000	0.002	0.023
Δ Tangible Investment	–0.014	0.001	–0.031	0.027	0.208
Intangible/Total Assets Ratio	0.158	0.022	0.000	0.210	0.251
Leverage Ratio	0.668	0.701	0.529	0.836	0.210
Sales (in million USD)	10.5	1.8	0.8	4.5	174
Assets (in million USD)	16.6	0.9	0.3	3.2	807
Number of Employees	54.0	13.3	8.0	29.0	614.7
Firm Ages	15.9	13	7	20	13.5
Macroeconomic Policy Shocks					
Long-Term Bond Yield (Forecast Error)	0.12	0.45	–0.20	0.62	0.65
Deviation from Taylor Rule	0.37	0.70	–0.40	1.36	2.18
Short-Term Policy Rate (Forecast Error)	–0.04	–0.02	–0.47	0.32	0.43
Government Consumption (Forecast Error)	0.76	0.69	0.30	1.17	0.70
Product Market Competition					
Lerner Index (Country-Sector Median)	0.06	0.05	0.04	0.08	0.04
Markup (Country-Sector Median)	1.97	1.81	1.38	2.38	0.81
Product Market Regulation	1.58	1.52	1.40	1.62	0.25
Regulatory Protection of Incumbents	1.24	1.25	1.08	1.35	1.24
Administrative Burden for Start-Ups	2.34	2.43	1.79	2.58	0.60

Note: Δ Intangible Investment is the difference in the average net investment in intangible assets (as a ratio of total assets) between post- and precrisis periods. Δ Tangible Investment is similarly defined. Intangible/Total Assets Ratio is the ratio of intangible assets to total (tangible + intangible) assets in the precrisis period. *Leverage Ratio* is defined as the average debt-to-assets ratio in the precrisis period. Lerner Index is computed as the average of *(EBITDA-Depreciation and Amortization)/Operating Revenue* in the precrisis period. Sales and Assets in the precrisis period are in million USD. Summary statistics of firm-level variables are based on 664,086 observations of the baseline estimation sample. Macroeconomic policy shocks are constructed at country level, while product market competition measures are constructed at country or country-sector level.

Our main dependent variable of interest is the change in intangible investment, defined as the difference in average investment in intangibles as a share of total assets between pre- and postcrisis periods:

$$\Delta Intangible\ Investment_{isc} = \frac{Intangible\ Investment_{isc,post}}{Total\ Assets_{isc,post}} - \frac{Intangible\ Investment_{isc,pre}}{Total\ Assets_{isc,pre}},$$

where total assets are in turn defined as the sum of intangible and tangible fixed assets, both of which are deflated by country-sector-level price indices to obtain real values.

We measure investment in intangibles on a net basis—that is, net of depreciation (or amortization), computing it as the change in real intangible assets.[8] One potential concern regarding this measure stems from the highly complex nature of international standards for intangible assets accounting.[9] In practice, the intangible assets reported on firms' balance sheets tend to be mostly acquired assets—with a clear transaction price, such as patents or software—or internally generated ones at the development phase—and thereby with estimable future economic benefits. This leaves out other types of internally generated intangibles, most notably R&D projects at the research stage. Therefore, intangible assets are likely to be both imperfectly reported and underreported. As a result, our econometric analysis is likely to be subject to classical measurement

[8]To be precise, given that the measure of gross intangible investment is not available, we retrieve the net intangible investment measure by differencing the intangible assets variable between two consecutive periods similarly to Ampudia, Beck, and Popov (2021) and Chen and Lee (2023), among others. We further note that as we focus on the "change" in net intangible investment measure between two consecutive periods, unless depreciation rates vary between two consecutive periods, it should be equivalent to considering the change in gross intangible investment.

[9]In principle, intangible assets include, but are not limited to, scientific or technical knowledge, design and implementation of new processes or systems, licenses, intellectual property, market knowledge, and trademarks such as brand names and publishing titles. According to International Accounting Standard (IAS) 38, however, only those that meet three criteria—identifiability, controllability, and estimability—should be recorded on the balance sheet.

error in the dependent variable, leading to attenuation bias and overly conservative results—against finding any statistically significant relationship. We will also check the robustness of our results to alternative measures of the dependent variable that are supposed to be less prone to potential measurement errors.[10]

To explore the role of firm-level financial vulnerabilities for intangible investment and their interplay with policies, we consider two variables that capture potential financial constraints faced by firms. The baseline measure is the precrisis average of leverage ratio to capture the degree of debt overhang risk. Giroud and Mueller (2017) discuss that U.S firms with a higher precrisis leverage ratio faced more acute financial constraints when credit conditions tightened afterwards. This is calculated as the ratio of the sum of current liabilities and long-term debt to total assets for corresponding periods. As a robustness check, we also consider the interest coverage ratio prior to the crisis, defined as total interest paid by the firm over its earnings before taxes, depreciation, and amortization of capital (EBITDA). This is supposed to capture the degree of drags on financing that stem from debt payments (Kalemli-Özcan, Laeven, and Moreno 2022).

2.2.2 Macroeconomic Policy Conditions

Postcrisis monetary conditions in a given country are measured in four alternative ways. The baseline measure is the average forecast error of long-term (10-year) government bond yields in the postcrisis period, relative to OECD forecasts for the year considered, as published in the fall issue of the *OECD Economic Outlook* in the previous year. This is intended to capture the surprise component of monetary

[10]There are growing economics, finance, and accounting literatures on the measurement of intangible investment and capital that propose alternative and robust approaches to measuring intangible capital and investment (e.g., Eisfeldt, Kim, and Panikolaou 2022; Enache and Srivastava 2018; Peters and Taylor 2017). However, they are mostly applicable to large, listed firms rather than to SMEs that comprise a large fraction of our sample firms. Instead, we checked the validity of our intangible assets variable by confirming a strong positive correlation with the number of patent applications from a within-firm regression of intangible assets on the number of patent applications in a subsample with firm-patent matches between PATSTAT and the ORBIS data sets provided by Bureau van Dijk.

conditions, that is, the extent to which they were more expansionary than expected postcrisis. One advantage of this measure, beyond its simplicity, is to capture relevant monetary conditions for firms better than short-term policy rates do, and to encompass the impact of both conventional and unconventional monetary policy measures that were implemented by major central banks after the crisis.

Alternatively, we consider more direct measures of monetary policy shocks. One is the deviation of the policy rate from its simple Taylor-rule-implied value in the postcrisis period, using standard Taylor rule parameters and following extensive previous literature (e.g., Bordo and Landon-Lane 2014; Bruno and Shin 2015; Coibion et al. 2017; Dell'Ariccia, Laeven, and Suare 2017). Another monetary policy shock measure is the forecast error of the short-term policy rate that is orthogonal to unexpected changes in output growth and inflation.[11] This is computed in two steps. In a first step, the difference between the actual and forecast short-term rate is calculated, along with similar differences for inflation and gross domestic product (GDP) growth, where the forecasts of short-term policy rates, inflation, and output growth are taken from Consensus Economics in October of the same year. In a second step, forecast errors for the short-term rate are regressed on forecast errors for inflation and GDP growth; residuals from this panel regression are then taken as the exogenous monetary policy shock in a given country and year. As such, both of these alternative measures, by construction, could also address potential concerns that our baseline measure might simply reflect correlated aggregate GDP growth conditions.

Finally, since fiscal policy can ease firms' credit constraints by raising aggregate demand and output, we also consider a fiscal policy shock measure in an extension of our analysis. We use the forecast error of the ratio of government consumption to GDP, following Auerbach and Gorodnichenko (2012). The forecasts are taken from the fall issue of the *OECD Economic Outlook* in the same year.

2.2.3 Product Market Competition Measures

The degree of competition faced by firms is measured in three ways, two of which are derived from firm-level market power measures.

[11] See, for example, Duval and Furceri (2018).

The baseline measure is the (median value of the) Lerner index for each country sector in the precrisis period. It is calculated as *(EBITDA-Depreciation and Amortization)/(Operating Revenue)* and represents an inverse measure of country-sector-level competition. Alternatively, we use firm-level markups. These are computed following the approach proposed by De Loecker and Warzynski (2012) and applied by De Loecker, Eeckhout, and Unger (2020) or Diez, Fan, and Villegas-Sanchez (2021) to document rising corporate market power in advanced economies. We take the median of firm markups in each country sector as a measure of (weak) competition.[12]

While firm-level-based measures are our preferred indicators because they aim to measure directly the strength of market competition and can be computed for each country industry, we also confirm the robustness of our results to using instead the economy-wide product market regulation (PMR) indicators published by the OECD. These are based on responses by national governments to extensive questionnaires covering a wide range of anticompetitive product market regulations (for details, see Koske et al. 2015). In our analysis, we consider the overall PMR indicator but also, given our focus on the role of incumbent firms' product market rents, two specific subindicators on barriers to entry and regulatory protection of incumbents.

2.3 Stylized Facts

For our differences-in-differences strategy to be valid, two conditions should be met. First, the 2008 GFC shock should be exogenous, and second, firms with different levels of financial vulnerabilities should have had a parallel trend in intangible investment growth prior to the crisis, with any divergence materializing only after the crisis. Regarding the first condition, there is broad consensus that the GFC was unforeseen by individual firms; for example, Cheng, Raina, and Xiong (2014) show that even managers in the securitized finance industry failed to identify the housing bubble. The second condition requires a careful look at the data to ensure that

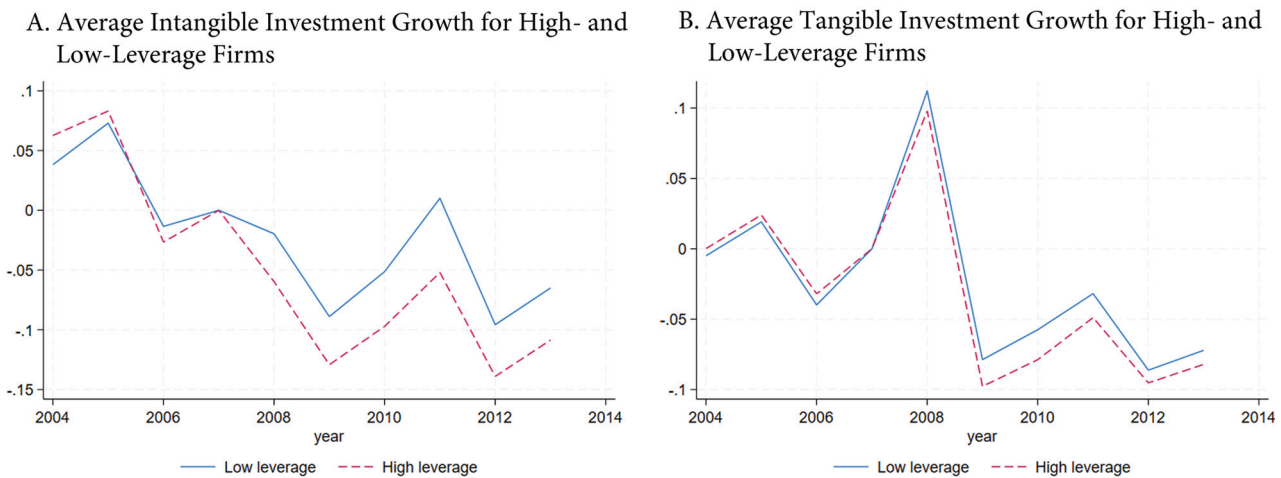
[12] We are grateful to Federico Diez, Jiayue Fan, and Carolina Villegas-Sanchez for sharing the estimated markup data with us.

our estimates will not be driven by more vulnerable firms having experienced slower intangible investment growth already before the crisis.

To this end, we run a regression of firm-level intangible investment growth on year dummies and four-digit country-sector fixed effects separately for high-leverage and low-leverage firms, where the leverage threshold used to split firms in those two groups is, in each country sector separately, the median across firms of the average leverage ratio over the precrisis period. Panel A in Figure 1 reports the evolution of the year dummy variable derived from these regressions—which basically captures average annual growth in intangible investment, expressed as a deviation from its country-sector average over the sample period—across high-leverage (red dashed line) and low-leverage (blue solid line) firms, respectively. The figure confirms that the second condition is satisfied: intangible investment by both sets of firms grew at a similar pace until the GFC, after which high-leverage firms started experiencing a greater decline in intangible investment than their low-leverage counterparts. Moreover, a corresponding chart for tangible investment in panel B indicates that the postcrisis divergence between high- and low-leverage firms was less pronounced for tangible investment, supporting our underlying premise that intangible investment is likely to be more dependent on continuous availability of external or internal sources of finance due, in particular, to its inherently limited pledgeability.

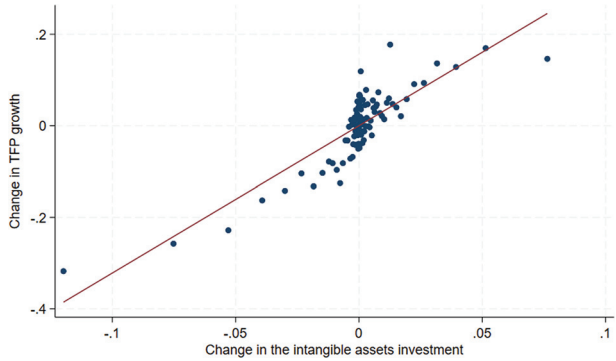
Figure 2 illustrates the relevance of these changes in intangible investment for changes in total factor productivity (TFP) between the precrisis and postcrisis periods. The TFP series for each firm is derived here from the estimation of a production function with labor and tangible capital, using the generalized method of moments (GMM) procedure proposed by Wooldridge (2009) to address the simultaneity problem stemming from the input choices and the firm's productivity, and also the critique of Ackerberg, Caves, and Frazer (2015). For each firm in the sample, the change in the intangible-to-total-assets ratio (in percent) between the pre- and postcrisis periods is calculated and then ranked. The resulting data are then broken into 100 quantiles, for each of which the median value of the change in the intangible-to-total-assets ratio is calculated. Each dot in the

Figure 1. Pre- and Post-GFC Trends in Intangible and Tangible Investment Growth in High-Leverage vs. Low-Leverage Firms



Note: This figure illustrates the evolution of average intangible (panel A) and tangible (panel B) investment growth in high-leverage versus low-leverage firms. Each series in the panel represents a coefficient estimate on year dummy variables from a regression of firm-level intangible (panel A) or tangible (panel B) investment growth on year dummies and country-sector fixed effects separately for high-leverage firms (red dashed line) and low-leverage firms (blue solid line), where the leverage threshold used to split the data in two groups is, in each country sector separately, the median across firms of the average leverage ratio over the precrisis period.

Figure 2. Change in Average TFP Growth and Average Intangible Investment Growth between the Pre-GFC and Post-GFC Periods



Note: For each firm in the sample, the change in the intangible-to-total-assets ratio (in percent) between the pre- and postcrisis periods is calculated and then ranked. The resulting data are then broken into 100 quantiles, for each of which the median value of the change in the intangible-to-total-assets ratio is calculated. Each dot in the figure represents this quantile-median, as a deviation from a country-sector fixed effect (x-axis). It is plotted against the quantile-median of the deviation of the change in average TFP growth from a country-sector fixed effect (y-axis). The post- and precrisis periods include five years after and before the 2008 crisis, respectively.

figure represents this quantile-median, as a deviation from a country-sector fixed effect (x-axis). It is plotted against the quantile-median of the deviation of the change in average TFP growth from a country-sector fixed effect (y-axis). The post- and precrisis periods include five years after and before the 2008 crisis, respectively. Overall, the figure shows a strong positive correlation between changes in intangible investment and TFP growth between the pre- and postcrisis periods, consistent with recent literature pointing to a sizable impact of intangible capital on productivity (e.g., Aw, Roberts, and Xu 2011; Doraszelski and Jaumandreu 2013). Incidentally, Figure 2 also confirms that, although far from fully comprehensive, the intangible assets included in firm balance sheets do contain relevant information for productivity growth and are therefore worth studying.

Now, we turn to investigating the role of financial frictions for intangible investment and their interplay with policies.

Table 2. Baseline Estimation Results: Intangible Investment and Leverage

	(1)	(2)
$Vulnerability_{isc}$	–0.005***	–0.014***
	(0.000)	(0.005)
$Vulnerability_{isc} \times Precrisis\ Physical\ Assets\ Ratio_{isc}$		0.010*
		(0.006)
Observations	664,086	664,086
R-squared	0.061	0.065
Country-Sector Fixed Effects	Yes	Yes

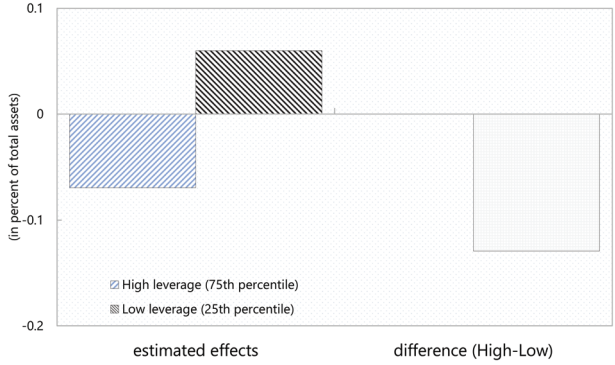
Note: The dependent variable is the difference in the average net investment ratio in intangible assets (ratio of intangible to total assets) between post- and precrisis periods. Firm-level vulnerability is the average debt-to-assets ratio in the precrisis period. The postcrisis period starts in 2008. Firm-specific controls (included but not reported) are firm age, total assets, and cash flow/assets ratio; the precrisis average ratio of physical assets in total assets and its interaction terms with the former three variables. All columns include country-sector fixed effects. Standard errors are clustered at the country-sector level. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

3. Empirical Results

Our starting point, as specified in (1), is to show, as also found by Duval, Hong, and Timmer (2020), that firms with preexisting balance sheet vulnerabilities tended to reduce intangible investment in the postcrisis period more than their less vulnerable peers within a given country-industry. The results are presented in Table 2. The estimated coefficient implies that firms with a 10 percentage point higher leverage ratio reduced their intangible investment rate more by around 0.05 percentage point (column 1). To get a better sense of the estimated effect, Figure 3 illustrates the difference in the estimated decline in intangible investment rate (relative to country-sector averages) between the 75th percentile (blue bar) and 25th percentile firms (shaded bar) in terms of the leverage ratio, which amounts to 0.15 percentage point (red bar).

Insofar as firms could still bring their physical assets as collateral or liquidate them to avoid cutting intangible investment

Figure 3. Illustration of the Baseline Estimation Results: Financial Frictions and Intangible Investment



Note: High (low) leverage corresponds to the 75th (25th) percentile of the cross-firm distribution of precrisis average leverage ratio. The green shaded bar indicates the difference in estimated effects for high- and low-leverage firms. Estimated coefficients are from column 1 in the baseline results table.

expenditure—which cannot be collateralized or liquidated easily—the extent to which firms cut intangible investment might be expected to be greater for firms that have few or no physical assets. To test for this, we further differentiate among firms depending on their asset pledgeability, measured as the share of tangible assets in total assets in the precrisis period, by interacting this measure with leverage. The results, which are reported in column 2 of Table 2, lend further support to the hypothesis that financial frictions affected intangible investment after the crisis: as shown by the statistical significance (at the 10 percent confidence level) of the interaction term, firms with a larger (smaller) share of physical assets turn out to have been less (more) affected by the tightening of credit conditions in 2008.

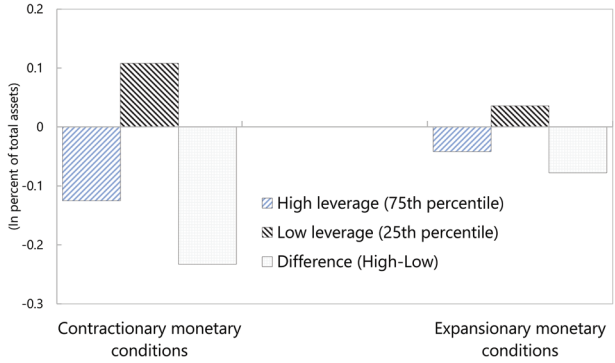
Turning to the role of expansionary monetary conditions in mitigating the adverse impact of financial constraints on intangible investment, Table 3 reports regression results from specification (2) in column 1. The positive and statistically significant coefficient estimate on the interaction term implies that more expansionary monetary conditions could dampen, and indeed prevent, a cut in intangible investment by financially constrained firms. The size of

Table 3. Baseline Estimation Results: Intangible Investment, Leverage, and Macro Policies

	(1)	(2)	(3)
$Vulnerability_{isc}$	–0.005***	–0.007***	–0.009***
	(0.000)	(0.001)	(0.001)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_{c}$	0.005***		0.009***
	(0.001)		(0.001)
$Vulnerability_{isc} \times Weak\ Competition_{sc}$		0.047***	0.061***
		(0.011)	(0.013)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_{c} \times Weak\ Competition_{sc}$			–0.074***
			(0.019)
Observations	664,086	664,086	664,086
R-squared	0.062	0.061	0.062
Country-Sector Fixed Effects	Yes	Yes	Yes

Note: The dependent variable is the difference in the average net investment ratio in intangible assets (as a ratio of total assets) between post- and precrisis periods. Firm-level vulnerability is measured as the average debt-to-assets ratio in the precrisis period. Expansionary monetary conditions is the average OECD forecast error for long-term (10-year government bond) interest rate in the postcrisis period as a measure of more-than-expected policy loosening. Weak competition is measured as the median precrisis Lerner index value in each country sector, reflecting the degree of profitability. The postcrisis period starts in 2008. Firm-specific controls (included in regressions but not reported) are firm age, total assets, and cash flow/assets ratio as well as their interaction terms with expansionary monetary conditions and/or weak competition measures. All columns include country-sector fixed effects. Standard errors are clustered at the country-sector level. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Figure 4. Illustration of the Baseline Estimation Results: The Role of Countercyclical Policy



Note: High (low) leverage corresponds to the 75th (25th) percentile of the cross-firm distribution of precrisis average leverage ratio. The green shaded bars indicate the difference in estimated effects for high- and low-leverage firms, separately for contractionary and expansionary monetary conditions. Estimated coefficients are from column 2 in the baseline results table. Expansionary/contractionary monetary conditions are defined as forecast errors in 10-year government bond yields by +/–50 bps.

the coefficient estimates is such that a more-than-expected reduction in the long-term external financing cost of some 100 basis points fully negates the adverse impact on intangible investment stemming from debt overhang risk. Figure 4 contrasts the estimated effects for firms with high and low leverage under two different scenarios—more-than-expected expansionary (right bars) and contractionary monetary conditions (left bars) by 50 bps—suggesting that adverse effects of financial frictions on intangible investment can be reduced by one-third under the cases considered (red bars in the middle).

These estimates have sizable implications for output. A back-of-the-envelope calculation of the output effects of weaker postcrisis intangible investment in more leveraged firms requires using an elasticity of output with respect to intangible capital, for which available estimates tend to vary substantially across data samples and methodologies, ranging roughly from 20 to 40 percent (Doraszelski and Jaumandreu 2013; Hall, Mairesse, and Mohnen 2010). Based on this range, our estimation results would imply that a 100 basis point negative surprise on monetary conditions could prevent a cumulative

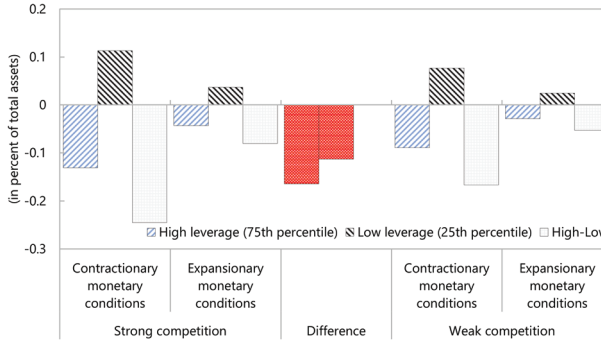
output loss of 1 to 2 percent for high-leverage firms (75th percentile of the leverage distribution) vis-à-vis their low-leverage counterparts over the five years after the crisis.[13]

As an intermediate step toward investigating potential complementarity between monetary and competition policies, we first check if competition had any impact on the relationship between financial frictions and intangible investment. Our premise is that the adverse effects of financial frictions on intangible investment should have been greater for firms facing high competition because, unlike their low-competition counterparts, they could not use monopoly rents to keep on financing intangible investment after the crisis. Regression results in column 2 of Table 3 support this view: we find that financial constraints have a larger adverse effect on intangible investment when competition is stronger (i.e., when the country-sector median Lerner index is lower).

We then examine potential complementarity between monetary and competition policies by running a regression of specification (3). To the extent that expansionary monetary conditions could help alleviate the adverse impact of financial constraints on intangible investment (column 1) and that such adverse effects are particularly strong in a more competitive environment (column 2), it should be the case that the role of countercyclical macroeconomic policy is more pronounced for firms facing high competition, suggesting potential complementarity—countercyclical policy that prevents a slowdown in intangible investment by constrained firms is more effective in a more competitive environment. This is precisely what column 3 in Table 3 reports, as illustrated in Figure 5. Coefficient estimates on

[13]The 0.15 percentage point difference in the decline in the ratio of intangible investment to total assets in Figure 1 corresponds to about a 1 percentage point difference in the ratio of intangible investment to intangible assets, or about a $1 \times 5 = 5$ percent cumulative loss in intangible capital. Applying a 20 to 40 percent return on this capital implies a 1 to 2 percent output loss in the high-leverage firm vis-à-vis its low-leverage counterpart—which, per the estimates in Table 3, is therefore the output loss prevented by a 100 basis point negative surprise on monetary conditions. Note that this back-of-the envelope calculation is performed only within each country sector. We conjecture that the aggregate effects of financial frictions on intangible investment, and thereby on output, are also likely to have played out across country sectors, with the more leveraged among them being more affected. Any such effects are absorbed by our four-digit country-sector fixed effects here.

Figure 5. Illustration of the Baseline Estimation Results: Complementarity between Product Market Competition and Countercyclical Policy



Note: High (low) leverage corresponds to the 75th (25th) percentile of the cross-firm distribution of precrisis average leverage ratios. The green shaded bars indicate the difference in estimated effects for high- and low-leverage firms in contractionary and expansionary monetary conditions, respectively, while the red bars measure the difference between them, separately for strong and weak competition environments. Estimated coefficients are from column 4 in the baseline results table. Expansionary/contractionary monetary conditions are defined as forecast errors in 10-year government bond yields by +/−50 bps. Weak (strong) competition corresponds to the 75th (25th) percentile of the country-sector distribution of precrisis average Lerner index values.

the triple interaction term are negative and statistically significant, reinforcing the alleviating role of expansionary conditions when firms face stronger competition. These results provide evidence of a complementarity between procompetitive product market reforms and countercyclical macroeconomic policy.

The estimated magnitude of this complementarity between procompetitive product market reforms and countercyclical macroeconomic policy is illustrated in Figure 5, which is an extension of Figure 4. Specifically, when product market competition is stronger (at the 25th percentile of the precrisis distribution of Lerner indices), the estimated cut in intangible investment by more-leveraged firms relative to their less-leveraged counterparts can be reduced from 0.25 to 0.08 percentage point when monetary conditions are more (rather than less) expansionary than expected (green shaded bars on the left). When competition is weaker (at the 75th percentile of the

Lerner index distribution), the corresponding numbers are smaller at 0.16 and 0.05 (green shaded bars on the right), and so is the difference between them—0.25 – 0.08 = 0.17 versus 0.16 – 0.05 = 0.11 (red solid and shaded bars in the middle), implying an overall 50 percent stronger effect of countercyclical macroeconomic policies in more competitive environments.

Table 4 checks whether our baseline results reflect the effects on intangible investment only or also capture those relative to tangible investment. We replace the dependent variable with the difference in the average ratio of intangible to tangible assets (column 1) or the difference in the average investment in tangible assets (scaled by total assets; column 2), both between the pre- and postcrisis periods. The estimation results confirm that the identified channel—financial frictions—through which countercyclical macroeconomic policies and product market competition shape the response of investment to credit conditions is more pronounced for intangible assets than it is for tangible ones.

4. Extensions and Robustness Checks

We perform a wide range of sensitivity analyses on our baseline results reported in the previous section. In particular, we show that our findings are robust to alternative measures of expansionary macroeconomic policies, product market competition, and firm balance sheet vulnerability.

Table 5 confirms that the baseline results are robust to alternative measures of expansionary monetary conditions. Keeping the baseline competition measure, we alternate the policy shocks measures: the deviation of the actual policy rate from Taylor-rule-implied rate (column 1); the forecast error of the actual short-term rate that is orthogonal to changes in inflation and output growth (column 2); and the forecast error of the government consumption expenditure to GDP (column 3). All of them show qualitatively identical results to the baseline results reported in Table 3. In particular, all double and triple interaction terms featured in column 3 of Table 3 remain statistically significant, with the partial exception of the triple interaction term testing for the complementarity between competition and countercyclical monetary policy, which is only borderline significant (at

Table 4. Baseline Estimation Results: Intangible Investment vs. Tangible Investment

	Intangible-to-Total-Assets Ratio (1)	**Investment in Tangible Assets (2)**
$Vulnerability_{isc}$	–0.022***	–0.017***
	(0.004)	(0.003)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_{c}$	0.027***	0.002
	(0.006)	(0.005)
$Vulnerability_{isc} \times Weak\ Competition_{sc}$	0.141***	–0.001
	(0.053)	(0.048)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_{c} \times Weak\ Competition_{sc}$	–0.233***	0.007
	(0.079)	(0.075)
Observations	664,086	674,266
R-squared	0.012	0.033
Country-Sector Fixed Effects	Yes	Yes

Note: The dependent variable is the difference in the average ratio of intangible assets to total (tangible + intangible) assets between post- and precrisis periods in column 1; it is the difference in the average net investment in tangible assets (as a ratio of total assets) between post- and precrisis periods in column 2. Firm-level vulnerability is measured as the average debt-to-assets ratio in the precrisis period. Expansionary monetary conditions is the average OECD forecast error for long-term (10-year government bond) interest rate in the postcrisis period as a measure of more-than-expected policy loosening. Weak competition is measured as the median precrisis Lerner index value in each country sector, reflecting the degree of profitability. The postcrisis period starts in 2008. Firm-specific controls (included in regressions but not reported) are firm age, total assets, and cash flow/assets ratio as well as their interaction terms with expansionary monetary conditions and/or weak competition measures. All columns include country-sector fixed effects. Standard errors are clustered at the country-sector level. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table 5. Alternative Measures of Macroeconomic Policy Shocks

	Deviation from Taylor Rule (1)	**Forecast Errors in Short-Term Policy Rate (2)**	**Forecast Errors in Government Consumption (3)**
$Vulnerability_{isc}$	–0.005***	–0.011***	–0.015***
	(0.001)	(0.001)	(0.001)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_{c}$	0.004***	0.010***	0.014***
	(0.000)	(0.003)	(0.001)
$Vulnerability_{isc} \times Weak\ Competition_{sc}$	0.019***	0.062***	0.099***
	(0.010)	(0.015)	(0.015)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_{c} \times Weak\ Competition_{sc}$	–0.016**	–0.072*	–0.121***
	(0.006)	(0.038)	(0.017)
Observations	664,086	571,482	647,836
R-squared	0.063	0.062	0.063
Country-Sector Fixed Effects	Yes	Yes	Yes

Note: The dependent variable is the difference in the average net investment in intangible assets (as a ratio of total assets) between post- and precrisis periods. Firm-level vulnerability is measured as the average debt-to-assets ratio in the precrisis period. Expansionary monetary conditions as a measure of more-than-expected policy loosening is the average deviation of policy rates from the Taylor-rule-implied one in the postcrisis period in column 1; the forecast error in monetary policy rates from Duval and Furceri (2018) in column 2; and the forecast error of government consumption expenditure to GDP from Duval and Furceri (2018) in column 3. Weak competition is measured as the median precrisis Lerner index value in each country sector, reflecting the degree of profitability. Firm-specific controls (included in regressions but not reported) are firm age, total assets, and cash flow/assets ratio as well as their interaction terms with expansionary monetary conditions and/or weak competition measures. All columns include country-sector fixed effects. Standard errors are clustered at the country-sector level. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

the 10 percent level) when the forecast error of the short-term rate is used.[14]

Likewise, Table 6 confirms that the baseline results are robust to alternative measures of product market competition. This time, we keep the baseline monetary condition measure, and alternate the competition measures: the country-sector median of estimated markups (column 1); OECD's overall product market regulation (PMR) indicator (column 2); OECD's subindicator on regulatory protection of incumbents (column 3); and OECD's subindicator on administrative burdens on start-ups (column 4). All columns indicate qualitatively identical results to the baseline results, with all relevant effects showing statistical significance at the 1 percent confidence level.

We conduct three additional sets of robustness checks on the sample, baseline specification, and firm-level balance sheet vulnerability variable, the results of which are summarized in Table 7. First, we shorten the time window to 2005–10 (two years before versus two years after the GFC), which also has the advantage of fully removing the 2010–12 euro-area crisis period. Since the adverse effects of financial frictions are likely to have been more acute right after the crisis, we expect the estimated effects to be at least as big as the baseline results. This is confirmed by slightly larger point estimates in absolute terms compared with those from the baseline estimation (column 1).

Second, we check the robustness of our results to an alternative measure of firm-level financial vulnerability, namely the interest coverage ratio. The higher the ratio is, the greater the debt burden is, and the more vulnerable the firm should be to a tightening of credit conditions. Again, this yields qualitatively identical results to the baseline regression (column 2).

Moreover, given that intangible investment data are potentially noisy, as discussed earlier, we replace the dependent variable with a

[14]In addition, we checked the possibility that the expansionary monetary policies could be associated with lower economic policy uncertainty and, hence, our findings might reflect the channel via the latter rathan than the former. Specifically, we ran a horse race regression between expansionary policy and uncertainty measures by including an exhaustive list of interaction variables and could confirm that the main findings are driven by expansionary policy measures rather than uncertainty measures.

Table 6. Alternative Measures of Product Market Competition

	Median Markup (Country Sector) (1)	Product Market Regulation (2)	Regulatory Protection of Incumbents (3)	Administrative Burden for Start-Ups (4)
$Vulnerability_{isc}$	–0.011***	–0.018***	–0.042***	–0.030***
	(0.001)	(0.002)	(0.003)	(0.003)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_c$	0.011***	0.041***	0.067***	0.052***
	(0.002)	(0.003)	(0.005)	(0.005)
$Vulnerability_{isc} \times Weak\ Competition_{sc}$	0.003***	0.008***	0.030***	0.009***
	(0.001)	(0.001)	(0.003)	(0.001)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_c \times Weak\ Competition_{sc}$	–0.004***	–0.021***	–0.049***	–0.017***
	(0.001)	(0.002)	(0.004)	(0.002)
Observations	664,086	664,086	664,086	664,086
R-squared	0.062	0.062	0.062	0.062
Country-Sector Fixed Effects	Yes	Yes	Yes	Yes

Note: The dependent variable is the difference in the average net investment in intangible assets (as a ratio of total assets) between post- and precrisis periods. Firm-level vulnerability is measured as the average debt-to-assets ratio in the precrisis period. Expansionary monetary conditions is the average OECD forecast error for long-term (10-year government bond) interest rate in the postcrisis period as a measure of more-than-expected policy loosening. Weak competition is measured as the median markup estimate in each country sector, reflecting the degree of profitability in column 1; the OECD indicator of product market regulation (PMR) in 2008 in column 2; the OECD indicator of regulatory protection of incumbents (RPI) in 2008; and the OECD indicator of administrative burdens for start-ups (ABS) in 2008 in column 4. The postcrisis period starts in 2008. Firm-specific controls (included in regressions but not reported) are firm age, total assets, and cash flow/assets ratio as well as their interaction terms with expansionary monetary conditions and/or weak competition measures. All columns include country-sector fixed effects. Standard errors are clustered at the country-sector level. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table 7. Further Robustness Checks

	Shorter Window (2005–10) (1)	**Alternative Vulnerability (Interest Coverage) (2)**	**Linear Probability (3)**	**Excluding Zeros (No Intangible Assets) (4)**	**Excluding M&A Firms (No Goodwill) (5)**
$Vulnerability_{isc}$	–0.013***	–0.002***	–0.175***	–0.010***	–0.008***
	(0.001)	(0.000)	(0.013)	(0.001)	(0.001)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_c$	0.011***	0.004***	0.078***	0.011***	0.009***
	(0.002)	(0.001)	(0.023)	(0.002)	(0.001)
$Vulnerability_{isc} \times Weak\ Competition_{sc}$	0.093***	0.012*	0.879***	0.069***	0.060***
	(0.015)	(0.007)	(0.209)	(0.016)	(0.013)
$Vulnerability_{isc} \times Expansionary\ Monetary\ Conditions_c \times Weak\ Competition_{sc}$	–0.100***	–0.028***	–0.623*	–0.096***	–0.073***
	(0.024)	(0.009)	(0.322)	(0.023)	(0.020)
Observations	615,143	664,453	664,086	518,048	650,533
R-squared	0.074	0.060	0.087	0.072	0.063
Country-Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the difference in the average net investment in intangible assets (as a ratio of total assets) between post- and precrisis periods. Firm-level vulnerability is measured as the average debt-to-assets ratio in the precrisis period except for in column 2, where it is measured as the interest coverage ratio (the average ratio of interest payments to earnings (EBITDA)) in the precrisis period. Expansionary monetary conditions is the average OECD forecast error for long-term (10-year government bond) interest rate in the postcrisis period as a measure of more-than-expected policy loosening. Weak competition is measured as the median precrisis Lerner index value in each country sector, reflecting the degree of profitability. Column 1 considers a shorter window between 2005 and 2010; column 3 corresponds to linear probability model by replacing the non-negative dependent variable with 1 (and 0 otherwise). Column 4 excludes observations without intangible assets in both periods, and hence, no change in intangible investment during the periods. Column 5 excludes observations with any M&A activity during the periods. The postcrisis period starts in 2008. Firm-specific controls (included in regressions but not reported) are firm age, total assets, and cash flow/assets ratio as well as their interaction terms with expansionary monetary conditions and/or weak competition measures. All columns include country-sector fixed effects. Standard errors are clustered at the country-sector level. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

dummy variable that takes value 1 for non-negative changes in net intangible investment between the pre- and postcrisis periods, and 0 otherwise (negative change). This linear probability model has the advantage of being potentially less prone to measurement error in the dependent variable. Again, results are qualitatively identical to the baseline specification (column 3). In a similar vein, we exclude those firms that have never had any intangible assets throughout the sample period—about 10 percent of the full sample. The estimation results are almost identical to the baseline results, with slightly bigger point estimates (column 4).

Relatedly, potential measurement issues due to mergers and acquisitions can be substantial to the extent that goodwill—an intangible asset that is created when one company acquires another company for a price greater than its net asset value—is likely to be unrelated to internally generated intangible assets (e.g., Ewens, Peters, and Wang 2024). We confirmed that our results are not simply driven by potential measurement issues due to mergers and acquisitions (M&As) by excluding all the firms with M&A activities, which are identified from the Zephyr, a comprehensive M&A data set compiled by Bureau Van Dijk. This subsample result is summarized in column 5.

5. Conclusion

Investment in intangible assets is an increasingly important driver of economic growth but, being nonpledgeable as collateral and hard to liquidate quickly, it is also potentially vulnerable to financial frictions. This implies that countercyclical macroeconomic policy could strengthen longer-term growth by sheltering intangible investment from adverse shocks, particularly so where strong product market competition prevents firms from self-financing their investments through rents. Using a large cross-country firm-level data set and focusing on the Global Financial Crisis and its aftermath, this paper finds strong support for these theoretical predictions. Our results highlight a complementarity between procompetition product market deregulation and countercyclical monetary (and fiscal) policy in fostering intangible investment and growth.

Our findings thus have strong implications for economic theory and policy that give rise to the possibility that countercyclical

macroeconomic policy persistently or even permanently affects growth. Moreover, insofar as product market competition can backfire when credit constraints bite in downturns, our results call for strengthening countercyclical macro policies alongside any market deregulation to foster growth.

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Public Funding of Banks and Firms in a Time of Crisis*

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We study public funding of banks and nonfinancial firms in a time of crisis. We find that bank capitalization is more effective in stabilizing the economy than direct funding to firms, but it also creates larger distortions. We show that the optimal, social-welfare-maximizing, structure of a public funding program depends on its size. Small funding programs should target banks, while large programs should be directed at nonfinancial firms. We provide an interpretation of the result in terms of dominated and undominated policies under genuine uncertainty.

JEL Codes: E44, G21, G28, G38, H12, H81.

1. Introduction

Governments often provide capital and other direct funding to banks and nonfinancial firms during economic crises. In the crises taking

*We are grateful to Steven Ongena (the Editor) and two anonymous referees for insightful and constructive comments. We also thank Alice Albonico, Gene Ambrocio, Michal Andrlé, Efrem Castelnuovo, Martin Ellison, Adam Gulan, Marlène Isoré, Esa Jokivuolle, Ilkka Kiema, Kevin Moran, Nigel McClung, Alessia Paccagnini, George Pennacchi, Jean-Stéphane Mésonnier, John Tsoukalas, Kozo Ueda, Harald Uhlig, Fabio Verona, Lauri Vilmi, and seminar participants at the Bank of Finland, HECER, the Universities of Hokkaido, Keio, Kyoto, Jyväskylä, Oxford, Padua, Pavia, and St. Gallen, and at the IMF, Council for Budget Responsibility (Slovakia), Czech National Bank, ISCEF, EEA, Dynare, CEF, MMF, AFSE, FEA, and at the International Rome Conference of Money, Banking and Finance for useful discussions and comments. Ripatti and Takalo also acknowledge financial support from the Yrjö Jahnsson Foundation and the OP Group Research Foundation and Ripatti from Research Council of Finland (Grant No. 340551). This work was developed while Ripatti was a visiting scholar at the Bank of Finland, whose hospitality is gratefully acknowledged. The views expressed in this paper do not necessarily reflect the views of the Bank of Finland. Author emails: markus.haavio@bof.fi; antti.ripatti@helsinki.fi; tuomas.takalo@bof.fi.

place between 1970 and 2007, these resolution measures were present in 33 episodes out of 42, and government capitalization of banks averaged around 8 percent of gross domestic product (GDP) (Laeven and Valencia 2012). During the Great Recession the Federal Reserve System (the Fed) and the U.S. Treasury injected capital and direct funding into both banks and nonfinancial firms, with the sizes of bank and nonbank financing programs reaching close to 5 percent and 3 percent of GDP, respectively (SIGTARP 2014; Labonte 2016).[1] During the COVID-19 crisis the Fed and the U.S. Treasury mostly supported nonfinancial firms, with the size of the funding programs exceeding 15 percent of GDP.[2]

In this paper we consider a government which has, in a time of crisis, decided to provide public funding to the private sector, and ask how the funding should be allocated between banks and nonfinancial firms. We show that the optimal *structure* of the program depends on its *size*: If the program is relatively small, the government should capitalize banks. But if the program is large enough, public funding should be allocated to nonfinancial firms.

To study the effects of public funding programs on banks' and firms' balance sheets, economic activity, and social welfare, we embed the dual moral hazard framework of Holmström and Tirole (1997) into a dynamic macro model. In their flexible framework (see Tirole 2006 for applications) entrepreneurs and banks can tap

[1]The U.S. Treasury injected equity capital in the financial sector and direct funding to the automotive industry via the Troubled Asset Relief Program (TARP), whose size was decided prior to the allocation of its funds. The Fed created the Commercial Paper Funding Facility and Term Asset-Backed Securities Loan Facility programs to provide liquidity to both the financial and real sectors. Similar funding programs were, for example, implemented in the European Union (EU) and U.K. (European Commission 2014; Grosse-Rueschkamp, Steffen, and Streitz 2019).

[2]Federal government provided lending through the Fed, Treasury, and Small Business Administration (see, e.g., https://www.covidmoneytracker.org/explore-data/interactive-table, accessed Febrary 6, 2023). The Fed introduced Primary and Secondary Market Corporate Credit Facilities, the Main Street Business Lending Program, the Paycheck Protection Program Liquidity Facility, and purchased mortgage-backed securities (e.g., https://www.federalreserve.gov/newsevents/pressreleases/monetary20200409a.htm, accessed May 12, 2020). Similar and even more sizable support programs were introduced in the EU and U.K.—see, e.g., https://www.ft.com/content/26af5520-6793-11ea-800d-da70cff6e4d3, accessed January 12, 2024.

into external funding for leveraging their investments, at the cost of moral hazard problems. Hence sufficiently large banks' and entrepreneurs' own stakes in the investment projects are needed to maintain their incentives. We work with a version of the model with endogenous monitoring intensity, where not only the sum of informed (i.e., bank and entrepreneurial) capital but also its composition matters. Depending on the ratio of aggregate bank capital to aggregate entrepreneurial capital, the basic agency problem in the economy is resolved in different ways: either entrepreneurs have sufficiently large stakes in the investment projects, which renders bankers' intensive monitoring unnecessary, or, alternatively, bankers have large stakes and strong monitoring incentives, in which case entrepreneurs' small stakes are enough to maintain their incentives.

We find an investment- and output-maximizing composition of informed capital, which depends on the efficacy of bankers' monitoring technology. In equilibrium the ratio of aggregate bank capital to aggregate entrepreneurial capital tends to be too low compared with the output-maximizing level. As a result of this relative *scarcity* of bank capital, a given change in bank capital has a larger impact on incentives and aggregate investment than a corresponding change in entrepreneurial capital.

While we model financial frictions as in Holmström and Tirole (1997), banks in our model have large balance sheets and diversified asset portfolios, but nonfinancial firms are small and specialized. As a result, firms are more vulnerable to idiosyncratic shocks while banks are more sensitive to aggregate investment shocks. After a negative aggregate shock, more entrepreneurs fail, but limited liability caps the loss at the micro level, while at the macro level specialization of nonfinancial firms protects entrepreneurs as a group from spillovers: successful entrepreneurs are not responsible for the unpaid debt of bankrupt entrepreneurs. Since banks absorb the loan losses and pay in full to their creditors, the negative macro shock has a levered effect on bank capital. Because of this *sensitivity* of bank capital to aggregate shocks, bank capital propagates shocks more extensively than entrepreneurial capital.

In a time of crisis, public funding can improve welfare by rendering the financial system more resilient in the face of adverse macro shocks. We show that the welfare benefits of a public funding program depend on its size, which determines the share of the private

sector's macro risk exposure taken over by the government. A larger program reduces bankers' ex post loan losses due to a macro shock by a larger percentage. The larger the size of the program and the larger the negative shock realization, the larger the welfare benefits (ex post) from the public intervention.

A program of a given size and welfare benefits from improved resilience (upon a shock realization) can be constructed by different combinations of bank capitalization and public funding of nonfinancial firms. We call this the *policy frontier*. We also show that the slope of the policy frontier depends on the size of the program: Due to the sensitivity of bank capital to aggregate shocks, smaller public ownership stakes in banks than in nonfinancial firms implement a given program size. But this relative advantage of bank capitalization becomes smaller as the size of the program grows. If the government has already taken over a large part of the macro risk in the banking sector, strengthening the banks' equity cushions further has a smaller relative effect compared with public funding of firms, which reduces banks' exposure to risks from the real sector.

However, public funding dilutes banks' and nonfinancial firms' existing owners' stakes and incentives. An optimal structure of a program, given its size, is a combination of bank capitalization and public funding of nonfinancial firms that minimizes welfare losses from distorted incentives. The size of the program affects its optimal structure. A given stabilization effect can be attained with a smaller public stake when the government targets banks rather than firms. But due to the relative scarcity of bank capital, each unit of public funds dilutes existing owners' stakes and incentives more when placed in banks rather than nonfinancial firms. Initially, this trade-off favors bank capitalization. When the desired stabilization effect is larger, there is a smaller difference between the required public stakes. Ultimately, for a sufficiently large program, its larger incentive distortions make bank capitalization inferior to the funding of nonfinancial firms from the welfare perspective.

In a time of crisis, policy design may take place under genuine uncertainty: the government does not necessarily know how severe the crisis will be, and it may even be unable to assign a probability distribution. What advice can be given to the government under such circumstances? Our analysis provides an answer to this question, since we characterize the sets of *dominated* and *undominated*,

or *Pareto-optimal*, policies under genuine uncertainty. A policy, say A, dominates another policy, say B, if A generates as high welfare as B after any negative shock realization, and higher welfare after some shock realizations. A policy is undominated, or Pareto optimal, if and only if it is not dominated by any other policy. We show that the mapping from the size of a program to its appropriate structure determines the sets of undominated and dominated policies. Small programs targeting banks, and large programs targeting nonfinancial firms, belong to the undominated set. A small public funding program directed at firms is dominated by a program of the same size directed at banks, while a large program allocated to banks is dominated by a program of the same size allocated to firms. All programs simultaneously funding both banks and firms are dominated by a program funding exclusively banks or firms with an appropriate structure. A government facing genuine uncertainty should select a funding program from the set of undominated options, and never choose a program which is dominated.

Our paper adds to the literature on the effects of government funding of banks and nonfinancial firms in a unified macro framework. Gertler and Kiyotaki (2010) study credit market interventions during the Great Recession, and show how the net benefits of the interventions are increasing with the severity of the crisis. Hirakata, Sudo, and Ueda (2013, 2017) extend the Bernanke, Gertler, and Gilchrist (1999) model to credit chains. In their model, capital injections to banks and firms lower the external finance premiums and stimulate the economy, but may also result in more macro volatility. Capital injections to financial intermediaries boost economic activity more than public funding of nonfinancial firms. Sims and Wu (2020) develop a version of the Gertler and Karadi (2011, 2013) model of financial intermediation, where financial intermediaries' possibilities to absorb corporate bonds depend on corporate cash flows. They compare the Fed's bond purchases from financial intermediaries (Wall Street QE) with bond purchases directly from nonfinancial firms (Main Street QE). If the cash flow constraint is unbinding, Wall Street QE and Main Street QE are substitutes, but if the constraint binds, financial intermediaries are unwilling to buy bonds, making Wall Street QE ineffective, while Main Street QE can still stimulate the economy. We complement the literature by analyzing the socially optimal allocation of public funds between banks

and nonfinancial firms when capital structure decisions and incentive problems in the financial and real sectors determine the social costs and benefits of public policies. We also characterize dominated and undominated policies under genuine uncertainty.

There is also a related literature on public funding of either banks or nonfinancial firms. For example, Philippon and Schnabl (2013) study efficient bank recapitalizations, while Bhattacharya and Nyborg (2013) use the menu of bailout plans as a screening device. In these papers, banks suffer from debt overhang. Curdia and Woodford (2011), Gertler and Karadi (2011, 2013), and Del Negro et al. (2017) study government funding of nonfinancial firms via large-scale asset purchases by the central bank, while Bianchi (2016) analyzes the ex post crisis mitigation and the ex ante moral hazard resulting from firm bailouts. In a difference to these papers, we emphasize the effects of public funding on intratemporal rather than intertemporal incentive problems. We also analyze public funding of both banks and nonfinancial firms, and present a criterion how to choose between these two.

A growing macrofinance literature applies the Holmström and Tirole (1997) framework. Contributions include Chen (2001), Aikman and Paustian (2006), Meh and Moran (2010), Christensen, Meh, and Moran (2011), Chang, Fernández, and Gulan (2017), Faia (2018), and Silvo (2019). We extend this framework in terms of our modeling of banks: a bank is a balance sheet structure with many bankers. We can thus combine diversified portfolios at the bank level with the Holmström and Tirole (1997) type incentive problems at the banker level.[3]

In the next section we describe the basic model. In Section 3, we explain why bank capital is likely to be scarce in equilibrium. In Section 4, we introduce an aggregate investment shock into the model, and explain why bank capital is more sensitive to these shocks than entrepreneurial capital. In Section 5, we calibrate the model,

[3]In the standard Holmström and Tirole (1997) framework, a bank's asset portfolio is assumed to be completely correlated. Together with the assumption that unsuccessful firm projects return zero, this renders debt indistinguishable from equity on the liability side of the bank's balance sheet: either the bank can pay to all stakeholders or it can pay to nobody. In our model with diversified portfolios, the claims of a bank's creditors and equity holders can be meaningfully distinguished when there are aggregate shocks.

and further analyze and illustrate the scarcity and sensitivity of bank capital. In Section 6, we analyze public funding of banks and nonfinancial firms and characterize the optimal structure of public funding. Section 7 concludes.

2. The Model

We consider a discrete-time infinite-horizon economy populated by households with three types of members: workers, entrepreneurs, and bankers. On the financial side of the economy, bankers manage financial intermediaries (banks) that obtain deposits from households and finance entrepreneurs. The real economy contains two sectors: (i) competitive firms producing final goods from labor supplied by workers and capital supplied by entrepreneurs, and (ii) entrepreneurs producing capital goods.

Households own banks and all firms, including those producing capital goods. Households also own the capital stock. The production of capital is subject to a dual moral hazard problem in the sense of Holmström and Tirole (1997). Entrepreneurs, who may obtain external finance from households and banks, are tempted to choose less productive projects with higher nonverifiable returns. Bankers can monitor entrepreneurs to mitigate their moral hazard temptations, but since banks use deposits from households to finance entrepreneurs, bankers have an incentive to avoid costly monitoring. The moral hazard problems may be solved by designing a proper financing contract. The timing of events in each period is summarized in Table 1, while Appendix A.1 provides a still more detailed description. The key part of the model is Stage 2, where finance and the real economy interact.

2.1 Households and Final Good Production

There is a continuum of identical households of measure unity. Within each household, there are three occupations: in every period t, a fraction of the household members become entrepreneurs, another fraction become bankers, and the rest remain workers. At the beginning of each period, an entrepreneur and a banker exit from their occupations at random according to a Poisson process with constant exit rates $1 - \lambda^e$, $\lambda^e \in (0, 1)$ and $1 - \lambda^b$, $\lambda^b \in (0, 1)$,

Table 1. Timeline of Events

Period Starts	
Stage 1	Survival probabilities realized and exiting bankers and entrepreneurs give their accumulated assets to households. Household members separate into their occupations. Consumption-savings and labor supply decisions are made. Final goods are produced using capital and labor.
Stage 2	Financial contracts are signed, depositors place their funds in banks, and banks finance entrepreneurs. Bankers choose monitoring intensity. Entrepreneurs choose the project type. Successful projects yield capital goods that are sold. Proceeds are divided according to the contract.
Period Ends	

respectively. The number of household members becoming entrepreneurs and bankers equals the number of exiting entrepreneurs and bankers. This construction permits us to introduce financial frictions in banks and firms, while retaining the tractability of the representative household structure, thus abstracting from consumption heterogeneity across different types of agents.[4]

The head of a household decides on behalf of its members how much they will work, consume, and invest in capital. In Section 2.2, we explain in detail how entrepreneurs invest in risky projects to produce capital goods and how bankers provide funding for

[4]See, e.g., Gertler and Kiyotaki (2010), Gertler and Karadi (2011, 2013), Christiano, Motto, and Rostagno (2014), Chang, Fernández, and Gulan (2017), Del Negro et al. (2017), Silvo (2019), and Sims and Wu (2020, 2021) for a similar construction.

these investments. In general, entrepreneurs and bankers earn higher returns on their risky investments than workers earn on their deposits. Hence, it is optimal for the household to let its entrepreneurs and bankers keep building up their assets until exiting their occupations. The exiting entrepreneurs and bankers give their accumulated assets to the household, which in turn provides new entrepreneurs and bankers with some initial investment capital. Within the household, there is perfect consumption insurance against the risks of entrepreneurs and bankers. Therefore, all household members consume an equal amount in each period.

The problem of a representative household is

$$\max_{\{C_t \geq 0, L_t \geq 0, K_t \geq 0\}_{t=0}^{\infty}} E_0 \left[\sum_{t=0}^{\infty} \beta^t \left(\frac{1}{1-\sigma} {C_t}^{1-\sigma} - \frac{\xi}{1+\phi} L_t^{1+\phi} \right) \right],$$

subject to an intertemporal budget constraint:

$$C_t + q_t K_{t+1} = W_t L_t + K_t \left[r_t^K + q_t(1-\delta) \right] + T_t. \tag{1}$$

In the household's utility function $\sigma > 0$, $\xi > 0$, and $\phi > 0$ are parameters; $\beta \in (0,1)$ is the time preference discount factor; and C_t and L_t denote consumption and hours worked in period t, respectively. In the budget constraint (1), W_t is the real wage, K_t the stock of physical capital, r_t^K the real rental rate of capital, q_t the price of capital goods, $\delta \in (0,1)$ the rate of depreciation of physical capital, and T_t denotes lump-sum transfers (net payouts from entrepreneurs and bankers) and (possible) taxes. Buying and selling claims to the capital stock allows a household to smooth consumption. We assume, as in Carlstrom and Fuerst (1997), that bank deposits are intraperiod and, consequently, they do not appear in the intertemporal budget constraint (1).[5]

In equilibrium, physical capital stock accumulates according to the law of motion

$$K_{t+1} = (1-\delta) K_t + p_H R I_t, \tag{2}$$

where I_t is investment in period t. This accumulation equation is standard save for the two parameters of capital good production,

[5]See also the discussion in Section 2.2.1.

$p_H \in (0,1)$ and $R > 1$, which will be defined more precisely in Section 2.2.

Solving the household's dynamic optimization problem yields the familiar first-order conditions for L_t and C_t, respectively: $\xi {L_t}^{\phi} C_t^{\sigma} = W_t$ and

$$1 = \beta E_t \left[(1 + r_{t+1}) \left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \right], \tag{3}$$

where $(1 + r_{t+1}) \equiv [r^K_{t+1} + q_{t+1}(1 - \delta)]/q_t$ is the intertemporal real interest rate. Competitive firms in the final good sector combine capital K_t and labor L_t using the Cobb-Douglas production function $Y_t = K_t^{\alpha} L_t^{1-\alpha}$, where $\alpha \in (0,1)$. Profit maximization results in the familiar equations for optimality conditions: $W_t = (1 - \alpha) Y_t / L_t$ and $r^K_t = \alpha Y_t / K_t$.

2.2 Financial Frictions

Capital demanded by firms in the final good sector is produced by entrepreneurs who are endowed with investment projects and some initial wealth. Entrepreneurs can also attempt to leverage their investments by borrowing from bankers and workers. It may be best to think that intermediation of entrepreneurial finance occurs only among households. To clarify how financial intermediation takes place, let us consider three households: A, B, and C. We can think that the workers of household A first deposit their funds with the banks of household B, who then invest the deposits in projects of household C's entrepreneurs along with their own bank capital. The term "deposits" should be interpreted broadly, encompassing both retail deposits and wholesale debt funding of banks. In particular, the marginal unit is always wholesale funding, and not covered by any deposit insurance scheme.

All successful investment projects transform i_t units of final goods into Ri_t ($R > 1$) verifiable units of capital goods, while failed projects yield nothing. The projects differ in their probability of success and in the amount of nonverifiable revenues they create. There is a "good" project that is successful with probability p_H and involves no nonverifiable revenues to the entrepreneur. We adopt the normalization $p_H R = 1$, so that the equilibrium law of motion of capital (2) is the same as in a standard growth model or real business cycle (RBC) model.

There is also a continuum of bad projects with a common success probability $p_L = p_H - \Delta p$, where $0 \leq p_L < p_H < 1$ and $\Delta p > 0$, but with differing amounts of nonverifiable revenues $h_t i_t$, $h_t \in \left(0, \overline{h}\right]$ attached to them. Nonverifiable revenues are proportional to investment size as in Holmström and Tirole (1997). Departing from Holmström and Tirole (1997), where bad projects generate nontransferable private benefit, we assume, in line with Meh and Moran (2010), Christensen, Meh, and Moran (2011), Faia (2018), and Silvo (2019), that private benefits are divisible and transferable.[6] In our case, this assumption is only needed to ensure the smoothness of out-of-equilibrium payoffs. If, in an out-of-equilibrium event, an entrepreneur had picked a bad project, her project returns should be transferable and divisible among her household members upon her exit from entrepreneurship. Further, we assume that $q_t p_H R = q_t > q_t p_L R + \overline{h}$ to ensure that the good project is preferable to all bad projects from the household's point of view.

Bankers are endowed with a variable-scale monitoring technology that enables them to constrain the entrepreneurs' project choice. Monitoring at the intensity level m_t $(m_t \geq 0)$ eliminates all bad projects where $h_t \geq h(m_t)$ from the entrepreneur's project choice set. The threshold level of nonverifiable revenues $h(m_t)$ is decreasing and convex in monitoring intensity: $h'(m_t) \leq 0, h''(m_t) \geq 0$, and $\lim_{m_t \to \infty} h'(m_t) = 0$. As in Christensen, Meh, and Moran (2011) and Silvo (2019), monitoring involves real costs for the bank: to obtain monitoring intensity m_t, a bank must pay $m_t i_t$ units of final goods to workers.[7] That is, the more a banker invests in monitoring, the less his bank can lend to entrepreneurs.

[6] An interpretatation is, reminiscent of Bolton and Scharfstein (1990), that project revenues are verifiable outside a household only up to R, or that only revenues in terms of capital goods are verifiable outside a household. Alternatively, following, e.g., Burkart, Gromb, and Panunzi (1998), we may think that an entrepreneur is able to divert part of her firm's resources to her own use at an interim stage. As in Burkart, Gromb, and Panunzi (1998), such expropriation of outside investors is costly. Here it is captured by the lower expected project returns if diversion takes place.

[7] Monitoring costs are transfers to workers, which do not enter the real resource constraint of the economy. This assumption is not quantitatively restrictive, as the total monitoring cost—while crucial for bankers' incentives—is very small relative to the size of the real economy. In the baseline calibration of the model, the steady-state monitoring cost mI is approximately 0.15 percent of total output Y, whereas consumption C is roughly 80 percent and investment I is roughly

Our assumption of variable-scale and endogenous monitoring intensity follows the modeling strategy in Holmström and Tirole (1997, Section IV.4). As explained by Holmström and Tirole (1997), endogenous monitoring intensity is needed for bank and entrepreneurial capital to have distinct roles at the macro level. If instead the monitoring intensity were fixed, the aggregate production of capital goods would only depend on the total amount of informed capital, i.e., the sum of bank and entrepreneurial capital. With endogenous monitoring intensity, also the composition of informed capital matters. This is an important feature for our analysis of public funding of banks and firms.

2.2.1 The Financing Contract

In each period t, there are three contracting parties: entrepreneurs, bankers, and depositors (workers). Following standard practice,[8] we assume limited liability and interperiod anonymity, and focus on the class of one-period optimal contracts where entrepreneurs invest all their own wealth n_t in their projects. The financial contract then stipulates how much of the required funding of the project of size i_t comes from banks (a_t) and depositors (d_t) and how the project's return R, in case of success, is distributed among the entrepreneur (R_t^e), her bankers (R_t^b), and depositors (R_t^w).

A banker, given his share of project returns, maximizes the bank's profits by choosing monitoring intensity, m_t. Banks behave

20 percent. (See Appendix C, especially Equation (C.4).) However, omitting the cost from the resource constraint allows the analytical characterization of the optimal structure of public funding in Section 6. Technically, this is because the model becomes modular such that frictions in financial intermediation affect the real part of the economy only indirectly through the agency problems.

[8]Similar one-period contracts are used in the macrofinance literature. Examples include models applying the Bernanke, Gertler, and Gilchrist (1999) financial accelerator (e.g., Hirakata, Sudo, and Ueda 2013, 2017; Christiano, Motto, and Rostagno 2014), the financial intermediation model of Gertler and Karadi (2011, 2013) and its extensions (e.g., Sims and Wu 2020, 2021), and macrofinance models using the Holmström and Tirole (1997) approach, cited in the Introduction. While evidently simplifying, the assumption is less controversial in our case, where the focus is not on relationship lending (in which case multiperiod contracts would be quintessential). A future work could, e.g., build on Holmström and Tirole (1998) and consider crisis management policies in a more dynamic macrofinance setting—see, e.g., Farhi and Tirole (2012) for an advance to this direction.

competitively. As a result, they choose the same financing contract and monitoring intensity that would be chosen by a single bank maximizing the entrepreneur's expected profits.[9] Intuitively, each entrepreneur chooses a bank that offers it the most favorable contract and monitoring intensity, and no bank is able to attract entrepreneurs if it does not choose a contract or monitoring intensity that maximizes firm profits. An optimal financing contract therefore solves the following program:

$$\max_{\left\{i_t, a_t, d_t, R_t^e, R_t^b, R_t^w, m_t\right\}} q_t p_H R_t^e i_t$$

subject to the entrepreneur's and her banker's incentive constraints,

$$q_t p_H R_t^e i_t \geq q_t p_L R_t^e i_t + h\left(m_t\right) i_t, \tag{4a}$$

$$q_t p_H R_t^b i_t \geq q_t p_L R_t^b i_t + \left(1 + r_t^d\right) m_t i_t, \tag{4b}$$

the depositors' and banker's participation constraints,

$$q_t p_H R_t^w i_t \geq \left(1 + r_t^d\right) d_t, \tag{4c}$$

$$q_t p_H R_t^b i_t \geq \left(1 + r_t^a\right) a_t, \tag{4d}$$

and two resource constraints on investment inputs and outputs,

$$a_t + d_t - m_t i_t \geq i_t - n_t, \tag{4e}$$

$$R \geq R_t^e + R_t^b + R_t^w. \tag{4f}$$

According to Equations (4e) and (4f), the aggregate supply of investment funds must satisfy their aggregate demand equation and the total returns must be enough to cover the total payments. Variable r_t^a in the banker's participation constraint (4d) denotes the rate of return on bank capital in period t and, similarly, variable r_t^d in the

[9] Alternatively, we could assume that a banker maximizes his own expected profits, with the banker's participation constraint (4d) being replaced by the entrepreneur's participation constraint $q_t p_H R_t^e i_t \geq \left(1 + r_t^n\right) n_t$, where r_t^n is the market rate of return to entrepreneurial capital. This alternative way of setting up and solving the contracting problem leads to exactly the same equilibrium relationships as the approach taken in the paper.

banker's incentive constraint (4b) and in the depositors' participation constraint (4c) is the rate of return on deposits during the capital good production stage of period t, i.e., Stage 2 in Table 1. Since deposits are intraperiod, we follow Carlstrom and Fuerst (1997) and set $r_t^d = 0$, so that the gross rate of return earned by households—or workers—in the capital good production stage is $1 + r_t^d = 1$. One may think that the alternative available for the households is to store the representative consumption good during Stage 2 of the period, to be consumed at the end of Stage 2; the rate of return to storage is 1. This assumption is also in line with simple RBC and growth models, where the representative consumption good is transformed one-to-one into capital goods, and the gross rate of return in this capital good production stage is 1.

Each entrepreneur wants to invest as much as possible without breaking the depositors' and the banker's participation and incentive constraints. Hence, all constraints bind in equilibrium. Using this equilibrium property, we solve the entrepreneur's program in two steps. First, we take the intensity of monitoring m_t and, by implication, the level of private revenues $h(m_t)$ as given and solve for the maximum size of the investment project i_t for a given level of entrepreneurial wealth n_t. Second, we solve for the equilibrium level of monitoring m_t.

2.2.2 Investment, Leverage, and Monitoring at the Project Level

In the Holmström and Tirole (1997) framework, the maximum investment size depends on the amount of funds that can be raised from the outside, which in turn depends on the amount of the project returns that can credibly be pledged to depositors. In Appendix A.2 we show that maximum investment size is

$$i_t = \frac{n_t}{g(r_t^a, q_t, m_t)}, \tag{5a}$$

in which

$$g(r_t^a, q_t, m_t) \equiv \frac{p_H}{\Delta p} h(m_t) + \left[1 + \frac{p_H}{\Delta p}\left(1 - \frac{1}{1 + r_t^a}\right)\right] m_t - \rho_t \tag{5b}$$

is the inverse degree of leverage, i.e., the smaller the value of $g(\cdot)$, the larger the size of the investment project i_t for a given level of

entrepreneurial wealth n_t. The first term on the right-hand side of Equation (5b) shows how agency problems in the nonfinancial firm reduce leverage by discouraging participation by outside investors. These agency problems can be mitigated through increased monitoring. However, the second term reveals that intense monitoring has two negative effects on leverage: it consumes resources that could otherwise have been invested in the project and makes it harder to satisfy the banker's incentive constraint. These two effects are captured by the first and second terms in square brackets, respectively.[10] In other words, more extensive monitoring activity worsens the agency problem between a bank and a depositor. To overcome this moral hazard and attract more deposits, a larger share of the investment project must be financed by bank capital. Finally, the term $\rho_t \equiv q_t - 1 > 0$ denotes the net rate of return on the good investment project; the larger the rate of return, the easier it is to attract outside funding.[11]

Given the competitively behaving banking sector, the optimal choice of m_t maximizes the entrepreneur's expected profits $p_H q_t R_t^e i_t$, which may be rewritten, by using Equations (4a) and (5a), as $(p_H/\Delta p)\, h\,(m_t)\, n_t / g\,(r_t^a, q_t, m_t)$. Therefore, the optimal level of monitoring solves the problem

$$\max_{m_t \geq 0} \frac{h\,(m_t)}{g\,(r_t^a, q_t, m_t)}. \tag{6}$$

As can be seen from Equations (5b) and (6), the effects of monitoring on the entrepreneur's expected payoff are complex. The numerator in problem (6) shows how a larger scope of extracting private revenues implies a larger equilibrium share of the project returns for the entrepreneur, which dilutes the monitoring incentives. Monitoring incentives are also adversely affected by the negative effects of monitoring costs on leverage (second term in $g\,(\cdot)$ in Equation (5b)). However, smaller agency problems enable larger leverage (first term in $g\,(\cdot)$ in Equation (5b)). This provides an incentive for monitoring.

[10] Note that in equilibrium we must have $r_t^a \geq 0$.

[11] See Lian and Ma (2021) for evidence on related cashflow-based financial constraints.

To derive a tractable analytic solution to problem (6), we specify the following functional form for $h(m_t)$:

$$h(m_t) = \begin{cases} \Gamma m_t^{-\frac{\gamma}{1-\gamma}} & \text{if } m_t > \underline{m} \\ \overline{h} & \text{if } m_t \leq \underline{m}, \end{cases} \tag{7}$$

where $\Gamma > 0$, $\overline{h} > 0$, $\gamma \in (0, 1)$, and $\underline{m} \geq 0$. The first row of Equation (7) shows how $h(m_t)$ is differentiable and strictly convex for $m_t > \underline{m}$ and that the monitoring technology is more efficient, the larger the value of γ or the smaller the Γ. The second row implies that there is a minimum efficient scale for monitoring investments or an upper bound for private revenues. This upper bound ensures that a bad project has a lower rate of return than a good project, even for low levels of m_t.[12]

Under the minimum scale requirement, the entrepreneur may choose a corner solution with no monitoring $m_t = 0,\ h(m_t) = \overline{h}$, or a unique interior solution with $m_t > \underline{m}$. In Appendix D.3 we determine the conditions under which we can rule out the corner solution. These conditions are met around the steady state, on which we focus in this paper. After substitution of Equations (5b) and (7), we can write the unique interior solution to the entrepreneur's problem (6) as

$$m_t = \frac{\gamma \rho_t}{1 + \frac{p_H}{\Delta p}\left(1 - \frac{1}{1+r_t^a}\right)}. \tag{8}$$

The optimal level of monitoring intensity characterized by Equation (8) has intuitive properties. It increases with the elasticity of monitoring technology (directly related to γ) and the rate of return on a good project (ρ_t). Moreover, the larger the negative effects of monitoring on leverage (which are in the denominator), the lower the optimal level of monitoring.

2.2.3 Aggregate Investment, Bank Capital, and Firm Capital

We proceed under the assumption that all projects will be monitored with the intensity given by Equation (8) and, as a result, all

[12]We experimented with many other functional forms besides specification (7), without gaining additional insights or simpler expressions.

entrepreneurial firms have the same capital structure. That is, for all projects, the ratios a_t/i_t, d_t/i_t, and n_t/i_t are the same.[13] Given this symmetry, moving from project level to economy-wide level in terms of capital structures is simple. Clearly,

$$\frac{a_t}{i_t} = \frac{A_t}{I_t}, \ \frac{d_t}{i_t} = \frac{D_t}{I_t}, \text{ and } \frac{n_t}{i_t} = \frac{N_t}{I_t}, \tag{9}$$

where capital letters stand for aggregate-level variables.

Combining (9) with the banker's incentive and participation constraints (4b) and (4d) links the equilibrium monitoring intensity m_t to the ratio A_t/I_t and to the rate of return to bank capital: $m_t = (\Delta p/p_H)(A_t/I_t)(1 + r_t^a)$. Since in equilibrium this must be the same as the monitoring intensity chosen at the project level, Equation (8), we get

$$1 + r_t^a = \left(1 + \frac{\Delta p}{p_H}\right)^{-1} \left(1 + \gamma \rho_t \frac{I_t}{A_t}\right). \tag{10}$$

For Equation (10) to characterize the equilibrium rate of return on bank capital, $1 + r_t^a$ has to be greater than 1, the rate of return available for households from deposits, or the storage technology. Near the steady state, the inequality $1 + r_t^a > 1$ holds if $\lambda^b < \beta$ (see Appendix D.2); this is the case with our baseline calibration (see Section 5).

Next, plugging (10) into (8) allows us to write

$$m_t = \left(1 + \frac{p_H}{\Delta p}\right)^{-1} \left(\frac{A_t}{I_t} + \gamma \rho_t\right). \tag{11}$$

The larger (relative) stakes the bankers have in the projects (high A_t/I_t), the greater their incentives to monitor intensively.

But by (5a) and (9), inverse firm leverage satisfies the equation $N_t/I_t = g(\cdot)$, where $g(\cdot)$ is given by (5b). Then applying Equations (10) and (11) allows us to express the entrepreneurs' maximum

[13] But project sizes differ: the larger the entrepreneur's wealth n_t, the larger her investment i_t.

incentive-compatible nonverifiable revenue from a "bad" project in terms of aggregate variables,

$$h_t = \frac{\Delta p}{p_H}\left(\frac{N_t}{I_t} + (1-\gamma)\,\rho_t\right). \tag{12}$$

In other words, if the nonverifiable revenue is at or below the threshold value given by Equation (12), the entrepreneurs choose the "good" project rather than the "bad" project. The larger the entrepreneurs' (relative) stakes in the projects (high N_t/I_t), the greater their incentives to choose the "good" project even when they are not subject to intense monitoring by bankers (i.e., when h_t is high). In equilibrium both bankers and entrepreneurs must face proper incentives.

Using (11) and (12), and noting that by (7) there is a trade-off between moral hazard in banks and firms, yields

$$\left(\frac{A_t}{I_t} + \gamma\rho_t\right)^{\gamma}\left(\frac{N_t}{I_t} + (1-\gamma)\,\rho_t\right)^{1-\gamma} = \left(\Gamma\frac{p_H}{\Delta p}\right)^{1-\gamma}\left(1 + \frac{p_H}{\Delta p}\right)^{\gamma}. \tag{13}$$

Equation (13) says that in equilibrium the aggregate investment level I_t in the economy depends on both aggregate bank capital A_t and aggregate entrepreneurial capital N_t.

The remaining period t equilibrium conditions are simple. Equations (4e) and (9) imply that aggregate deposits in the banking system are given by $D_t = (1+m_t)\,I_t - (A_t + N_t)$. The aggregate investment level is part of a simple aggregate resource constraint $Y_t = C_t + I_t$. While monitoring involves real costs for banks, it consumes no aggregate resources. As explained at the beginning of Section 2.2, monitoring involves a transfer of final goods from banks to workers, and is hence included in the lump-sum transfers T_t in the household's budget constraint (1). For more discussion, see also footnote 7.

Finally, we need to determine the evolution of aggregate bank and entrepreneurial capital. At the beginning of the next period $t+1$, the shares $1-\lambda^e$ and $1-\lambda^b$ of entrepreneurs and bankers, respectively, exit their professions and surrender their wealth to the household. More concretely, one may think that in each period the banks and firms pay a constant share of their (gross) revenue as

dividends to the households who own them.[14] The surviving entrepreneurs and bankers then have aggregate wealth $\lambda^e q_t p_H R_t^e I_t$ and $\lambda^b q_t p_H R_t^b I_t$, respectively. In Stage 1 of period $t+1$ they place their funds in the production of the final good, earning the same rate of return as the households. As a result, the aggregate amount of capital held by bankers at the beginning of (the investment) Stage 2 of period $t+1$ is given by $A_{t+1} = \lambda^b q_t p_H R_t^b I_t(1 + r_{t+1})$, which can be combined with conditions (4d) and (9) to obtain the following law of motion for the aggregate bank capital:

$$A_{t+1} = A_t \left(1 + r_t^a\right) \lambda^b (1 + r_{t+1}), \tag{14}$$

where $(1 + r_t^a)$ is given by (10). The law of motion of aggregate entrepreneurial capital is $N_{t+1} = \lambda^e q_t p_H R_t^e I_t(1 + r_{t+1})$, which we can rewrite as

$$N_{t+1} = N_t \left(1 + r_t^n\right) \lambda^e (1 + r_{t+1}), \tag{15a}$$

where

$$1 + r_t^n \equiv q_t p_H R_t^e \left(\frac{I_t}{N_t}\right) = 1 + (1 - \gamma)\, \rho_t \left(\frac{I_t}{N_t}\right) \tag{15b}$$

denotes the rate of return on entrepreneurial capital during Stage 2 of period t. The latter form of (15b) follows from (4a), (9), and (12).

2.3 Equilibrium

The equilibrium of the model is a sequence

$$\left\{K_{t+1}, L_t, Y_t, r_{t+1}, W_t, r_t^K, C_t, I_t, q_t, \rho_t, r_t^a, r_t^n, m_t, h_t, A_{t+1}, N_{t+1}, D_t\right\}_{t=0}^{\infty}$$

that satisfies Equations (2)–(3), (10)–(15a,b), and the following unnumbered equations presented in Sections 2.1 and 2.2: $1 + r_{t+1} = [r_{t+1}^K + q_{t+1}(1 - \delta)]/q_t$, $\xi L_t^{\phi} C_t{}^{\sigma} = W_t$, $Y_t = K_t^{\alpha} L_t^{1-\alpha}$, $W_t = (1 - \alpha) Y_t / L_t$, $r_t^K = \alpha Y_t / K_t$, $Y_t = C_t + I_t$, $D_t = (1 + m_t)\, I_t - (A_t + N_t)$, and $\rho_t = q_t - 1$.

[14] This assumption is standard in much of the macrofinance literature. There is also empirical evidence backing the view that especially banks strive to keep their dividend stream rather stable. One reason may be that dividend payments signal economic strength. See e.g., Floyd, Li, and Skinner (2015).

3. Relative Scarcity of Bank Capital

We provide an analytical solution of the steady state in Appendix D.2. If $\max\left\{\lambda^e, \lambda^b\right\} < \beta$ financial constraints bind in (and near) the steady state, essentially bank capital and entrepreneurial capital are scarce.[15] As explained in Section 2.2, the production of capital goods is constrained by the availability of A_t and N_t (see Equation (13)). The level of investments is suboptimally low in the following sense. Consider a small perturbation where, starting from the steady state, investments rise by a small amount dI in the current period, and the proceeds are consumed in the next period. In the current period, there is less consumption, which implies a decrease in current-period utility equal to $-U_C dI$ (where U_C is marginal utility of consumption in steady state). In the next period, (discounted) utility rises by $\beta U_C \left(r^K + 1 - \delta\right) dI$, where $r^K + 1 - \delta$ is the (social) rate of return to investment (in steady state). Hence, the overall change in utility is $\Delta U = \left[\beta\left(r^K + 1 - \delta\right) - 1\right] U_C dI$. The household's Euler equation (3), however, implies that in steady state $\beta\left(r^K/q + 1 - \delta\right) - 1 = 0$, where the steady-state price of capital $q > 1$, due to financial frictions in capital good production. Then $\Delta U = \rho\left[1 - \beta\left(1 - \delta\right)\right] U_C dI > 0$, where $\rho = q - 1 > 0$ is the steady-state net return on the investment project. Hence, an increase in the level of investments raises welfare, and likewise a decrease of investments from the steady-state level lowers welfare.

While both bank capital and firm capital are scarce, also the composition of informed capital—the relative scarcity of A_t and N_t—affects investments in an important way. Let $\nu_t \equiv A_t/N_t$ denote the ratio of bank capital to entrepreneurial capital, and call it the ratio of informed capital. We show in Appendix A.3 that if $\max\left\{\lambda^e, \lambda^b\right\} < \beta$, there exists a steady state where the ratio of informed capital (ν) is given by

[15] A similar condition arises in many models with macrofinancial linkages. Examples include models applying the Bernanke, Gertler, and Gilchrist (1999) financial accelerator (e.g., Hirakata, Sudo, and Ueda 2013, 2017; Christiano, Motto, and Rostagno 2014), the model of financial intermediation developed by Gertler and Karadi (2011, 2013) and recently extended by Sims and Wu (2020, 2021), and macrofinance models using the Holmström and Tirole (1997) approach, cited in the Introduction. Intuitively, the exit rate of entrepreneurs and bankers has to be high enough so that the economy does not outgrow financial constraints.

$$\nu = \frac{\gamma}{1-\gamma}\left(\frac{\frac{\beta}{\lambda^e}-1}{\frac{\beta}{\lambda^b}\left(1+\frac{\Delta p}{p_H}\right)-1}\right). \tag{16}$$

Next, we determine the value of ν_t (denoted by ν^{**}) that would maximize leverage and investments in the economy and, by implication, the economy's output. We show in Appendix A.4 that

$$\nu^{**} = \frac{\gamma}{1-\gamma}. \tag{17}$$

Hence, the investment-maximizing ratio of informed capital is equal to the elasticity of monitoring technology. To interpret this result, first recall that in equilibrium both bankers and entrepreneurs channel all their wealth into the investment projects, and the ratio $\nu = A/N$ reflects their relative stakes. Now, suppose that banks have access to an efficient monitoring technology (the elasticity $\gamma/(1-\gamma)$ is large). In such case, an arrangement that maximizes aggregate investments involves intense monitoring. As the entrepreneurs' moral hazard problems are effectively alleviated, more funds for entrepreneurs' investments can be raised from depositors. Ensuring that bankers have incentives to monitor intensively, however, requires sufficiently large banker stakes (i.e., a high ratio $\nu^{**} = A/N$).

In contrast, if the monitoring technology is not efficient (the elasticity $\gamma/(1-\gamma)$ is small), intensive monitoring is less useful. Then, in order to attract funding from depositors, it is better that entrepreneurs, rather than bankers, have large stakes and strong incentives to see that the projects succeed. Hence a low ratio $\nu^{**} = A/N$ maximizes investment scale.

Comparison of Equations (16) and (17) yields the following result:

PROPOSITION 1. $\nu \lesseqgtr \nu^{**}$ *if* $\frac{\lambda^b}{\lambda^e} \lesseqgtr 1+\frac{\Delta p}{p_H}$, *i.e., bank capital is scarcer than firm capital if* $\frac{\lambda^b}{\lambda^e} < 1+\frac{\Delta p}{p_H}$, *while firm capital is scarcer than bank capital if* $\frac{\lambda^b}{\lambda^e} > 1+\frac{\Delta p}{p_H}$.

Holmström and Tirole (1997, Section IV.4) conjecture that bank capital is likely to be scarcer than firm capital. Proposition 1 suggests that this conjecture is likely to be true when the dual moral

hazard model, with endogenous monitoring intensity, is embedded into a dynamic macro framework. The scarcity of bank capital prevails in a steady state for a larger range of parameter values than the scarcity of entrepreneurial capital: only if the bankers' survival probability is higher than the entrepreneurs' survival probability by a factor strictly larger than 1 can the bankers accumulate more capital than that needed to maximize investments and output in the economy. In Section 5, we further argue that the relative scarcity of bank capital is the empirically relevant case.

Differentiating Equation (13) around the steady state yields (see Appendix A.5)

$$\left.\frac{dN}{dA}\right|_I = -\frac{1+\frac{\Delta p}{p_H}-\frac{\lambda^b}{\beta}}{\left(1+\frac{\Delta p}{p_H}\right)\left(1-\frac{\lambda^e}{\beta}\right)}. \tag{18}$$

We view $I_t\left(A_t, N_t\right)$ as given by Equation (13) as the economy's production technology. Then, we may define $\left|dN/dA\right|_I \equiv MRTS$ as the absolute value of the steady-state marginal rate of technical substitution of bank and entrepreneurial capital. We state the following result:

Corollary 1. *$MRTS \gtreqless 1$ if $\frac{\lambda^b}{\lambda^e} \lesseqgtr 1+\frac{\Delta p}{p_H}$, i.e., if bank capital is scarcer than firm capital, $MRTS > 1$, while if firm capital is scarcer than bank capital, $MRTS < 1$.*

Corollary 1 has the following interpretation: if bank capital is scarcer than firm capital, increasing bank capital boosts aggregate investment more than increasing firm capital by an equal amount (and vice versa if firm capital is scarce). Corollary 1 will play a key role in our analysis of (Pareto) optimal public funding policies, in Section 6.

To better understand the mechanism that leads to the (relative) underprovision of bank capital, we consider the case where $\lambda^e = \lambda^b$. Then, Proposition 1 unambiguously implies that in a steady state bank capital is scarce relative to firm capital.

Dividing the law of motion of A_{t+1} by that of N_{t+1} (see the derivation of Equations (14) and (15a,b)) shows that in a steady state we have

$$\nu = \frac{R^b}{R^e}.$$

That is, because it is optimal for the household to let its entrepreneurs and bankers retain and reinvest all their earnings, bankers and entrepreneurs accumulate capital in relation to their conditional project returns in a steady state. Next note that maximizing leverage is practically equivalent to maximizing the (expected) pledgeable income, $p_H q_t \left(R - R_t^b - R_t^e\right)$ (i.e., the highest revenue share that can be pledged to depositors without jeopardizing entrepreneurs' and bankers' incentives), minus the cost of monitoring, m_t. But there is a trade-off: an increase in the bank monitoring will increase the entrepreneur's pledgeable income but reduce the banker's pledgeable income and consume funds that could otherwise have been loaned to entrepreneurs. Therefore the investment-maximizing amount of bank involvement solves the following program: $\max_{m_t \geq 0} p_H q_t \left(R - R_t^b - R_t^e\right) - m_t$ subject to Equations (4a), (4b), (7), and $r_t^d = 0$. The first-order condition for this problem may be written as $\left(R_t^b + m_t / \left(p_H q_t\right)\right) / R_t^e = \gamma / \left(1 - \gamma\right)$. Using $\nu^{**} \equiv \gamma/(1-\gamma)$, a steady-state version of this condition can be written as

$$\nu^{**} = \frac{R^b + \frac{m}{p_H q}}{R^e}.$$

This suggests how the aggregate leverage is maximized when bankers' accumulation of capital also takes into account the real costs of monitoring in addition to their revenue share. In a steady state, however, the bankers' capital accumulation only reflects their revenue share. Therefore, in a steady state bank capital is scarce.

4. Aggregate Uncertainty and Sensitivity of Bank Capital

Until now we have assumed that investment projects only involve idiosyncratic uncertainty. In this section, we introduce an aggregate shock by assuming that in some period t project success probabilities are given by $\widetilde{p}_{\tau t} \equiv p_\tau(1 + \varepsilon_t)$, $\tau \in \{H, L\}$, in which $\varepsilon_t \in [\underline{\varepsilon}, 1/p_H - 1)$, with $\underline{\varepsilon} > -1$, is an unanticipated change in the success probabilities of all projects. Such an investment shock may be due, e.g., to a disruptive technology or to a correction to initial

market misperceptions. The shock is realized after financing contracts have been signed, monitoring and project choices have been made, and the price of capital goods has been determined.

Neither the pricing of capital goods nor financial contracts can be made contingent on realization of the unanticipated shock. While in theory it could be possible to contract on the aggregate level of capital goods produced, in practice such contracts are rare. For example, Allen and Gale (1997) argue that financial crises are rare and thus have minor implications on contracts; in our case the shock capturing a crisis event is unexpected and hence noncontractible. In essence, capital goods are sold via forward contracts where the price of capital goods is agreed upon simultaneously with the (other) terms of the financing contract, before the delivery of capital goods occurs (see Appendix A.1 for a detailed timing of events). Thus, the price of capital goods in period t, q_t, is unaffected by the shock in period t.

To model the effects of an aggregate shock, we make the distinction between *bankers* and *banks* explicit. In our model, each bank employs a large number of bankers. Funds from the depositors are collected at the bank level and are allocated to individual bankers in such a way that the constraints of the financial contract (Equations (4)) are satisfied.[16] Each banker monitors a single investment project. If the project succeeds, the entrepreneur retains her share of the project returns (R_t^e). The rest of the returns ($R - R_t^e$) are credited to the common account of the bank. If the project fails, neither the entrepreneur nor the bank gets anything. After the returns from all successful projects of the bank are collected, the bank compensates its bankers and refunds depositors according to the financing contract. A banker is paid only if the project that he monitored was successful. In other words, we assume that depositors' claims are senior within a bank; depositors are first paid from the bank's common funds, after which the successful bankers share the remainder.

For brevity, we assume the success probability of the good project is large enough so that a bank never defaults on deposit contracts on the equilibrium path and, hence, in equilibrium deposits are always redeemed at par and the bank's sequential service constraint never binds. As a result, entrepreneurs and depositors always receive their

[16]This is in the interest of the bank. If an individual banker does not monitor, the remaining bankers within the bank suffer expected losses.

promised share of project returns, whereas bankers may get less (in the case of a negative shock) or more (in the case of a positive shock) than stipulated by the initial financing contract.

Following an investment shock in period t, the aggregate entrepreneurial capital at the end of period t is given by $\widetilde{N}_t(\varepsilon_t) = I_t p_H q_t R_t^e (1+\varepsilon_t)$. Even though each successful entrepreneur gets her share R_t^e according to the financing contract, the aggregate entrepreneurial capital is reduced (increased) in the aftermath of a negative (positive) investment shock because a smaller (larger) fraction of the entrepreneurs are successful. The evolution of aggregate entrepreneurial capital can be rewritten as

$$\widetilde{N}_t(\varepsilon_t) = N_t(1+r_t^n)(1+\varepsilon_t), \tag{19}$$

where N_t is (period t) entrepreneurial capital before the investment stage (Stage 2 in Table 1) and $(1+r_t^n)$ is the expected rate of return to entrepreneurial capital in the investment stage, in the absence of an aggregate investment shock, given by (15b).

In contrast, following an investment shock in period t, the aggregate bank capital at the end of period t is given by $\widetilde{A}_t(\varepsilon_t) = I_t p_H q_t \left[R_t^b + (R - R_t^e)\varepsilon_t\right]$. Using conditions (4b), (4c) (recalling that $r_t^d = 0$), (4d), (4f), and (9), the evolution of aggregate bank capital can be rewritten as

$$\widetilde{A}_t(\varepsilon_t) = A_t(1+r_t^a)(1+BL_t\varepsilon_t), \tag{20a}$$

where A_t is (period t) bank capital before the investment stage and $(1+r_t^a)$ is the rate of return to bank capital in the investment stage, in the absence of an aggregate investment shock, given by (10), while

$$BL_t = 1 + \frac{D_t}{(1+r_t^a)A_t} \tag{20b}$$

is the *bank leverage accelerator of shocks*. Equation (20b) shows how, compared with the effect of the shock on aggregate entrepreneurial capital, its effect on aggregate bank capital is amplified by the term $D_t/((1+r_t^a)A_t)$. In the aftermath of a negative shock, not only do fewer bankers see their projects succeed, but each successful banker gets a smaller share of the revenues because of the seniority of depositors' claims. As a result, the higher the bank leverage (the

debt-to-equity ratio $D_t/((1 + r_t^a)A_t)$), the higher the multiplier of the shock.

The dynamics of entrepreneurial and bank capitals differ after an aggregate shock because banks are larger and more diversified than firms: each bank intermediates funding to many firms. The small size of an individual firm protects entrepreneurs as a group against levered impacts of adverse shocks: if an investment project fails, the firm goes bankrupt and the entrepreneur loses her equity, but other entrepreneurs cannot be held accountable for these losses. In contrast, even when a (larger-than-expected) number of investment projects in a bank's portfolio fail, the bank pays its creditors in full and the adverse shocks are absorbed by bankers' equity.

The period $t + 1$ values of entrepreneurial capital and bank capital, before the period $t + 1$ capital good production stage (i.e., after Stage 1, but before Stage 2 of period $t + 1$), are linked to the end-of-period t values by the equations

$$N_{t+1}(\varepsilon_t) = \lambda^e(1 + r_{t+1})\widetilde{N}_t(\varepsilon_t) \tag{21}$$

and

$$A_{t+1}(\varepsilon_t) = \lambda^b(1 + r_{t+1})\widetilde{A}_t(\varepsilon_t). \tag{22}$$

Here, the only difference in the dynamics of entrepreneurial capital and bank capital derives from the different exit rates of entrepreneurs and bankers (λ^e and λ^b). Although a shock has an asymmetric effect on the sharing of project revenues, it does not affect the conditional project returns. Therefore, the effect of the shock on the accumulation of physical capital is again directly related to its effect on project success probability. The aggregate physical capital in period $t + 1$, following an investment shock in period t, is given by $K_{t+1}(\varepsilon_t) = (1 - \delta)K_t + I_t(1 + \varepsilon_t)$.

5. Calibration

We follow the RBC literature in calibrating the parameters of the real block (see Appendix C.1). The upper panel of Table 2 shows the resulting parameters (the period is one year and the parameter values are adjusted accordingly). Calibration of the parameters of the financial block involves matching the steady-state

Table 2. Calibrated Parameter Values

Parameter	Value	Note
Parameters of the Macro Block		
β	0.98	Discount Factor
α	0.33	Capital Share
δ	0.10	Rate of Decay of Capital
ξ	2	Parameter of the Disutility of Labor
ϕ	0.5	$1/\phi$ Frisch Elasticity of Labor Supply
σ	2	$1/\sigma$ Elasticity of Intertemporal Substitution
Parameters of the Financial Block		
λ^e	0.9382	Survival Rate of Entrepreneurs
λ^b	0.8754	Survival Rate of Bankers
p_H	0.95	Success Probability of a Good Project
$\frac{\Delta_p}{p_H}$	0.1674	$\Delta p \equiv p_H - p_L = 0.159$
γ	0.4005	$\frac{\gamma}{1-\gamma}$ Elasticity of Monitoring Function
Γ	0.0032	Parameter of Monitoring Function

values of the financial variables to empirical moments. Based on the findings in the empirical literature (see Appendix C.1), we set the excess return on entrepreneurial capital (r^n) to 4.5 percent nonfinancial firms' capital-asset ratio (CRF) to 45 percent, the excess returns on bank capital (r^a) to 12 percent, banks' capital-asset ratio (CRB) to 8 percent, and their monitoring-cost-asset ratio (MRB) to 1.5 percent. In Appendix C.2, we show that the parameters of the financial block can be expressed in terms of the matched data moments as follows: $\lambda^e = \frac{\beta}{1+r^n}$, $\lambda^b = \frac{\beta}{1+r^a}$, $\frac{\Delta p}{p_H} = \frac{MRB}{CRB(1+r^a)}$, $\frac{\gamma}{1-\gamma} = \left(\frac{r^a CRB + MRB}{r^n CRF}\right)(1-CRF)$, and $\Gamma = \left(\frac{1+r^n}{1+r^a}\right)\left(\frac{CRF}{CRB}\right)(1-CRF)^{\frac{\gamma}{1-\gamma}} MRB^{\frac{1}{1-\gamma}}$.

With the calibration based on observed data moments, we can have a new look at the relative scarcity and sensitivity of bank capital. Proposition 1 implies that bank capital is scarce if $\lambda^b/\lambda^e < 1 + \Delta p/p_H$. Our calibration suggests that $\lambda^b/\lambda^e = 0.93$, whereas $1 + \Delta p/p_H = 1.17$. More precisely, Equations (C.5) and (C.6) in Appendix C.2 imply that $\lambda^b/\lambda^e = (1+r^n)/(1+r^a)$. Hence, the relative excess returns reflect relative scarcity. Next, using the banker's incentive constraint (4b) and participation constraint (4d), together with the aggregation equation (9), all evaluated at the steady state,

yields $\Delta p/p_H = mI/\left((1+r^a)\,A\right)$. This expression has a natural interpretation. Monitoring costs mI constitute a part of the cost of financial intermediation and, unlike the return to bank capital $(1+r^a)\,A$, this part of the cost of intermediation does not translate into new banker-owned capital. As argued in Section 3, this is one reason why bank capital is scarce in equilibrium. While these observations are useful for interpreting Proposition 1, Equation (C.7) in Appendix C.2 (re)expresses $\Delta p/p_H$ in terms of the data moments we match: $\Delta p/p_H = MRB/\left((1+r^a)\,CRB\right)$. In sum, the relative scarcity of bank capital prevails if

$$r^n < r^a + \frac{MRB}{CRB}.$$

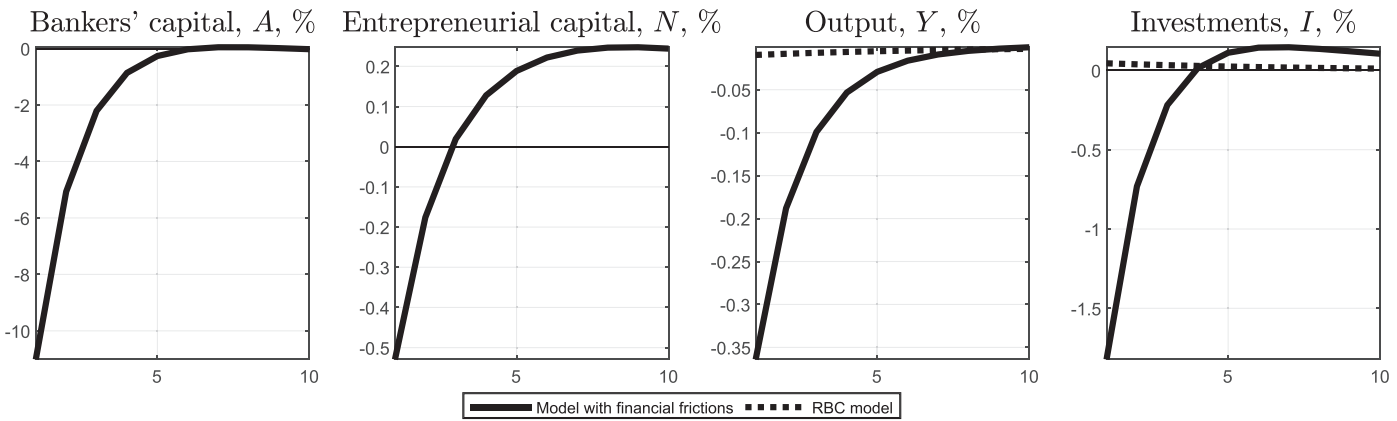
This condition is likely to hold: e.g., Hirtle and Stiroh (2007) and Albertazzi and Gambacorta (2009) estimate the return on bank equity (r^a) to be 12–14 percent in the U.S., whereas the average return on firm capital (r^n) is often estimated to be much lower (see, e.g., Fama and French 2002).

Figure 1 shows the impulse responses of some key real- and financial-sector variables to a negative investment shock. (The impulse responses of the whole set of variables to an investment shock are given in Appendix C.3.) As a (first-best) benchmark, we show the impulse responses of the macrovariables for the standard RBC model.[17] In the RBC model, the shock has small effects. There is a little less physical capital after a negative investment shock, and this slightly lowers the production capacity and output of the economy. Investments increase a little to restore the lower-than-anticipated capital stock.

In our model with banks, investment falls and financial intermediation greatly amplifies the impact of the investment shock on aggregate investment and output. The reason is threefold. First, as shown in Section 2.2, aggregate investment scale depends on bank capital and firm capital. Second, as discussed in Section 3, as well as in the present section, bank capital is scarce relative to entrepreneurial wealth: a change in bank capital has a larger effect on aggregate investment than an equal change in entrepreneurial wealth. Third,

[17]Equations in Section 2.1, together with $q_t = 1\ \forall t$ and $Y_t = C_t + I_t$, characterize the textbook RBC model.

Figure 1. Impulse Responses to a Negative Investment Shock (1 percentage point decrease in success probabilities)



Note: The shock has zero persistence. Horizontal scale refers to years.

as explained in Section 4, an investment shock has a strong effect on bank capital. Also output (the production of the representative good) drops significantly. This is because the capital-good-producing entrepreneurial firms demand less of the representative good, which they use as an input. Due to lower demand, output declines in equilibrium. Financial frictions amplify the effect of the shock on other macrovariables as well (Figure C.1 in Appendix C.3).

6. Public Funding of Banks and Firms

We characterize the optimal allocation of the public support between banks and nonfinancial firms at an early stage of a crisis. For example, public funding policies and credit guarantees designed in the early stages of the Global Financial Crisis and the COVID-19 crisis broadly targeted banks and firms rather just troubled ones, strengthening their balance sheets and shifting aggregate risk to the public sector.[18] In our model, debt and equity are distinct components of banks' capital structure, and we model government support of banks to take place in terms of equity injections. In the case of nonfinancial firms, debt and (outside) equity are indistinguishable,

[18]For example, TARP was introduced in October 2008 to make the financial system more crisis resilient, and it primarily targeted healthy institutions, often against their own wishes (see, e.g., Veronesi and Zingales 2010; Bernanke 2015; Bernanke, Geithner, and Paulson Jr. 2019; Berger and Roman 2020). As Bernanke, Geithner, and Paulson Jr. (2019, pp. 90–91) write:

> We needed to launch the program quickly . . . so on Columbus Day, Hank summoned the CEOs of nine of the most important financial firms to the Treasury. The three of us . . . explained that we expected all nine of them to accept Treasury capital up to equivalent of 3 percent of their risk-weighted assets, a total of $125 billion in TARP investments, along with FDIC guarantees of any new debt they issued through June 2009 . . . all of the banks were reluctant to take the government as an investor. But we reminded them that none of them should be confident they had enough capital to survive the severe recession that lay ahead, much less the runs that would accompany a meltdown of the system . . . In the ensuing months, we would move quickly to inject capital into nearly 700 smaller banks, a critically important step toward stabilizing and recapitalizing the entire banking system.

In the COVID-19 crisis, many public funding programs were already introduced in March 2020—see, e.g., https://www.ft.com/content/26af5520-6793-11ea-800d-da70cff6e4d3, accessed January 12, 2024.

as in Holmström and Tirole (1997), making both debt and equity interpretations of public funding to nonfinancial firms possible.[19]

The government demands for its investments an expected rate of return of $1+r_t^g$, which includes a penalty relative to the market rate, $r_t^g > 0$. Otherwise, banks and firms would want to be funded by the government. Also, the need of politicians to signal their toughness to voters may motivate such a penalty rate in practice. Public funding is provided for a single period and injected before the financial contracts are signed. Participation in the government funding program is mandatory for all banks and firms. Although the mandatory participation here is a simplifying assumption, it also mitigates potential problems arising from the stigma associated with the use of government funds with a penalty rate.[20] Finally, while the government provides funding, it does not participate in running or monitoring the investment projects.

We summarize the main insights from the analysis of optimal policies in three remarks and one proposition. Remark 1 characterizes the (relative) incentive distortions and welfare losses caused by public bank and firm funding. Remark 2 establishes that welfare benefits from a more resilient financial system are proportional to the size of the funding program and (ex post) to the size of the shock, but do not depend on its structure. Remark 3 tells how a program of a given size can be constructed with different combinations of public bank and firm funding. These remarks lead to the main result of the paper, Proposition 2, which shows how the optimal structure of a funding program depends on its size.

6.1 Social Costs of Public Funding: Distorted Incentives

We show in Appendix B.1 that the public funding of banks and nonfinancial firms results in an aggregate investment level (I_t^*) that is implicitly given by the equation

[19] If the investment project succeeds, the firm can pay both creditors and equity holders. If the project fails, the firm can pay neither.

[20] The penalty rate is in line with Bagehot's dictum. As explained by Bernanke (2015, p. 148): "The penalty rate encourages banks to look first to private markets for funding, rather than relying on the Fed. But a side effect of this arrangement was that banks feared they would look weak if it became known that they had borrowed from the Fed—and that would make it even harder from them to attract private funding."

$$\left(\frac{A_t - r_t^g A_t^g}{I_t^*} + \gamma\rho_t\right)^{\gamma} \left(\frac{N_t - r_t^g N_t^g}{I_t^*} + (1-\gamma)\,\rho_t\right)^{1-\gamma} = \left(\Gamma\frac{p_H}{\Delta p}\right)^{1-\gamma} \left(1 + \frac{p_H}{\Delta p}\right)^{\gamma}, \tag{23}$$

in which $A_t^g \geq 0$ and $N_t^g \geq 0$ denote the aggregate amounts of government funds injected into banks and entrepreneurial firms, respectively.

Equation (23) is identical to Equation (13) except for the negative terms $-r_t^g A_t^g$ and $-r_t^g N_t^g$ in the numerators of the left-hand side. Thus, public funding of banks and nonfinancial firms *lowers* the aggregate investment level. Since $r_t^g > 0$, government-owned capital dilutes bankers' and entrepreneurs' stakes in the projects and, consequently, their incentives to monitor and invest. Bankers' weaker monitoring incentives make bank participation costlier for entrepreneurs, further reducing their investment incentive.

Since lower investments imply lower welfare (see Section 3), the government keeps the premium on its funding small to minimize these adverse welfare effects of public funding. Assuming that $r_t^g = dr^g$ is small, and totally differentiating (23) at the steady state, yields

$$\left|\frac{N^g}{A^g}\right|_I = \frac{-\frac{dI}{dA}dr^g}{-\frac{dI}{dN}dr^g} = \left|\frac{dN}{dA}\right|_I = MRTS = \frac{1 - \frac{\lambda^b}{\beta} + \frac{\Delta p}{p_H}}{\left(1 + \frac{\Delta p}{p_H}\right)\left(1 - \frac{\lambda^e}{\beta}\right)},$$

in which we use the definition *MRTS* familiar from Equation (18) and Corollary 1. Here *MRTS* tells how many units of public funds in nonfinancial firms correspond to a unit of public funds in banks in terms of welfare losses. Since $MRTS > 1$ is likely to hold (see Sections 3 and 5), public funding invested in banks tends to be more distortionary than when invested in nonfinancial firms. This property reflects the scarcity of banker-owned capital near the steady state (Proposition 1, Corollary 1): capital injections into banks dilute bankers proportionally more than corresponding injections into firms dilute entrepreneurs. Our baseline calibration yields $MRTS = 5.5$.

Besides its distortionary effects in the current period, public funding, which commands a premium, is costly for bankers and

entrepreneurs in terms of lower revenues and wealth in the subsequent periods. We assume that the government grants the entrepreneurs and bankers a lump-sum refund from its premium revenues. Such a refund eliminates the harmful effects of lower insider wealth on future investments, while keeping public funding unattractive for individual entrepreneurs and bankers—see Appendix B.1.3.

Thanks to this elimination of harmful effects of public funding on the future periods, all welfare losses from public funding are transmitted through its distorting effects on current investments. We can then apply the result established in Equation (18) and Corollary 1 to analytically compare the funding of banks and firms in terms of welfare losses. We summarize the key finding of this subsection by the following remark:

REMARK 1. *Public stakes in banks and firms distort incentives, which lowers welfare. In terms of the welfare losses, each unit of public funds in banks equals MRTS units of public funds in firms where MRTS is likely to be larger than one.*

6.2 Social Benefits of Public Funding: Enhanced Resilience

Although public funding causes distortions, it also renders the financial system more resilient to negative aggregate shocks. In Appendix B.1.4, we show that when the government provides funding for banks (A_t^g) and nonfinancial firms (N_t^g), the dynamics of nongovernment-owned bank capital after an investment shock (ε_t) is characterized by Equation (22) in which $\widetilde{A}_t(\varepsilon_t)$ and BL_t of Equations (20a) and (20b), respectively, are replaced by[21]

$$\widetilde{A}_t^*(\varepsilon_t) = A_t(1 + r_t^a)(1 + BL_t^*\varepsilon_t) \tag{24a}$$

and

$$BL_t^* = 1 + \frac{D_t - A_t^g - N_t^g}{(1 + r_t^a)A_t + A_t^g}. \tag{24b}$$

[21]The expression (24b) holds as an approximation in the sense that $BL(A_t^g, N_t^g, dr_t^g)\varepsilon_t$ (the effect of the shock on banker-owned capital; see Equation (24a)) is equal to $BL^*(A_t^g, N_t^g)\varepsilon_t$ plus additional terms which are proportional to the product $dr_t^g \times \varepsilon_t$. We assume that these additional terms are so small that they can be ignored (see Appendix B.1.4).

Comparison of Equations (20b) and (24b) suggests that government funding of banks lowers their leverage because the total bank equity is enhanced, thanks to equity A_t^g purchased by the government (see the denominator of the last term of Equation (24b)), and because government-owned capital A_t^g crowds out debt funding from households (the numerator of the last term of Equation (24b)): since banks need to pledge a part of their income to the government, less can be pledged to households. Public funding of nonfinancial firms N_t^g also lowers bank leverage: if the government funds nonfinancial firms, they borrow less from banks, which in turn borrow less from households. Crowding out happens since firms need to pledge a part of their revenues to the government, and as a result they can pledge less to banks, which can in turn pledge less to households. However, public funding of nonfinancial firms does not strengthen the equity buffer of the banking system.

Equations (24a) and (24b) show how public funding changes the structure of bank balance sheets, making the banking sector more resilient to negative aggregate shocks. Since banks are large and diversified, aggregate shocks have a levered impact on their equity (see Section 4). Public funding lowers the shock accelerator on the bank side. However, public funding has no impact on the vulnerability of the entrepreneurial sector as a whole to the aggregate shock. Entrepreneurial firms are small and nondiversified, and limited liability protects entrepreneurs as a group against negative spillovers. While a negative aggregate investment shock increases entrepreneurial failures, there is no shock accelerator. The loss of aggregate entrepreneurial wealth is proportional to the number of failing projects, and hence to the size of the negative aggregate shock, irrespective of whether the entrepreneurs are funded by banks or by the government. Similarly, public funding leaves the dynamics of capital stock intact, since the accumulation of new capital also depends on the share of failing projects, and is therefore directly related to the size of the investment shock.

Since public funding only affects the resilience of banks, the welfare benefits of public funding focus on the banking sector. We show in Appendix B.2 that the welfare benefits of public funding, in the face of a negative macro shock $\varepsilon_t < 0$, are given by the measure

$$\Delta \widetilde{V} = -\widetilde{V}_{\widetilde{A}} BRE_t S_t \varepsilon_t, \tag{25}$$

in which $\widetilde{V}_{\widetilde{A}} > 0$ is the steady-state value of the derivative of the household's value function with respect to the bankers' end-of-period capital, $BRE_t = (1 + r_t^a)\, BL_t A_t$ is the *banks' risk exposure* to a (negative) macro shock under laissez-faire, and

$$S_t = 1 - \frac{BL_t^*}{BL_t} \tag{26}$$

measures the share of the risk exposure shifted from banks to the government.

Equation (25) shows how public funding makes banks less vulnerable to a negative aggregate investment shock and therefore reduces the welfare losses due to the shock: $\Delta\widetilde{V} > 0$ if $\varepsilon_t < 0$. Government-owned capital absorbs part of the loan losses and, hence, mitigates the bankers' loan losses. After a negative shock hits, banks are better capitalized than they would be under laissez-faire and can lend more to nonfinancial firms which, as a result, can invest more than they could in a laissez-faire scenario. Since investments are suboptimally low (see Section 3), this improves welfare, compared with laissez-faire.

According to Equation (25) the social benefits of the program are proportional to the measure S_t, which can take values between 0 and $1-1/BL_t$ (where the maximum S_t corresponds to $BL_t^* = 1$). We can also call S_t the *size* of the public funding program. A public funding program of, say, size $S_t = 0.2$ means that the government takes over 20 percent of banks' total macro risk exposure—and the program reduces bankers' loan losses by 20 percent following a negative macro shock.

We show in Appendix B.3 that the fiscal costs of the funding program are given by $FC_t = -BRE_t S_t \varepsilon_t$, which measures the government's losses from a public funding program of size S_t if a negative shock $\varepsilon_t < 0$ hits the economy. If the fiscal costs have to be covered by distortionary taxes, the resulting welfare losses from taxation depend on FC_t. Hence, although modeling distortionary taxes is beyond the scope of this paper, combining this observation with Equation (25) implies that the net welfare benefits of the program, net of possible losses from distortionary taxation, depend on the size of the program, S_t.

The following remark summarizes the main result of this subsection:

Remark 2. *A public funding program makes the economy more resilient in the face of a negative macro shock. Welfare gains of the program are proportional to the size of the program and to the size of the realized macro shock.*

Equation (25) also implies that if there is a *positive* aggregate shock ($\varepsilon_t > 0$), public funding *lowers* social welfare: $\Delta\widetilde{V} < 0$ if $\varepsilon_t > 0$. Since public funding distorts incentives irrespective of the sign of ε_t (see Section 6.1), the government should consider financial support of banks and firms only in times of economic hardship.

6.3 The Policy Frontier

To relate the size of the program S_t to the public funding of banks and firms, we show in Appendix B.3 that

$$BRE_t S_t = BL_t^* A_t^g + N_t^g. \tag{27}$$

Hence, a program of size S_t can be implemented with any combination of A_t^g and N_t^g satisfying Equation (27). We call the different combinations of A_t^g and N_t^g satisfying Equation (27) the *policy frontier*. A particular combination of A_t^g and N_t^g from the policy frontier defines the *structure* of the program.

In Equation (27), BL_t^* is (the absolute value of) the slope of the policy frontier: in terms of resilience, each unit of A_t^g corresponds to $BL_t^* \geq 1$ units of N_t^g. The relative efficiency of bank capitalization in stabilization reflects the effects captured by Equation (24b). Bank capitalization (A_t^g) makes the banks less vulnerable to a negative aggregate shock both by strengthening their equity cushion and by reducing the amount of outside debt on the liability side of their balance sheets. If the government funds firms, they borrow less from banks, which in turn borrow less from households. Hence public funding of firms also makes banks less vulnerable to aggregate shocks by reducing the asset side of their balance sheets, i.e., the banks' firm loan portfolios. Here BL_t^* is not only the slope of the policy frontier but also a measure of bank leverage when public policy is in place. A policy that essentially works through the asset side of bank balance sheets (firm funding) requires BL_t^* times larger public stakes than a policy which boosts bank equity (bank capitalization). The slope of the policy frontier depends on the size of the

program: we can rewrite Equation (26) as $BL_t^* = BL_t(1 - S_t)$. To summarize, we have the following remark:

REMARK 3. *In terms of the resilience of the economy, each unit of public funding in banks equals* $BL_t^* = BL_t(1 - S_t)$ *units of public funding in nonfinancial firms.*

6.4 Optimal Structure of Public Funding: Targeting Banks or Firms?

We take the size of a public funding program (S_t) as predetermined, e.g., by a political process, and characterize an optimal structure of the program: how should the public funds be allocated between banks and nonfinancial firms? Our choice to focus on the optimal structure with a given size is motivated by uncertainty faced by the government in a time of crisis. Genuine uncertainty might even prevent the government from assigning a distribution to a negative macro shock, which would make the determination of an optimal S_t impossible. If we assume away genuine uncertainty, finding the optimal level of S_t would imply balancing the welfare gains from stabilization against the welfare losses from distorted incentives and from distortionary taxes (which we do not model). Alternatively, since the welfare benefits of stabilization and the possible welfare losses due to distortionary taxes are both proportional to the program size (Remark 2) and independent of its structure, we may regard S_t as being fixed at a desired level and seek an optimal structure of the funding program that minimizes its incentive distortions.[22] In Section 6.5 we discuss how the optimal structure of the public funding program relates to the notion of dominated and undominated policies.

Considering an economy near the steady state and taking S as given, we maximize welfare with respect to the structure of the public funding program. Our main result, which holds even if the

[22]One may think, e.g., that the government knows the tax system in place and can assess its distortionary impact. In the absence of genuine uncertainty, the government may find the optimal trade-off between (expected) welfare gains from resilience and (expected) welfare losses from distorted incentives and distortionary taxes. A more explicit treatment of distortionary taxes, along the lines of Holmström and Tirole (2013), is a topic for future research.

program is implemented under genuine uncertainty and financed by distorting taxes, follows:

Proposition 2. *Assume that* $1 < MRTS < BL$. *There exists a threshold value* $S^* = 1 - MRTS/BL$ *such that* $0 < S^* < 1 - 1/BL$. *(a) If* $S < S^*$, *it is optimal to capitalize banks,* $A^g = S \times BRE/[(1 - S)BL]$ *and* $N^g = 0$. *(b) If* $S > S^*$, *it is optimal to fund nonfinancial firms,* $A^g = 0$ *and* $N^g = S \times BRE$.

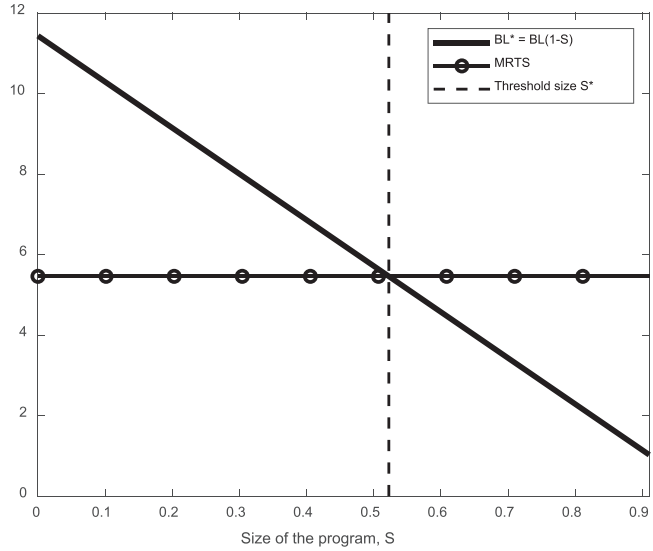
Proof. See Appendix B.4.

If the size of the funding program is below the threshold S^*, the government should target banks, while if the program size is above S^*, the government should target nonfinancial firms. The threshold S^* is increasing in the *sensitivity* of bank capital to macro shocks under laissez-faire (captured by BL) and decreasing in the relative *scarcity* of bank capital (captured by $MRTS$). We show in Appendix B.5 that in any equilibrium (or model calibration) with a meaningful role for financial intermediation, $MRTS/BL < 1$. Intuitively, the opposite case $MRTS/BL > 1$, characterized by scarce bank capital and a banking system struggling to raise outside funding, would correspond to a situation (or model calibration) where financial intermediation is so ineffective and costly that the entrepreneurial firms choose to bypass the banking system and raise funding directly from households.[23] Thus, if the condition in Proposition 1 holds and $MRTS > 1$, the optimal policy consists of two regimes, with a threshold value $S^* \in (0, 1 - 1/BL)$. Our baseline calibration with $MRTS = 5.5$ and $BL = 11.4$ yields $S^* = 0.52$. Hence, the threshold S^* corresponds to the government taking over roughly half of the banks' macro risk exposure. In Appendix B.5, we present equations linking $MRTS$, BL, and S^* to the data moments used in the calibration of the model, and conduct robustness analysis with respect to the calibration.

Using Equation (26), we may rewrite the condition $S \gtreqless S^*$ as $MRTS \gtreqless BL^*$. To interpret this condition, think of implementing a program of size S by funding either banks or firms. Given Remark 3, BL^* times smaller public ownership stakes are needed if

[23]This is the corner solution with $m_t = 0$ and $h_t = \overline{h}$.

Figure 2. The Optimal Structure of a Program Depends on Its Size



Note: If BL^* is larger (smaller) than $MRTS$, it is optimal to fund banks (firms).

the government targets banks rather than nonfinancial firms. However, since each unit of public funds creates $MRTS$ times larger distortions in banks (Remark 1), the relative welfare losses from distortions are given by $\widehat{WLD} = WLD^{A^g}/WLD^{N^g} = MRTS/BL^*$, where WLD^{A^g} and WLD^{N^g} denote welfare losses when the government targets banks and firms, respectively. Evidently, the program should target banks if $\widehat{WLD} < 1$, and firms if $\widehat{WLD} > 1$. Hence, the choice boils down to comparing $MRTS$ and BL^*. See Figure 2.

The size of the program matters for the optimal structure because (the absolute value of) the slope of the policy frontier equals the target level of the bank leverage accelerator, which in turn decreases with the size of the program $BL^* = BL(1 - S)$—see Remark 3 and Figure 2. Recall that the government can lower the bank leverage accelerator to the target level BL^* either by (i) strengthening the banks' balance sheets through public bank capitalization or (ii) reducing the size of banks' balance sheets, and the

exposure of banks to nonfinancial firms, by providing public funding directly to nonfinancial firms. Alternative (ii), which essentially works through the asset side of bank balance sheets, requires BL^* times larger public (ownership) stakes than alternative (i), which works through the equity buffer. This is intuitive, as BL^* also measures the assets-to-equity ratio of banks when policy (ii) is in place. The more (fewer) assets there are compared with equity, the more (less) effective, in relative terms, the policy that strengthens equity. The banks' assets-to-equity ratio, however, decreases with the size of the program.

6.5 Dominated and Undominated Policies

Proposition 2 may also be interpreted as characterizing the sets of *dominated* and *undominated*, or *Pareto-optimal*, policies (for a formal proof, see Appendix B.4). A policy (A^g, N^g, S) dominates an alternative policy $(A^{g\prime}, N^{g\prime}, S')$ if (A^g, N^g, S) generates as high social welfare as $(A^{g\prime}, N^{g\prime}, S')$ for all shock realizations $\varepsilon_t < 0$, and strictly higher welfare for some shock realizations. A policy (A^g, N^g, S) is undominated if and only if there is no alternative that dominates it.

The sets of dominated and undominated policies are characterized by the mapping from the size of a program to its appropriate structure given in Proposition 2. Since the distortions and the welfare losses caused by a public funding program depend on its structure while the welfare benefits of the program depend on its size and (ex post) on the shock realization (the larger the program and the larger the negative shock realization, the larger the benefits), but are independent of the structure, the program can belong to the set of undominated policies if and only if its structure minimizes the welfare losses from distortions, given its size. If not, welfare (after any shock realization) could be raised by keeping the size of the program fixed but reoptimizing its structure—meaning that the policy is dominated.

Proposition 2 implies that small funding programs ($S < S^*$) targeting banks and large programs ($S > S^*$) targeting firms are undominated. If the government implements one of these programs, there exists no alternative program that would generate as high welfare after all (negative) shock realizations. By contrast, any small

public funding program ($S < S^*$) targeting firms is dominated by a program of the same size but targeting banks, while any large program ($S > S^*$) funding banks is dominated by a program of the same size but directed at firms. Similarly, all mixed programs, simultaneously funding both banks and firms, are dominated by pure programs with the structure described in Proposition 2.

These results are useful for decision-making under genuine uncertainty, as they indicate funding policies to be considered and policies to be avoided. A benevolent, welfare-maximizing government should choose a policy that belongs to the undominated set. It should implement no dominated policy, irrespective of its beliefs about the probability and severity of the crisis. See Appendix B.6 for a numerical example.

6.6 Welfare Losses from Non-optimal Structure of Public Funding

Assume that the government fails to follow the prescriptions of Proposition 2 and implements a relatively small funding program ($S < S^*$) for nonfinancial firms or a relatively large program ($S > S^*$) for banks, or, alternatively, finances both banks and firms simultaneously. How significant are the welfare losses resulting from such non-optimal structures?

We examine this question in Appendix B.7. We find that if the program size S is around the threshold S^*, it does not matter much whether the government allocates funds to banks, firms, or both. However, the larger the gap between S^* and S, the larger the excess welfare losses from a non-optimal structure (see Figures B.1 and B.2 in Appendix B.7). From a policy perspective, the result is reassuring: the larger the welfare losses from a suboptimal structure, the easier it is to follow the prescriptions of Proposition 2 even if the threshold S^* is not known exactly.

We also show in Appendix B.7 that funding simultaneously both banks and firms creates a smaller excess welfare loss than funding exclusively either banks or firms with a wrong amount. Thus, if the government is uncertain about the desired size of the program, choosing a mixed program may be a robustly optimal strategy. (Robust optimization here means minimizing the maximum excess welfare loss due to a suboptimal structure.) In Appendix B.8, we

study the implementation of such a robust optimal mixed program under two scenarios: (i) The government does not know S^* for sure. (ii) The government implements a staggered program which can initially be smaller than S^*, but has an option to expand the program so that eventually $S > S^*$. We show that in a robust optimal mixed program the share of funds allocated to nonfinancial firms relative to banks should be increasing in S, a finding that echoes the results of Proposition 2.

7. Conclusions

In this paper we develop a macrofinance model in which both banks' and firms' balance sheets matter. We show that, in equilibrium, bank capital tends to be scarce compared with firm capital. Then, a given change in bank capital has a larger impact on aggregate investment than a corresponding change in firm capital. We also show that bank capital is more sensitive to aggregate shocks than firm capital.

Public funding affects the incentives and the balance sheet structures of banks and firms. Our main result links the socially optimal composition of a crisis funding program to its size. Small programs should target banks, while large programs should be directed at nonfinancial firms. Our baseline calibrations suggest that programs in which the government takes over more (less) than 50 percent of the macro risk from the private sector should be implemented through firm (bank) funding.

The result reflects the relative scarcity and sensitivity of bank capital. Due to its scarcity, public funding distorts incentives more when placed in banks rather than in nonfinancial firms. Given the sensitivity of bank capital, however, smaller public stakes are needed in banks than in firms to stabilize the economy. The relative effectiveness of bank capitalization in stabilizing the economy depends on the size of the program. Initially, capital injections to banks have a large proportional effect on the resilience of the financial system, but this effect diminishes if the government takes over a larger share of the macro risk.

In terms of policy design under genuine uncertainty, a contribution of this paper is to characterize the menu of crisis funding programs from which the government should choose: which policies

to consider and which to exclude. Our results imply that small funding programs targeting banks and large programs targeting firms are on the table since they belong to the set of undominated policies. The government should pick its policy from this set. Conversely, small funding programs targeting firms and large funding programs targeting banks are off the table, since they are dominated.

Appendix A. Model

A.1 Timing of Events

Within each period t there are two main stages. At the beginning of Stage 1, the survival probabilities of bankers and entrepreneurs are realized and exiting bankers and entrepreneurs give their accumulated assets to households. Household members then separate into their occupations, the heads of households make their consumption-savings decisions, and final goods are produced using capital and labor.

The production of capital goods takes place in Stage 2, which is divided into five substages: First, financing contracts among entrepreneurs, bankers, and depositors (workers) are signed. These contracts determine whether and how the project is financed, its size, and how eventual revenues are divided. Depositors place their funds in banks, which extend funding to entrepreneurs according to the financing contract. Second, bankers choose their intensity of monitoring. Third, entrepreneurs choose their projects. Fourth, successful projects yield new units of capital goods that are sold. Finally, the proceeds are divided among depositors, bankers, and entrepreneurs according to the terms of the financial contract.

While entrepreneurs are assumed to sell the capital goods that they produce, note that our equations in Section 2.1 show that final good firms rent (rather than own) the capital stock that they need in production. This is consistent with the existence of perfectly competitive capital rental firms, fully owned by households. These capital rental firms purchase capital goods from successful entrepreneurs, rent capital services to final goods firms, and refund the rental income to their owners. Note also that, as in Holmström and Tirole (1997), bankers can commit to monitoring before

entrepreneurs make their project choice. This sequential timing rules out mixed strategy equilibria.

A.2 Investment Size at Project Level

In this appendix section, we derive Equations (5a) and (5b). From the entrepreneur's and banker's incentive constraints, (4a) and (4b), we see that the entrepreneur and the banker must get no less than $R_t^e = \frac{h(m_t)}{q_t \Delta p}$ and $R_t^b = \frac{m_t}{q_t \Delta p}$, respectively, in case of success, as otherwise they will misbehave. Then the return-sharing constraint (4f) shows that depositors can be promised at most

$$R_t^w = R - \frac{m_t + h\left(m_t\right)}{q_t \Delta p}. \tag{A.1}$$

Substituting Equation (A.1) for the depositor's participation constraint (4c) yields

$$p_H \left\{ q_t R - \frac{m_t + h\left(m_t\right)}{\Delta p} \right\} = \frac{d_t}{i_t}. \tag{A.2}$$

Next, we combine the banker's incentive constraint (4b) with his participation constraint (4d) and the input resource constraint (4e) to obtain

$$\frac{d_t}{i_t} = 1 + m_t - \frac{p_H}{\Delta p} \left(\frac{1}{1 + r_t^a} \right) m_t - \frac{n_t}{i_t},$$

which can be then substituted for Equation (A.2). Solving the resulting equation for i_t gives Equation (5a) and expression (5b).

A.3 Steady-State Structure of Informed Capital

In this section, we derive Equation (16). Substitution of the incentive constraints (4a) and (4b), together with Equation (7) and $r^d = 0$ for law of motion of A_{t+1} and that of N_{t+1} (see the derivation of Equations (14) and (15a)) gives

$$A_{t+1} = \left(1 + r_{t+1}\right) \frac{p_H}{\Delta p} \lambda^b m_t I_t$$

and

$$N_{t+1} = \left(1 + r_{t+1}\right) \frac{p_H}{\Delta p} \lambda^e \Gamma m_t^{-\frac{\gamma}{1-\gamma}} I_t.$$

Thus, in a steady state we must have

$$A = (1+r)\frac{p_H}{\Delta p}\lambda^b m I \tag{A.3}$$

and

$$N = (1+r)\frac{p_H}{\Delta p}\lambda^e \Gamma m^{-\frac{\gamma}{1-\gamma}} I. \tag{A.4}$$

Here and in what follows we denote a steady state of some time-dependent variable X_t by X, i.e., $\lim_{t\longrightarrow\infty} X_t = X$. Dividing Equation (A.3) by Equation (A.4) implies that

$$\nu \equiv \frac{A}{N} = \frac{\lambda^b}{\lambda^e}\frac{m^{\frac{1}{1-\gamma}}}{\Gamma}. \tag{A.5}$$

Next, substitution of Equation (10) for Equation (8) yields, after some algebra, the steady-state value of m as

$$m = \frac{\gamma\rho + \frac{A}{I}}{1+\frac{p_H}{\Delta p}}. \tag{A.6}$$

Equation (13) can be rewritten at a steady state as

$$\frac{\gamma\rho + \frac{A}{I}}{1+\frac{p_H}{\Delta p}} = \left[\frac{\frac{p_H}{\Delta p}\Gamma}{(1-\gamma)\rho + \frac{N}{I}}\right]^{\frac{1-\gamma}{\gamma}}. \tag{A.7}$$

Combining Equations (A.6) and (A.7) and solving for ρ yields

$$\rho = \frac{1}{1-\gamma}\left(\frac{p_H}{\Delta p}\Gamma m^{-\frac{\gamma}{1-\gamma}} - \frac{N}{I}\right). \tag{A.8}$$

Inserting Equation (A.8) into (A.6) gives

$$m\left(1+\frac{p_H}{\Delta p}\right) = \frac{\gamma p_H \Gamma}{(1-\gamma)\Delta p} m^{-\frac{\gamma}{1-\gamma}} + \frac{A}{I} - \frac{\gamma N}{(1-\gamma) I}.$$

After substituting Equations (A.3) and (A.4) for the above formula, we obtain

$$1+\frac{\Delta p}{p_H} = \Gamma m^{-\frac{1}{1-\gamma}}\left[\frac{\gamma}{1-\gamma} + \lambda^e (1+r)\left(\frac{\lambda^b}{\lambda^e}\frac{m^{1+\frac{\gamma}{1-\gamma}}}{\Gamma} - \frac{\gamma}{1-\gamma}\right)\right].$$

By using the definition of ν from Equation (A.5), this can be rewritten as

$$\nu \frac{\lambda^e}{\lambda^b}\left(1+\frac{\Delta p}{p_H}\right) = \frac{\gamma}{1-\gamma} + \lambda^e (1+r)\left(\nu - \frac{\gamma}{1-\gamma}\right).$$

Solving for ν from the above equation gives

$$\nu = \left(\frac{\gamma}{1-\gamma}\right)\left[\frac{\frac{1}{\lambda^e} - 1 - r}{\frac{1}{\lambda^b}\left(1+\frac{\Delta p}{p_H}\right) - 1 - r}\right]. \tag{A.9}$$

Finally, from the household's Euler equation (3), we see that in steady state we must have

$$1 + r = \frac{1}{\beta}. \tag{A.10}$$

Using Equation (A.10), Equation (A.9) can be rewritten as

$$\nu = \left(\frac{\gamma}{1-\gamma}\right)\left[\frac{\frac{\beta}{\lambda^e} - 1}{\frac{\beta}{\lambda^b}\left(1+\frac{\Delta p}{p_H}\right) - 1}\right]. \tag{A.11}$$

It is evident that $\nu > 0$ if the following condition holds:

$$\beta > \max\left\{\lambda^e, \lambda^b\right\}. \tag{A.12}$$

A.4 Investment-Maximizing Structure of Informed Capital

In this section, we derive Equation (17). Let $G_t = (A_t + N_t)/I_t$. We study the following (dual) problem. We take the level of aggregate investment I_t as given. We seek the value of ν_t that maximizes the aggregate leverage $1/G_t = I_t/(A_t + N_t)$ and, by implication, minimizes the aggregate amount of informed capital $A_t + N_t$ needed for a given level of aggregate investment. Using $A_t/I_t = \nu_t G_t/(1+\nu_t)$ and $N_t/I_t = G_t/(1+\nu_t)$ (and recalling that $r_t^d = 0$), we can rewrite Equation (13)—which determines the equilibrium aggregate investment level I_t—as

$$\left(\frac{\nu_t G_t}{1+\nu_t} + \gamma\rho_t\right)^{\gamma}\left[\frac{G_t}{1+\nu_t} + (1-\gamma)\rho_t\right]^{1-\gamma} = \left(\frac{\Gamma p_H}{\Delta p}\right)^{1-\gamma}\left(1+\frac{p_H}{\Delta p}\right).$$

Differentiating this equation with respect to G_t and ν_t gives

$$\left.\frac{dG_t}{d\nu_t}\right|_{I_t} = \frac{G_t\left\{1-\gamma-\left(\frac{\nu_t G_t}{1+\nu_t}+\gamma\rho_t\right)^{-1}\left[\frac{G_t}{1+\nu_t}+(1-\gamma)\,\rho_t\right]\gamma\right\}}{(1+\nu_t)\left\{\left(\frac{\nu_t G_t}{1+\nu_t}+\gamma\rho_t\right)^{-1}\left[\frac{G_t}{1+\nu_t}+(1-\gamma)\,\rho_t\right]\gamma\nu_t+1-\gamma\right\}}. \tag{A.13}$$

The aggregate leverage is maximized when G_t is minimized. A potential minimum is obtained if the term in the curly brackets in the numerator on the right-hand side of Equation (A.13) is zero, i.e., if

$$\frac{\frac{\nu_t}{1+\nu_t}G_t+\gamma\rho_t}{\frac{G_t}{1+\nu_t}+(1-\gamma)\,\rho_t}=\frac{\gamma}{1-\gamma}.$$

This equation simplifies to

$$\nu_t=\frac{\gamma}{1-\gamma}\equiv\nu^{**}.$$

From Equation (A.13), we then observe that $dG_t/d\nu_t|_{I_t} < 0$ for $\nu_t < \nu^{**}$ and $dG_t/d\nu_t|_{I_t} > 0$ for $\nu_t > \nu^{**}$. Therefore, ν^{**} characterizes the value of ν_t that minimizes G_t and thereby maximizes the aggregate leverage and output.

A.5 Calculation of Marginal Rate of Technical Substitution

Differentiating (13) with respect to A_t and N_t gives

$$\left.\frac{dN_t}{dA_t}\right|_I=-\left(\frac{\gamma}{1-\gamma}\right)\left[\frac{\frac{N_t}{I_t}+(1-\gamma)\,\rho_t}{\frac{A_t}{I_t}+\gamma\rho_t}\right].$$

Evaluating this at a steady state and using Equations (A.8) and (A.6) in the numerator and the denominator of the term in the square brackets, respectively, yields, after some algebra,

$$\left.\frac{dN}{dA}\right|_I=-\left(\frac{\gamma}{1-\gamma}\right)\left(\frac{\Gamma m^{-\frac{1}{1-\gamma}}}{1+\frac{\Delta p}{p_H}}\right).$$

Using Equation (A.5) to substitute $\lambda^b/(\lambda^e\nu)$ for $\Gamma m^{-\frac{1}{1-\gamma}}$ and Equation (A.11) to eliminate $\gamma/[(1-\gamma)\nu]$, we get

$$\left.\frac{dN}{dA}\right|_I = -\frac{1+\frac{\Delta p}{p_H}-\frac{\lambda^b}{\beta}}{\left(1+\frac{\Delta p}{p_H}\right)\left(1-\frac{\lambda^e}{\beta}\right)}.$$

Appendix B. Policy

B.1 Public Funding

Assume that the government injects an aggregate amount A_t^g of capital into the banking system and an aggregate amount N_t^g of capital into nonfinancial corporations. The government demands the rate of return $r_t^g > 0$ for its investments. One may think that the government buys bank equity at the (unit) price $Q_t^b = (1+r_t^{a*})/(1+r_t^g)$ and firm equity at the price $Q_t^e = (1+r_t^{n*})/(1+r_t^g)$, where r_t^{a*} and r_t^{n*} denote the (expected) rate of return of bank capital and firm capital, respectively, when the public funding program is in place.

Let $\omega_t^b \equiv A_t^g/A_t \geq 0$ and $\omega_t^e \equiv N_t^g/N_t \geq 0$. Then $a_t^g = \omega_t^b a_t$ is the quantity of government-owned capital in an individual bank's balance sheet, and $n_t^g = \omega_t^e n_t$ public funding allocated to nonfinancial firms. Also, $R_t^{gb} = R_t^b\omega_t^b/Q_t^b$ and $R_t^{ge} = R_t^e\omega_t^e/Q_t^e$ are the (expected) shares of the proceeds going to the government in the banking sector and in the nonfinancial corporate sector, respectively.

B.1.1 Implications for the Financing Contract

With government participation, the optimal financing contract solves the following program:

$$\max_{\{i_t,a_t,a_t^g,n_t^g\ d_t,R_t^e,R_t^b,R_t^{gb},R_t^{ge},R_t^w,m_t\}} q_t p_H R_t^e i_t$$

subject to the entrepreneur's and her banker's incentive constraints (4a) and (4b), the depositors' and the banker's participation constraints (4c) and (4d), the resource constraints for investment inputs and outputs

$$a_t + a_t^g + d_t - m_t i_t \geq i_t - n_t - n_t^g, \tag{B.1}$$

$$R \geq R_t^e + R_t^b + R_t^{gb} + R_t^{ge} + R_t^w, \tag{B.2}$$

the sizes of government capital injections in banks and nonfinancial corporations

$$a_t^g = \omega_t^b a_t, \tag{B.3}$$

$$n_t^g = \omega_t^e n_t, \tag{B.4}$$

and the terms of those injections

$$R_t^{gb} = \frac{\omega_t^b}{Q_t^b} R_t^b \tag{B.5}$$

$$R_t^{ge} = \frac{\omega_t^e}{Q_t^e} R_t^e. \tag{B.6}$$

Substitution of $R_t^b = m_t / (q_t \Delta p)$, $R_t^e = h(m_t) / (q_t \Delta p)$, and Equations (B.5) and (B.6) into the return-sharing constraint (B.2) shows that depositors can be promised at most

$$R_t^w = R - \frac{\left(1 + \frac{\omega_t^b}{Q_t^b}\right) m_t + \left(1 + \frac{\omega_t^e}{Q_t^e}\right) h(m_t)}{q_t \Delta p}. \tag{B.7}$$

Substituting Equation (B.7) for the depositor's participation constraint (4c) yields

$$p_H \left\{ q_t R - \frac{\left[\left(1 + \frac{\omega_t^b}{Q_t^b}\right) m_t + \left(1 + \frac{\omega_t^e}{Q_t^e}\right) h(m_t)\right]}{\Delta p} \right\} = \frac{d_t}{i_t}. \tag{B.8}$$

Next, we combine the banker's incentive constraint (4b) with his participation constraint (4d), the input resource constraint (4e), and the sizes of government capital injections (B.3) and (B.4) to obtain

$$\frac{d_t}{i_t} = 1 + m_t - \left(1 + \omega_t^b\right) \frac{p_H}{\Delta p} \left(\frac{1}{1 + r_t^a}\right) m_t - \left(1 + \omega_t^e\right) \frac{n_t}{i_t}. \tag{B.9}$$

Combining Equations (B.8) and (B.9), and noting that $Q_t^b = (1 + r_t^a)/(1 + r_t^g)$ and $Q_t^e = (1 + r_t^n)/(1 + r_t^g)$, the program boils down to

$$\max_{m_t \geq 0} \frac{h(m_t)}{\widehat{g}(r_t^a, r_t^g, q_t, m_t)}, \tag{B.10}$$

in which

$$\widehat{g}(r_t^a, r_t^g, q_t, m_t) \equiv (1 + \omega_t^e (1 + r_t^g)) \frac{p_H}{\Delta p} h_t(m_t) + \left[1 + \frac{p_H}{\Delta p}\left(1 - \frac{1}{1 + r_t^a}\right) + \omega_t^b \frac{p_H}{\Delta p}\left(\frac{r_t^g}{1 + r_t^a}\right)\right] m_t - \rho_t$$

is the inverse firm leverage. Given the monitoring technology (7), the unique interior solution to the problem (B.10) is

$$m_t^* = \frac{\gamma \rho_t}{1 + \frac{p_H}{\Delta p}\left(1 - \frac{1}{1 + r_t^a}\right) + \omega_t^b \frac{p_H}{\Delta p}\left(\frac{r_t^g}{1 + r_t^a}\right)}. \tag{B.11}$$

Comparing (B.11) with (8) indicates that public ownership in banks, which dilutes bankers' stakes, lowers monitoring intensity.

B.1.2 Implications for Incentives and Investments

Equation (B.11) characterizes the equilibrium monitoring intensity with government participation. Note that the banker's incentive and participation constraints (4b) and (4d) (together with the aggregation condition (9)) imply that in equilibrium the bankers' monitoring intensity must also be characterized by $m_t = (\Delta p / p_H)(A_t / I_t)(1 + r_t^{a*})$. Combining these observations, we get the rate of return to banker-owned capital

$$1 + r_t^{a*} = \frac{1 + \gamma \rho_t \frac{I_t^*}{A_t} - \omega_t^b r_t^g}{1 + \frac{\Delta p}{p_H}} = \frac{1 + \gamma \rho_t \frac{I_t^*}{A_t} - r_t^g \frac{A_t^g}{A_t}}{1 + \frac{\Delta p}{p_H}}. \tag{B.12}$$

Comparing (B.12) with (10) indicates that the return to banker-owned capital is lower when public policies are in place. Plugging Equation (B.12) into (B.11) then yields

$$m_t^* = \left(1 + \frac{p_H}{\Delta p}\right)^{-1} \left(\left(1 - \omega_t^b r_t^g\right) \frac{A_t}{I_t^*} + \gamma \rho_t\right)$$
$$= \left(1 + \frac{p_H}{\Delta p}\right)^{-1} \left(\frac{A_t - r_t^g A_t^g}{I_t^*} + \gamma \rho_t\right). \tag{B.13}$$

Comparing Equations (B.13) and (11) reveals that public ownership in banks dilutes bankers' stakes. Hence, bankers have weaker incentives to monitor intensively. Next, Equations (B.1), (B.3), and (B.4) together with the aggregation Equation (9) imply that

$$\frac{D_t^*}{I_t^*} = 1 + m_t^* - \frac{\left(1 + \omega_t^b\right) A_t + \left(1 + \omega_t^e\right) N_t}{I_t^*}$$
$$= 1 + m_t^* - \frac{A_t + A_t^g + N_t + N_t^g}{I_t^*}. \tag{B.14}$$

Then applying (9) to Equation (B.8), and plugging in expressions (B.12), B.13), and (B.14), allows us to see how the entrepreneurs' maximum incentive-compatible nonverifiable revenue from a "bad" project depends on public policies and aggregate variables

$$h_t^* = \frac{\Delta p}{p_H} \left(\frac{N_t - r_t^g N_t^g}{I_t^*} + (1 - \gamma) \rho_t\right). \tag{B.15}$$

Comparing (12) and (B.15) reveals that public stakes in firms dilute the entrepreneurs' stakes. As a result the entrepreneurs have weaker incentives to choose the "good" project. Combining (B.15) with (4a) yields the expected rate of return to entrepreneurial capital

$$1 + r_t^{n*} = 1 + (1 - \gamma) \rho_t \left(\frac{I_t^*}{N_t}\right) - \omega_t^e r_t^g$$
$$= 1 + (1 - \gamma) \rho_t \left(\frac{I_t^*}{N_t}\right) - r_t^g \left(\frac{N_t^g}{N_t}\right), \tag{B.16}$$

which is defined in the same way as in (15b). Comparing (B.16) with (15b) indicates that the return to entrepreneurial capital is lower when public policies are in place. But m^* given by (B.13) and h^*

given by (B.15) are linked by the monitoring technology (7). Then, assuming that there is monitoring in equilibrium, we get

$$\left(\frac{A_t - r_t^g A_t^g}{I_t^*} + \gamma\rho_t\right)^{\gamma} \left(\frac{N_t - r_t^g N_t^g}{I_t^*} + (1-\gamma)\,\rho_t\right)^{1-\gamma} = \left(\frac{p_H}{\Delta p}\Gamma\right)^{1-\gamma} \left(1 + \frac{p_H}{\Delta p}\right)^{\gamma}. \tag{B.17}$$

This is Equation (23) of the main text. This equation implicitly determines the aggregate investment level I_t^* in the economy when the government funds banks, nonfinancial firms, or both.

Taken together, Equations (B.12), (B.13), (B.15), (B.16), and (B.17) indicate that public funding dilutes the insiders' stakes in the investment projects, and as a result bankers find it more tempting not to monitor, while entrepreneurs face stronger incentives to choose a "bad" project with nonverifiable revenues. Since the severity of these moral hazard problems also increases with the scale of the investment projects, aggregate investments in equilibrium must be lower when the public funding program is in place.

When public policy is introduced, Stage 1 of period t is already behind. Hence, L_t and Y_t are given, and these variables are not affected by policy. Then period t consumption C_t^* is given by the aggregate resource constraint $C_t^* = Y_t - I_t^*$. Therefore, current investment, I_t^*, is a sufficient statistic when evaluating how the distortions from period t public policy affect the current period t.

B.1.3 Public Funding: Dynamic Implications of Distortions

Given Equation (B.16), the end-of-period t entrepreneurial capital is given by

$$\widetilde{N}_t^* = (1 + r_t^{n*})\,N_t = N_t + (1-\gamma)\,\rho_t I_t^* - r_t^g N_t^g. \tag{B.18}$$

In particular, the last term $-r_t^g N_t^g$ is the direct effect of public funding. Since government funding commands a premium r_t^g, it raises revenues equal to $r_t^g N_t^g$, and this in turn lowers the revenues accruing to the entrepreneurs.

Given Equation (B.12), the end-of-period t banker-owned capital is given by

$$\widetilde{A}_t^* = (1 + r_t^{a*})\, A_t = \frac{A_t + \gamma \rho_t I_t^*}{1 + \frac{\Delta p}{p_H}} - \frac{r_t^g A_t^g}{1 + \frac{\Delta p}{p_H}}. \tag{B.19}$$

Once again, the last term in (B.19) is the direct effect of public funding. To understand why the direct effect is equal to $-r_t^g A_t^g / (1 + \frac{\Delta p}{p_H})$, rather than $-r_t^g A_t^g$ (as it might seem intuitive), note that, given Equation (B.13), public funding lowers banks' monitoring intensity and monitoring costs:

$$m_t^* I_t^* = \frac{A_t + \gamma \rho_t I_t^*}{1 + \frac{p_H}{\Delta p}} - \frac{r^g A_t^g}{1 + \frac{p_H}{\Delta p}},$$

where $-r^g A_t^g / (1 + \frac{p_H}{\Delta p}) = -\frac{\Delta p}{p_H} r^g A_t^g / (1 + \frac{\Delta p}{p_H})$ is the direct effect. Now, while the government earns the amount $r_t^g A_t^g$, only the share

$$r_t^g A_t^g - \left(\frac{\frac{\Delta p}{p_H}}{1 + \frac{\Delta p}{p_H}} \right) r_t^g A_t^g = \frac{r_t^g A_t^g}{1 + \frac{\Delta p}{p_H}}$$

is paid by the bankers, while the remaining share $\frac{\Delta p}{p_H} r^g A_t^g / (1 + \frac{\Delta p}{p_H})$ is paid by the workers—or households. (Remember that we assume that the banks pay the monitoring costs to the workers.)

To eliminate the harmful direct effects on future bank and firm capital, we assume that the government rebates the revenues from the premium back to the entrepreneurs, bankers, and workers in a lump-sum manner. This minimizes welfare losses while still keeping public funding unattractive for individual entrepreneurs and bankers, and hence avoiding intertemporal moral hazard. Since entrepreneurs receive a lump-sum rebate $r_t^g N_t^g$ and bankers receive a lump-sum rebate $r_t^g A_t^g / (1 + \frac{\Delta p}{p_H})$, Equations (B.18) and (B.19) yield

$$\widetilde{N}_t^* = N_t + (1 - \gamma)\, \rho_t I_t^* = (1 + r_t^n)\, N_t \tag{B.20}$$

and

$$\widetilde{A}_t^* = \frac{A_t + \gamma \rho_t I_t^*}{1 + \frac{\Delta p}{p_H}} = (1 + r_t^a)\, A_t, \tag{B.21}$$

where $(1 + r_t^n)$ and $(1 + r_t^a)$ are given by Equations (15b) and (10), respectively, (with I_t replaced by I_t^* in these equations) while the (middle-of) period $t + 1$ values are given by

$$N_{t+1}^* = \lambda^e \left(\frac{r_{t+1}^K + (1 - \delta)\, q_{t+1}}{q_t} \right) \widetilde{N}_t^* \tag{B.22}$$

and

$$A_{t+1}^* = \lambda^b \left(\frac{r_{t+1}^K + (1 - \delta)\, q_{t+1}}{q_t} \right) \widetilde{A}_t^*. \tag{B.23}$$

Hence, since the lump-sum rebates eliminate the direct effects, all the distorting effects of period t public funding to future insider wealth run through period t investments I_t^*.

Note that the distorting effects of the program affect also physical capital K_{t+1}^*, the third period $t+1$ state variable, through period t investments I_t^*. Hence, I_t^* is a sufficient statistic when evaluating how the distortions from period t public policy affect future periods. Finally, since I_t^* is a sufficient statistic for both period t (see Section B.1.2 of this appendix) and for future periods, I_t^* is also a sufficient statistic for the (current and future) price of capital, q_t.

B.1.4 Implications for Effects of an Investment Shock

In the aftermath of an investment shock, the project success probabilities are given by $\widetilde{p}_{\tau t} \equiv p_\tau(1 + \varepsilon_t)$, $\tau \in \{H, L\}$. Then, in equilibrium, the aggregate revenue from the projects is $\widetilde{p}_{Ht} q_t R I_t^*$. From that revenue, entrepreneurs and the government (which has invested in nonfinancial firms) are paid $\widetilde{p}_{Ht} q_t R_t^e I_t^*$ and $\widetilde{p}_{Ht} q_t R_t^{ge} I_t$, respectively. The remaining, stochastic, revenue is left to banks, which have to pay the fixed sum D_t^* to depositors, or outside debt holders. What is left is divided between bankers $(\widetilde{p}_{Ht} q_t \widetilde{R}_t^b I_t)$ and the government $(\widetilde{p}_{Ht} q_t \widetilde{R}_t^{gb} I_t)$, where the ex post shares $\widetilde{R}_t^b$ and $\widetilde{R}_t^{gb}$ depend on the shock realization ε_t. Since the bankers' and the government's revenues are proportional to their respective ownership shares, the ratio $\widetilde{R}_t^{gb}/\widetilde{R}_t^b$ must be the same as the ratio R_t^{gb}/R_t^b, given by Equation (B.5). Evidently, bankers and the government absorb the losses due to the aggregate investment shock in proportion to their revenue/ownership shares, implying that the share of losses absorbed by bankers is $R_t^b / \left(R_t^b + R_t^{gb} \right) = \left(1 + \frac{\omega_t^b}{Q_t^b} \right)^{-1}$.

Then, following an investment shock in period t, the aggregate bank capital at the end of period t is given by

$$\begin{aligned}\widetilde{A}_t^*(\varepsilon_t) &= I_t^* p_H q_t \left[R_t^b + \left(\frac{R_t^b}{R_t^b + R_t^{gb}} \right) (R - R_t^e - R_t^{ge})\, \varepsilon_t \right] \\ &= I_t^* p_H q_t \left[R_t^b + \left(\frac{R_t^b}{R_t^b + R_t^{gb}} \right) \left(R_t^b + R_t^{gb} + R_t^w \right) \varepsilon_t \right],\end{aligned} \tag{B.24}$$

where the last form follows from Equation (B.2). Using (4b), (4c), (4d), (9), (B.5), and (B.11), together with $Q_t^b = (1 + r_t^{a*}) / (1 + r_t^g)$, $\omega_t^b = A_t^g / A_t$, and $r_t^d = 0$, allows us to rewrite (B.24) as follows:

$$\begin{aligned}&\widetilde{A}_t^*(\varepsilon_t) \\ &\quad = A_t (1 + r_t^{a*}) \left[1 + \left\{ 1 + \left(\frac{1}{1 + r_t^g} \right) \left(\frac{D_t^*}{(1 + r_t^{a*}) A_t + A_t^*} \right) \right\} \varepsilon_t \right],\end{aligned} \tag{B.25}$$

where $(1 + r_t^{a*})$ is given by (B.12) while (B.14) implies that

$$D_t^* = (1 + m_t^*) I_t^* - (A_t + A_t^g + N_t + N_t^g).$$

Next, assuming that (i) bankers receive a lump-sum rebate $r_t^g A_t^g / (1 + \frac{\Delta p}{p_H})$ (see Appendix B.1.3) and (ii) $r_t^g = dr_t^g > 0$ is small, we get

$$\widetilde{A}_t^*(\varepsilon_t) = A_t (1 + r_t^a)(1 + BL_t^* \varepsilon_t) \; + O(dr_t^g \varepsilon_t), \tag{B.26}$$

where

$$BL_t^* = 1 + \frac{D_t - A_t^g - N_t^g}{(1 + r_t^a) A_t + A_t^g}. \tag{B.27}$$

Assuming that the terms $O(dr_t^g \varepsilon_t)$, which are of the order $dr_t^g \times \varepsilon_t$, can be disregarded, Equation (B.26) yields (24a) in the main text, while (B.27) is (24b).

B.2 Public Funding and the Resilience of the Banking Sector: Welfare Implications

Let us consider the welfare implications of public funding when a (negative) aggregate shock hits the economy. To do so, it is useful to

analyze the end-of-period values of bankers' wealth, $\widetilde{A}_t(\varepsilon_t)$, entrepreneurial wealth, $\widetilde{N}_t(\varepsilon_t)$, and physical capital, $\widetilde{K}_t(\varepsilon_t)$. $\widetilde{A}_t(\varepsilon_t)$, $\widetilde{N}_t(\varepsilon_t)$, and $\widetilde{K}_t(\varepsilon_t)$ are the values of the state variables after the investment stage of period t, when the investment shock is realized, while A_t, N_t, and K_t are the corresponding values before the investment stage of period t (but after the production stage of period t). (Also note that A_{t+1}, N_{t+1}, and K_{t+1} are the values of the state variables in period $t+1$, after the production stage but before the investment stage). Under laissez-faire, the end-of-period aggregate banker-owned wealth is given by Equation (20a). If there is a public funding program in place, the end-of-period bankers' wealth is given by Equation (24a). The end-of-period entrepreneurial wealth is given by the Equation (19) and the end-of-period physical capital is characterized by

$$\widetilde{K}_t(\varepsilon_t) = K_t + I_t(1+\varepsilon_t)$$

whether or not public policies are in place.[24]

The welfare of the representative household from the next period $(t+1)$ onward depends on these end-of-period (t) values of the state variables. Under laissez-faire, the value function is $\widetilde{V}(\widetilde{A}_t(\varepsilon_t), \widetilde{N}_t(\varepsilon_t), \widetilde{K}_t(\varepsilon_t))$, while if there is a public funding program in place, welfare is given by $\widetilde{V}(\widetilde{A}^*_t(\varepsilon_t), \widetilde{N}_t(\varepsilon_t), \widetilde{K}_t(\varepsilon_t))$. Since $\widetilde{A}^*_t(\varepsilon_t) > \widetilde{A}_t(\varepsilon_t)$, when $\varepsilon_t < 0$, we have $\widetilde{V}(\widetilde{A}^*_t(\varepsilon_t), \widetilde{N}_t(\varepsilon_t), \widetilde{K}_t(\varepsilon_t)) > \widetilde{V}(\widetilde{A}^*_t(\varepsilon_t), \widetilde{N}_t(\varepsilon_t), \widetilde{K}_t(\varepsilon_t))$. In particular (if ε_t is small enough), the welfare gain from public funding can be approximated by

$$\begin{aligned}\Delta\widetilde{V} &= \widetilde{V}(\widetilde{A}^*_t(\varepsilon_t), \widetilde{N}_t(\varepsilon_t), \widetilde{K}_t(\varepsilon_t)) - \widetilde{V}(\widetilde{A}_t(\varepsilon_t), \widetilde{N}_t(\varepsilon_t), \widetilde{K}_t(\varepsilon_t)) \\ &\approx \widetilde{V}_{\widetilde{A}}\left[\widetilde{A}^*_t(\varepsilon_t) - \widetilde{A}_t(\varepsilon_t)\right] = \widetilde{V}_{\widetilde{A}}(1+r^a_t) A_t (BL^*_t - BL_t)\varepsilon_t \\ &= -\widetilde{V}_{\widetilde{A}} BRE_t S_t \varepsilon_t,\end{aligned}$$

where $\widetilde{V}_{\widetilde{A}}$ is the derivative of the value function with respect to $\widetilde{A}$, $BRE_t = (1+r^a_t) BL_t A_t$ is the banks' (macro) risk exposure

[24]Note that the impact of the shock on the (middle-of-period) $t+1$ entrepreneurial wealth $\widetilde{N}^*_{t+1}(\varepsilon_t)$ depends on public funding. This is because the impact of the shock on the period $t+1$ price of capital q_{t+1} depends on public policies. However, the connection from (period t) public policies to q_{t+1} and $\widetilde{N}^*_{t+1}(\varepsilon_t)$ goes through $\widetilde{A}^*_t(\varepsilon_t)$.

under laissez-faire, and $S_t = (BL_t - BL_t^*)/BL_t$ measures the size of the public funding program. This is Equation (25) in the main text.

B.3 The Fiscal Size of the Funding Program and Derivation of the Policy Frontier

If the government funds nonfinancial firms—say the government buys a diversified (market) portfolio of firm debt—the losses it incurs are directly proportional to the size of the firm funding program N_t^g and to the size of the (negative shock) ε_t. However, if the government capitalizes banks, its losses are amplified. With an equity stake A_t^g in banks, the government stands to lose $A_t^g BL_t^*\left(A_t^*, N_t^g; r_t^g\right)\varepsilon_t$ if a negative shock $\varepsilon_t < 0$ hits. Taken together, the losses, or the fiscal costs, of a public funding program (A_t^g, N_t^g) can be expressed as

$$FC\left(A_t^g, N_t^g; r_t^g, \varepsilon_t\right) = -A_t^g BL_t^*\left(A_t^*, N_t^g; r_t^g\right)\varepsilon_t - N_t^g\varepsilon_t. \qquad \text{(B.28)}$$

Assuming $r_t^g = dr_t^g$ is small, so that terms of the order $dr_t^g\varepsilon_t$ can be disregarded, Equation (B.28) can be rewritten as

$$\begin{aligned} FC\left(A_t^g, N_t^g; \varepsilon_t\right) &= -A_t^g\left(1 + \frac{D_t - A_t^g - N_t^g}{Q_t^b A_t + A_t^g}\right)\varepsilon_t - N_t^g\varepsilon_t \\ &= -\left(\frac{Q_t^b A_t}{Q_t^b A_t + A_t^g}\left(A_t^g + N_t^g\right) + \frac{A_t^g}{Q_t^b A_t + A_t^g} D_t\right)\varepsilon_t \\ &= -Q_t^b A_t\left(\frac{D_t}{Q_t^b A_t} - \frac{D_t - A_t^g - N_t^g}{Q_t^b A_t + A_t^g}\right)\varepsilon_t \\ &= -\left(1 + r_t^a\right) A_t\left(BL_t - BL_t^*\right)\varepsilon_t = -BRE_t S_t\varepsilon_t. \end{aligned}$$

However, since $FC\left(A_t^g, N_t^g; r_t^g, \varepsilon_t\right) = BRE_t S_t\varepsilon_t$, Equation (B.28) yields

$$BRE_t S_t = BL_t^* A_t^g + N_t^g.$$

This is the policy frontier (27).

B.4 Proof of Proposition 2

The aim here is to find the optimal structure of public funding (A_t^g, N_t^g), and to link the desired structure to the size of the funding program S_t. We also show how the mapping from the size to

the appropriate structure defines the sets of undominated and dominated policies.

Assume that the economy is initially in a steady state, and is hit by a negative investment shock ($\varepsilon_t < 0$). We assume that there is genuine uncertainty, and we do not specify a probability distribution over the negative shock realizations. Let us denote the discounted sum of present and future household utility, given a funding program (A_t^g, N_t^g, S_t), the premium on public funding r_t^g, and a shock realization $\varepsilon_t < 0$ by $V = V(A_t^g, N_t^g, S_t; r_t^g; \varepsilon_t; \cdot)$. Given this environment, our objective is to narrow down the policy options that the government should consider under genuine uncertainty. We aim at characterizing two sets of policies: the undominated set, which includes policies that the government should consider, and the dominated set, which includes policies that the government should avoid.

The next step is to bring in more structure into the relationsip between the policy program and household welfare, $V(A_t^g, N_t^g, S_t; r_t^g; \varepsilon_t; \cdot)$. We assume that the (excess) return on public funds, $dr_t^g = r_t^g - r_t^d$, is small enough, compared with the other terms, so that its cross-terms with the shock, which are proportional to $\varepsilon_t \times dr_t^g$, can be ignored in the analysis. This assumption allows us to decouple, and analyze separately, the welfare benefits of the program (which are proportional to ε_t) and the welfare losses of the program (which are proportional to dr_t^g). This is shown in Appendix B.1, Section B.1.4. See in particular Equation (B.26), which shows where the cross-terms would enter.

On the welfare benefit side of the program, the size of the program S_t, defined in Equation (26), is a sufficient statistic. All programs (A_t^g, N_t^g, S_t) which lie on the policy frontier, i.e., satisfy Equation (27), give rise to the same level of stabilization, or enhanced resilience, (S_t) in the face of negative macro shock ε_t. Hence, the welfare benefits of the program, after a negative shock realization $\varepsilon_t < 0$, are proportional to the product $S_t\varepsilon_t$. See Equation (25) and the underlying analysis in Appendix B.2. Furthermore, we show in Appendix B.3 that the fiscal costs of the funding program are given by $FC_t = -BRE_tS_t\varepsilon_t$, which measures the government's losses from a public funding program of size S_t if a negative shock $\varepsilon_t < 0$ hits the economy. If the fiscal costs have to be covered by distortionary taxes, the resulting welfare losses from taxation depend on FC_t. Hence, the net welfare benefits of the program, net of possible losses from distortionary taxation, are proportional to $S_t\varepsilon_t$.

As shown in Appendix B.1, Subsections B.1.2 and B.1.3, the current investments are a sufficient statistic of the social welfare costs arising from the distorting effects of public funding. That is, the distorting effects of the program to all model variables (current and future), are transmitted through current investments, $I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g; \cdot\right)$. Therefore, the harmful effects of the program on social welfare, given by the value function (V), are also transmitted through current investments. If program (A_t^g, N_t^g, S_t) gives rise to lower (higher) current investments than an alternative program $\left(A_t^{g\prime}, N_t^{g\prime}, S_t'\right)$, then program (A_t^g, N_t^g, S_t) creates larger (smaller) welfare losses than program $\left(A_t^{g\prime}, N_t^{g\prime}, S_t'\right)$.

Hence, we can conclude that the mapping from a policy package (A_t^g, N_t^g, S_t) to social welfare (V) has the following structure:

$$V = V(I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g, \cdot\right), S_t\varepsilon_t; \varepsilon_t, \cdot),$$

subject to (27). Our task is to find policies (A_t^g, N_t^g, S_t) such that there do not exist alternative policies $\left(A_t^{g\prime}, N_t^{g\prime}, S_t'\right)$ that would dominate (A_t^g, N_t^g, S_t). We say that a policy $\left(A_t^{g\prime}, N_t^{g\prime}, S_t'\right)$ dominates the policy (A_t^g, N_t^g, S_t) if $\left(A_t^{g\prime}, N_t^{g\prime}, S_t'\right)$ gives rise to at least as high utility as (A_t^g, N_t^g, S_t) in all states of the world, and higher utility in some states of the world. Here the different states of the world correspond to different (negative) shocks realizations $\varepsilon_t < 0$. More formally, the set of undominated policies (A_t^g, N_t^g, S_t) is defined as follows:

$$\begin{aligned}
&\text{Find } A_t^g \;\geq\; 0,\; N_t^g \geq 0 \text{ and } S_t, \\
&\qquad\qquad\qquad\qquad \text{such that } \nexists\, A_t^{g\prime},\; N_t^{g\prime}, S_t' \\
&V(I_t^*\left(A_t^{g\prime} dr_t^g, N_t^{g\prime} dr_t^g, \cdot\right), S_t'\varepsilon_t; \varepsilon_t, \cdot) \geq V(I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g, \cdot\right), \\
&\qquad\qquad\qquad\qquad S_t\varepsilon_t; \varepsilon_t, \cdot), \forall \varepsilon_t < 0 \\
&\qquad\qquad\qquad\qquad \text{subject to} \\
&\qquad\qquad BRE_t S_t = N_t^g + BL_t(1 - S_t)A_t^g, \\
&\qquad\qquad BRE_t S_t' = N_t^{g\prime} + BL_t(1 - S_t')A_t^{g\prime}.
\end{aligned}$$

Next, recall that S_t is a sufficient statistic of the social welfare benefits of a program (A_t^g, N_t^g, S_t). Likewise, S_t' is a sufficient statistic of the social welfare benefits of an alternative program $(A_t^{g\prime}, N_t^{g\prime}, S_t')$. Then if S_t' is larger (smaller) than S_t, the program

$(A_t^{g\prime}, N_t^{g\prime}, S_t')$ gives rise to larger (smaller) social welfare benefits than (A_t^g, N_t^g, S_t) after any negative shock realization $\varepsilon_t < 0$. If $S_t' = S_t$, the programs $(A_t^{g\prime}, N_t^{g\prime}, S_t')$ and (A_t^g, N_t^g, S_t) give rise to the same social welfare benefits after any negative shock realization $\varepsilon_t < 0$. We may say that policy $(A_t^{g\prime}, N_t^{g\prime}, S_t')$ dominates policy (A_t^g, N_t^g, S_t) if $S_t' = S_t$ (so that both policies result in the same welfare benefits after any shock realization $\varepsilon_t < 0$) but $(A_t^{g\prime}, N_t^{g\prime}, S_t')$ generates smaller distortions and welfare losses than (A_t^g, N_t^g, S_t). Since current investments, I_t^*, are a sufficient statistic for welfare losses, we can conclude that $(A_t^{g\prime}, N_t^{g\prime}, S_t')$ dominates (A_t^g, N_t^g, S_t) if and only if $I_t^*\left(A_t^{g\prime} dr_t^g, N_t^{g\prime} dr_t^g, \cdot\right) > I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g, \cdot\right)$ and $S_t' = S_t$.

We can find the set of undominated policies in the following way. We choose a target level (S_t) for the stabilization of the financial system, that is the size of the program. Then we find the stucture of the program (A_t^g, N_t^g) that minimizes distortions or, equivalently, maximizes $I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g; \cdot\right)$ subject to (27). More formally,

$$\max_{\{A_t^g, N_t^g\}} I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g; \cdot\right)$$

subject to

$$BRE_t S_t = N_t^g + BL_t(1 - S_t)A_t^g,\ A_t^g \geq 0,\ N_t^g \geq 0,$$

where S_t, BRE_t, and BL_t are taken as given. The corresponding *Lagrangian* is

$$\mathcal{L} = I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g; \cdot\right) + \eta_1\left[N_t^g + BL_t(1 - S_t)A_t^g - BRE_t \times S_t\right] + \eta_2 A_t^g + \eta_3 N_t^g,$$

where η_1, η_2, and η_3 are Lagrangian multipliers. The first-order conditions with respect to A_t^g and N_t^g are

$$\frac{\partial I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g; \cdot\right)}{\partial A_t^g} + \eta_1 BL_t(1 - S_t) + \eta_2 = 0 \tag{B.29}$$

$$\frac{\partial I_t^*\left(A_t^g dr_t^g, N_t^g dr_t^g; \cdot\right)}{\partial N_t^g} + \eta_1 + \eta_3 = 0. \tag{B.30}$$

The Kuhn-Tucker conditions associated with the constraints $A_t^g \geq 0$ and $N_t^g \geq 0$ are

$$\eta_2 = 0 \text{ if } A_t^g > 0, \quad \eta_2 > 0 \text{ if } A_t^g = 0$$
$$\eta_3 = 0 \text{ if } N_t^g > 0, \quad \eta_3 > 0 \text{ if } N_t^g = 0.$$

Next note that Equation (23) implies that in the neighborhood of the steady state

$$\frac{\frac{\partial I_t^*}{\partial A_t^g}}{\frac{\partial I_t^*}{\partial N_t^g}} = \frac{-\frac{\partial I_t}{\partial A_t} dr_t^g}{-\frac{\partial I_t}{\partial N_t} dr_t^g} = \left|\frac{dN}{dA}\right|_I = MRTS.$$

There are three types of solutions, or three regimes:

(i) If $A^g > 0$ and $N_t^g = 0$, we have $\eta_2 = 0,\ \eta_3 > 0$. Then dividing (B.30) by (B.29) gives, after some straightforward algebra,

$$\frac{1}{MRTS} = \frac{1}{BL_t(1-S_t)} + \frac{\eta_3}{\eta_1}\frac{1}{BL_t(1-S)}$$
$$\Rightarrow MRTS < BL_t(1-S_t),$$

where the inequality follows, since $\eta_1 > 0$ and $\eta_3 > 0$.

(ii) If $A_t^g = 0$ and $N_t^g > 0$, we have $\eta_2 > 0,\ \eta_3 = 0$. Dividing (B.29) by (B.30) then gives

$$MRTS = BL_t(1-S_t) + \frac{\eta_2}{\eta_1} \Rightarrow MRTS > BL_t(1-S_t),$$

where the inequality follows, since $\eta_1 > 0$ and $\eta_2 > 0$.

(iii) If $A_t^g > 0$ and $N_t^g > 0$, we have $\eta_2 = 0,\ \eta_3 = 0$. Dividing (B.29) by (B.30) then gives

$$MRTS = BL_t(1-S_t).$$

It is easy to see that this characterization of undominated policies gives us a mapping from the size of the program (S_t) to the optimal structure of the program (A_t^g, N_t^g). Let us define $S_t^* = 1 - MRTS/BL_t$. (i) If $S_t < S_t^*$ the optimal structure is $A_t^g = (BRE_t/BL_t)\,(S_t/(1-S_t))$, $N_t^g = 0$. (ii) If $S_t > S_t^*$ the optimal structure is $A_t^g = 0,\ N_t^g = BRE_t \times S_t$. (iii) If $S_t = S_t^*$, any structure $A_t^g \geq 0,\ N_t^g \geq 0$ which satisfies (27) is optimal. Note that (iii) is a knife-edge case, with measure zero.

Finally, all policies (A_t^g, N_t^g, S_t) which do not belong to the undominated set are dominated. ■

B.5 The Threshold Size of a Public Funding Program

In this section, we express the threshold size of a public funding program, S^*, with the help of the observable data moments used in the calibration of the model. We also examine the sensitivity of the threshold size S^* to the calibration.

Expressing S^* in Terms of Data Moments. Remember that $S^* = 1 - MRTS/BL$. Let us first express the bank leverage accelerator (under laissez-faire), BL, in terms of the data moments used in calibration (see Section 5 and Appendix C.2). Using (C.2) and (C.3) in Appendix C.2 we get

$$BL = \frac{1 + MRB + r^a CRB}{(1 + r^a)\, CRB}. \tag{B.31}$$

Note that since $\left(\frac{1+MRB+r^a CRB}{1+r^a}\right)$ tends to be rather close to unity, we get $BL \approx CRB^{-1}$.

Next, plugging Equations (C.5), (C.6), and (C.7) in Appendix C.2 into (18) allows us to express $MRTS$ in terms of the data moments we use in calibrating the model:

$$MRTS = \frac{(1 + r^n)\,(r^a CRB + MRB)}{r^n\,((1 + r^a)\, CRB + MRB)}, \tag{B.32}$$

where MRB is a measure of banks' monitoring costs, relative to banks' assets. To gain some further intuition, it is useful to re-express $MRTS$ as

$$MRTS = \left(\frac{1 + \frac{MRB}{r^a CRB}}{1 + \frac{MRB}{(1+r^a)CRB}}\right)\left(\frac{r^a}{r^n}\right)\left(\frac{1 + r^n}{1 + r^a}\right).$$

Note that the terms $1 + \frac{MRB}{r^a CRB}$ and $\left(\frac{r^a}{r^n}\right)$ are potentially quite large (evidently depending on calibration), while the remaining terms $1 + \frac{MRB}{(1+r^a)CRB}$ and $\left(\frac{1+r^n}{1+r^a}\right)$ tend to be close to unity. Then

$$MRTS \approx (r^a + MRB/CRB)\,/r^n.$$

We now turn to the conditions under which $MRTS < BL$, so that $S^* = 1 - \frac{MRTS}{BL} > 0$. Applying Equations (B.31) and (B.32), one can show that this is the case if and only if

$$\frac{1+r^n}{r^n} < \left(\frac{1+r^aCRB+MRB}{r^aCRB+MRB}\right)\left(1+\frac{MRB}{(1+r^a)\,CRB}\right). \quad \text{(B.33)}$$

In Appendix D.3, however, we show that the model has an equilibrium with a meaningful role for financial intermediation if and only if $r^n > r^aCRB + MRB$ (see condition (D.43)). This condition can be rewritten as

$$\frac{1+r^n}{r^n} < \frac{1+r^aCRB+MRB}{r^aCRB+MRB}. \quad \text{(B.34)}$$

Note that (B.34) implies (B.33). Hence, if there is an equilibrium where banks intermediate funding and monitor entrepreneurial firms, there exists a threshold value $S^* > 0$.

Finally, combining (B.31) and (B.32) yields

$$\begin{aligned} S^* &= 1 - \frac{MRTS}{BL} = 1 - \left(\frac{r^aCRB+MRB}{1+r^aCRB+MRB}\right) \\ &\quad \left(\frac{(1+r^n)\,CRB}{r^n\left((1+r^a)\,CRB+MRB\right)}\right) \\ &= 1 - \left(\frac{r^a+\frac{MRB}{CRB}}{CRB^{-1}+r^a+\frac{MRB}{CRB}}\right)\left(\frac{1+r^n}{r^n\left(1+r^a+\frac{MRB}{CRB}\right)}\right). \end{aligned} \quad \text{(B.35)}$$

To gain some further intuition, note that $CRB^{-1} + r^a + \frac{MRB}{CRB} \approx CRB^{-1}$, while the term $\frac{1+r^n}{1+r^a+\frac{MRB}{CRB}}$ tends to be rather close to unity (evidently depending on the calibration). Thus, we get

$$S^* \approx 1 - \left(r^aCRB + MRB\right)/r^n.$$

These findings are numerically illustrated in Table B.1, which reports the threshold size S^*, given by (B.35), for different values of the data moments r^a, CRB, and MRB, while $r^n = 4.5\%$ follows the baseline calibration.

B.6 Dominated and Undominated Policies: Example

We assume that the utility function involves internal habit persistence, and the subutility function for consumption is

Table B.1. Threshold Size S^* with Different Calibrations of the Financial Block (baseline calibration in bold)

		CRB								
$r^a = 10\%$		**4.0**	**5.0**	**6.0**	**7.0**	**8.0**	**9.0**	**10.0**	**11.0**	**12.0**
MRB	0.5	0.81	0.79	0.77	0.74	0.72	0.69	0.67	0.65	0.63
	1.0	0.74	0.71	0.68	0.66	0.63	0.61	0.58	0.56	0.54
	1.5	0.68	0.64	0.61	0.58	0.55	0.53	0.50	0.48	0.45
	2.0	0.63	0.58	0.55	0.52	0.48	0.46	0.43	0.40	0.37
	2.5	0.58	0.54	0.49	0.46	0.42	0.39	0.36	0.33	0.30
	3.0	0.55	0.49	0.45	0.40	0.37	0.33	0.30	0.27	0.24
	3.5	0.51	0.45	0.40	0.36	0.32	0.28	0.24	NA	NA
		CRB								
$r^a = 12\%$		**4.0**	**5.0**	**6.0**	**7.0**	**8.0**	**9.0**	**10.0**	**11.0**	**12.0**
MRB	0.5	0.80	0.77	0.74	0.71	0.68	0.66	0.63	0.60	0.57
	1.0	0.72	0.69	0.66	0.63	0.60	0.57	0.54	0.51	0.49
	1.5	0.66	0.62	0.59	0.55	**0.52**	0.49	0.46	0.43	0.40
	2.0	0.61	0.57	0.53	0.49	0.45	0.42	0.39	0.36	0.33
	2.5	0.57	0.52	0.47	0.43	0.39	0.36	0.32	0.29	0.26
	3.0	0.53	0.47	0.42	0.38	0.34	0.30	0.26	0.23	0.19
	3.5	0.50	0.44	0.38	0.33	0.29	NA	NA	NA	NA

(*continued*)

Table B.1. (Continued)

$r^a = 14\%$		**CRB**								
		4.0	**5.0**	**6.0**	**7.0**	**8.0**	**9.0**	**10.0**	**11.0**	**12.0**
MRB	0.5	0.78	0.75	0.71	0.68	0.65	0.62	0.59	0.55	0.52
	1.0	0.71	0.67	0.63	0.60	0.57	0.53	0.50	0.47	0.44
	1.5	0.65	0.60	0.56	0.53	0.49	0.46	0.42	0.39	0.36
	2.0	0.60	0.55	0.50	0.46	0.42	0.39	0.35	0.32	0.28
	2.5	0.55	0.50	0.45	0.41	0.36	0.32	0.29	0.25	0.21
	3.0	0.52	0.46	0.40	0.35	0.31	0.27	0.23	NA	NA
	3.5	0.49	0.42	0.36	0.31	NA	NA	NA	NA	NA

Note: CRB is the capital ratio of banks (%), MRB is the ratio of banks' monitoring costs to their assets (%), and r^a is the return on bank equity (%). Following the baseline calibration, we set the return on firm equity $r^n = 4.5\%$. NA means that the "no-corner-solution condition" ((D.43) in Appendix D.3) is not satisfied. In these cases the suggested calibration is not valid.

$u(C_t, C_{t-1}) = ((C_t - bC_{t-1})^{1-\sigma})/(1-\sigma)$, where the habit parameter is set to $b = 0.8$. In our simple model, financial frictions introduce a wedge on the consumption/investment margin only. Habit persistence provides a simple way to amplify the welfare effects of the friction while introducing a minimal departure from the basic model.

To keep the illustrative example as simple as possible, we consider a case with two possible shock realizations: the small shock is $\varepsilon_t = -0.005$ while the large shock is $\varepsilon_t = -0.03$. For illustrative simplicity, we assume that there are also two possible funding program sizes. The size of a small program is 0.3 and the size of a large program is 0.8. The premium or the penalty rate that the government charges is $r^g = 0.1$. All welfare gains and losses (measured as changes in the household's value function) are expressed as a percentage of (per-period) steady-state consumption.

Welfare Gain from Stabilization. Note that welfare gain does not depend on the structure of the program.

	Small Shock	Large Shock
Small Program	0.36%	2.15%
Large Program	0.95%	5.71%

Welfare Loss from Distortions. Note that welfare loss from distortions does not depend on the shock realization.

	Banks	Firms
Small Program	0.25%	0.38%
Large Program	2.57%	1.01%

Net Welfare Gain. Net welfare gain is equal to welfare gain from stabilization minus welfare loss from distortions.

	Small Program		Large Program	
	Banks	Firms	Banks	Firms
Small Shock	**0.11%**	–0.02%	–1.62%	**–0.06%**
Large Shock	**1.90%**	1.77%	3.14%	**4.70%**

Interpreting the Results. We assume that there is genuine uncertainty. When choosing the policy, the government does not know which shock (small or large) will realize, and it cannot even assign a probability distribution. However, our results narrow the options that a benevolent government should consider under genuine uncertainty. A small funding program targeting firms and a large program targeting banks are *dominated*. The government should never choose either of these programs. A small program targeting banks and a large program targeting firms belong to the set of *undominated* policies. The government should choose its policy from this set (in bold).

B.7 Non-optimal Structure of Public Funding and Excess Welfare Losses

How important is it to get the structure of the public funding program right? How significant are the (excess) welfare losses resulting from a non-optimal structure? In this section, we address this question from two slightly different, but complementary, angles. First, we benchmark the non-optimally structured program with an optimally structured program with the same size (and the same social benefits from resilience), and compare the welfare losses from distortions. Second, within the set of undominated policies (characterized by Proposition 2) we choose a benchmark program which gives rise to the same level distortions as the non-optimal candidate program, but has a bigger size and hence brings about greater social benefits in terms of enhanced resilience.

B.7.1 Benchmarking to an Optimally Structured Program with the Same Size

If the government chooses to fund nonfinancial firms, the amount $N^g = BRE \times S$ of public funding is needed, and the welfare losses from distortions (WL) are proportional to $WL(A^g = 0, N^g = BRE \times S) \propto S$. If the government chooses to capitalize banks, fewer funds are needed $A^g = \left(\frac{BRE}{BL}\right)\left(\frac{S}{1-S}\right) \leq BRE \times S$, but since each unit of public funding creates $MRTS$ times more distortions when placed in banks than when placed in firms, the

resulting welfare losses are proportional to $WL(A^g = \left(\frac{BRE}{BL}\right)\left(\frac{S}{1-S}\right), N^g = 0) \propto \left(\frac{S}{1-S}\right)\left(\frac{MRTS}{BL}\right) = S\left(\frac{1-S^*}{1-S}\right)$. It is easy to see that the minimum welfare loss ($WL^{\min}$), corresponding to the optimal structure of the funding program (see Proposition 2) is (proportional to) $WL^{\min} \propto S \times \min\left\{1, \frac{1-S^*}{1-S}\right\}$, while the maximum welfare loss that arises if the government funds nonfinancial firms with a small program ($S < S^*$) and banks with a large program ($S > S^*$) is (proportional to) $WL^{\max} \propto S \times \max\left\{1, \frac{1-S^*}{1-S}\right\}$. Denote the *excess welfare loss* resulting from a non-optimal structure of the program by ΔWL. It is easy to conclude that

$$\Delta WL \leq WL^{\max} - WL^{\min} \propto \frac{S}{1-S}\left|S - S^*\right|. \tag{B.36}$$

The expression on the right-hand side of the inequality (B.36) gives the maximum value of the excess welfare loss. This maximum excess welfare loss is realized if only nonfinancial firms are funded when bank capitalization would be optimal (and vice versa). If, instead, the government implements some form of mixed program and funds both banks and nonfinancial firms, the excess welfare loss is given by the expression

$$\Delta WL \propto \frac{M^g}{1-S}\left|S - S^*\right|, \tag{B.37}$$

where

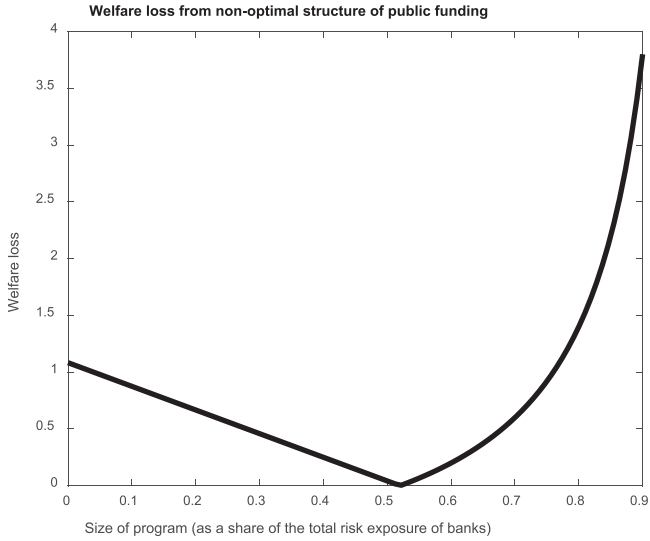
$$M^g = \begin{cases} N^g/BRE & \text{if } S < S^* \\ BL(1-S)A^g/BRE & \text{if } S > S^* \end{cases} \tag{B.38}$$

denotes the misallocation of public funding.

In order to further analyze how important the choice of the program structure is, it useful to compare the excess welfare loss, due to a non-optimal structure, with the minimum welfare loss when the structure is chosen optimally. If the government funds only banks or only firms with the wrong amount, relative excess welfare loss $\Delta\widehat{WL} = \Delta WL/WL^{\min}$ can be expressed as follows:

$$\Delta\widehat{WL} = \frac{\Delta WL}{WL^{\min}} = \max\left\{\frac{S^* - S}{1-S^*}, \frac{S - S^*}{1-S}\right\}. \tag{B.39}$$

Figure B.1. Welfare Loss from Non-optimal Structure of Public Funding



If the government implements a mixed program,

$$\Delta\widehat{WL} = \frac{M^g}{S} \max\left\{\frac{S^* - S}{1 - S^*}, \frac{S - S^*}{1 - S}\right\}. \tag{B.40}$$

Figure B.1 shows how the (maximum) relative excess welfare loss (the right-hand side of (B.39)) depends on the size of the program with our baseline calibration. The figure indicates that choosing the optimal structure of the program is important if the program is either very small or very large (since in these cases the maximum relative excess welfare loss is large), while it is less important for medium-sized programs. Indeed when the size is the program approaches the threshold value S^* (from either side), the maximum excess relative welfare loss approaches zero.

B.7.2 Benchmarking to an Optimally Structured Program with a Larger Size

Pure Programs with the Wrong Structure. (i) Consider a small program, with $S < S^*$. Assume that the program is

(non-optimally) implemented by public funding to nonfinancial firms. Hence $N^g = BRE \times S$, and the welfare losses from distorted investments are (proportional to) $WL \propto S$. Next, assume that the government capitalizes banks instead. Since each unit of public stakes distorts the economy $MRTS$ times more when allocated to banks than when placed in firms, $A^{g\prime} = \frac{BRE}{MRST} \times S$ gives rise to the same welfare losses from distortions as the original program. Denote the size or the alternative program, targeting banks, by S'. The size S' can be solved from Equation (27). That is,

$$BRE \times S' = BL\,(1 - S')\,\frac{BRE}{MRTS} \times S.$$

This gives

$$\frac{S'}{1 - S'} = \frac{S}{1 - S^*}$$

or

$$S' = \frac{S}{1 + S - S^*}. \tag{B.41}$$

Clearly $S' > S$, when $S < S^*$. Also note that $S' < S^*$ when $S < S^*$. Hence, the program of size S' is indeed optimally implemented by bank capitalization.

(ii) Consider next a large program, with $S > S^*$. Assume that the program is (non-optimally) implemented by public bank capitalization. Hence, $A^g = \frac{BRE}{BL}\left(\frac{S}{1-S}\right)$, and the welfare losses from distorted investments are (proportional to) $WL \propto \frac{MRTS}{BL}\frac{S}{1-S} = \left(\frac{1-S^*}{1-S}\right)S$. Next assume that the government funds nonfinancial firms instead. Since each unit of public stakes distorts the economy $MRTS$ times more when allocated to banks than when placed in firms, $N^{g\prime} = BRE\left(\frac{MRTS}{BL}\right)\left(\frac{S}{1-S}\right) = BRE\left(\frac{1-S^*}{1-S}\right)S$ gives rise to the same welfare losses from distortions as the original program. Denote the size of the alternative program, targeting firms, by S'. The size S' can be solved from Equation (27). That is,

$$BRE \times S' = BRE\left(\frac{1 - S^*}{1 - S}\right)S.$$

This gives

$$S' = \left(\frac{1-S^*}{1-S}\right) S. \tag{B.42}$$

Clearly $S' > S$, when $S > S^*$.

Note that (B.42) is only valid if $S' \leq S^{\max} = 1 - \frac{1}{BL}$, or $S \leq \frac{S^{\max}}{1+S^{\max}-S^*}$. If $S > \frac{S^{\max}}{1+S^{\max}-S^*}$, we choose as the (optimally structured) benchmark a program with the maximum size. This benchmark, which targets nonfinancial firms only, gives rise to distortion-related welfare losses which are proportional to

$$WL' \propto S^{\max}.$$

Since $\frac{S}{1-S} > \frac{S^{\max}}{1-S^*}$, it is easy to conclude that $WL' < WL$ (where $WL \propto \left(\frac{1-S^*}{1-S}\right) S$).

Mixed Programs. Let us next consider mixed funding programs, with $A^g > 0$ and $N^g > 0$. The welfare loss due to distorted incentives is (proportional to)

$$WL \propto MRTS \times A^g + N^g,$$

while the size of the program is

$$S = \frac{BL \times A^g + N^g}{BRE + BL}. \tag{B.43}$$

(To get this result solve $BRE \times S = BL\,(1-S)\,A^g + N^g$ for S.)

(i') First assume that the program is (relatively) small, i.e., $S < S^*$. Further assume that, instead of implementing the (non-optimal) candidate program, the government (only) capitalizes banks. Public stakes $A^{g\prime}$ placed in banks give rise to the same level of distortions and welfare losses as the candidate program. Hence, $A^{g\prime}$ can be solved from the equation

$$MRTS \times A^{g\prime} = MRTS \times A^g + N^g$$

and

$$A^{g\prime} = A^g + \frac{N^g}{MRTS}. \tag{B.44}$$

The size of the alternative program, S', can be solved from Equation (27). Hence, we get

$$\frac{S'}{1-S'} = \frac{BL}{BRE} A^{g\prime} = \frac{BL}{BRE}\left(A^g + \frac{N^g}{MRTS}\right), \tag{B.45}$$

where the last form is derived using (B.44). Next, it is useful to re-express Equation (B.45) in terms of S (the size of the non-optimal candidate program) and $M^g = N^g/BRE$ (the misallocation of public funding under the non-optimal program). Using (B.43) one can re-express (B.45) as

$$\frac{S'}{1-S'} = \left(\frac{S}{1-S}\right)\left[1 + \left(\frac{S^* - S}{1-S^*}\right)\frac{M^g}{S}\right]. \tag{B.46}$$

Finally, Equation (B.46) can be solved for S'

$$S' = \left(\frac{1 - S^* + (S^* - S)\frac{M^g}{S}}{1 - S^* + S\,(S^* - S)\frac{M^g}{S}}\right) S. \tag{B.47}$$

Note that when $M^g = S$ (and the government funds only nonfinancial firms in the non-optimal candidate program), Equation (B.47) boils down to (B.41).

(ii') Assume now that the program is (relatively) large, i.e., $S > S^*$. Further assume that, instead of implementing the (non-optimal) candidate program, the government (only) targets nonfinancial. Public stakes

$$N^{g\prime} = MRTS \times A^g + N^g$$

in nonfinancial firms give rise to the same level of welfare losses from distorted incentives as the (non-optimally structured) candidate program. The size of the alternative program, S', can be solved from Equation (27). Hence, we get

$$S' = \frac{N^{g\prime}}{BRE} = \frac{MRTS \times A^g + N^g}{BRE}. \tag{B.48}$$

Next, it is useful to re-express Equation (B.48) in terms of S (the size of the non-optimal candidate program) and

$M^g = BL\,(1-S)\,A^g/BRE$ (the misallocation of public funding under the non-optimal program). Using (B.43) one can re-express (B.48) as

$$S' = \left(1 + \left(\frac{S - S^*}{1 - S}\right)\frac{M^g}{S}\right) S. \tag{B.49}$$

Note that when $M^g = S$ (and the government funds only banks in the non-optimal candidate program), Equation (B.49) boils down to (B.42). Finally, note that Equation (B.49) is only valid if $S' \leq S^{\max} = 1 - \frac{1}{BL}$ or, equivalently, $S \leq S^{**}$, where

$$S^{**} = \frac{1 + S^{\max} - \widehat{M}S^* - \sqrt{\left(1 + S^{\max} - \widehat{M}S^*\right)^2 - 4\left(1 - \widehat{M}\right)S^{\max}}}{2\left(1 - \widehat{M}\right)} \tag{B.50}$$

and $\widehat{M} = M^g/S$. When $\widehat{M} \to 1, S^{**} \to \frac{S^{\max}}{1+S^{\max}-S^*}$. If $S > S^{**}$, we have $S' = S^{\max}$.

Assessing the Welfare Losses from a Non-optimal Structure. Remember that the welfare gains from enhanced stability are (approximately) proportional to the size of the program (see Equation (25) in the main text; see also Appendix B.2). The difference between the size of the optimally structured benchmark program (S') and the candidate program (S) is a measure of the welfare losses due to the non-optimal structure

$$\Delta WL^* \propto \Delta S = S' - S \leq \begin{cases} \left(\frac{S^* - S}{1+S-S^*}\right) S & \text{if } S < S^* \\ \left(\frac{S - S^*}{1-S}\right) S & \text{if } S^* > S. \end{cases}$$

To further assess the magnitude of these welfare losses, it is useful to divide ΔS by S (since the social welfare benefits from enhanced resilience of the candidate program are proportional to S). If the government funds only banks or only firms with the wrong amount, we obtain

$$\Delta\widehat{WL}^* = \frac{\Delta S}{S} = \begin{cases} \frac{S^* - S}{1+S-S^*} & \text{if } S < S^* \\ \frac{S - S^*}{1-S} & \text{if } S > S^*. \end{cases} \tag{B.51}$$

If the government implements a mixed program, we get

$$\Delta\widehat{WL}^{*} = \frac{\Delta S}{S} = \begin{cases} \frac{(S^{*}-S)(1-S)\frac{M^{g}}{S}}{1-S^{*}+S(S^{*}-S)\frac{M^{g}}{S}} & \text{if } S < S^{*} \\ \left(\frac{S-S^{*}}{1-S}\right)\frac{M^{g}}{S} & \text{if } S > S^{*}, \end{cases} \tag{B.52}$$

where M^{g} (the misallocation of public funding under a mixed program) is given by (B.38). Note that Equations (B.51) and (B.52) are only valid if $S' \leq S^{\max} = 1 - 1/BL$ or, equivalently, $S \leq S^{**}$, where S^{**} is defined in (B.50). If $S > S^{**}$, we have $\Delta\widehat{WL}^{*} = \Delta S/S = S^{\max}/S - 1$.

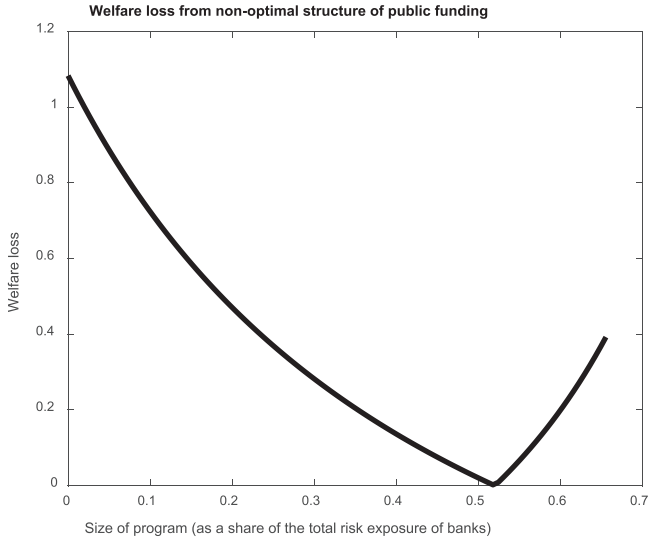
Figure B.2 shows how the maximum relative welfare loss (the right-hand side of (B.51)) depends on the size of the program under our baseline calibration for $S \in (0, S^{**})$, where $S^{**} = \frac{S^{\max}}{1+S^{\max}-S^{*}}$; under our baseline calibration, $S^{**} = 0.66$. The figure essentially indicates that if the program size S is around the threshold value S^{*}, it does not matter much whether the government allocates funds to banks, firms, or both. However, the larger the gap between S^{*} and S, the larger are the excess welfare losses from a non-optimal structure. Indeed, for (very) small programs, $\Delta\widehat{WL}^{*} = \Delta S/S \approx 1$, meaning that in this case the (excess) welfare loss from a non-optimal structure (funding firms when one should fund banks) is of the same order of magnitude as the stabilization-related welfare benefits from the candidate program. Overall, we get the same results as above in Appendix B.7.1 when using the welfare loss measure $\Delta\widehat{WL}$ (see expression (B.39) and Figure B.1).

B.8 Robustly Optimal Public Funding of Both Banks and Firms

First Example: The Government Does Not Know the Threshold S^{*}. According to Proposition 2, the threshold size of public funding is $S^{*} = 1 - MRTS/BL$. Assume the government does not know $MRTS$ (which tells how much more distorting it is to fund banks rather than nonfinancial firms), but believes with sufficient certainty that $MRTS$ lies somewhere between $MRTS_1$ and $MRTS_2$, where $MRTS_2 < MRTS_1$. This implies that the threshold size $S^{*} \in [S_1^{*}, S_2^{*}]$, where

$$S_i^{*} = 1 - \frac{MRTS_i}{BL},\ i \in \{1, 2\}.$$

Figure B.2. Welfare Loss from Non-optimal Structure of Public Funding



If the size of the program the government wants to implement (S) is either smaller than S_1^* or larger than S_2^*, the situation is unproblematic: the government should capitalize banks (if $S < S_1^*$), or fund nonfinancial firms (if $S > S_2^*$). However, if $S \in (S_1^*, S_2^*)$, the government faces a dilemma: it may incur an excess welfare loss as large as $\Delta WL \propto S\left(\frac{MRTS_1}{BL(1-S)} - 1\right) = \frac{S}{1-S}(S - S_1^*)$ if it targets banks (but funding nonfinancial firms would be the optimal strategy) or as large as $\Delta WL \propto S\left(1 - \frac{MRTS_2}{BL(1-S)}\right) = \frac{S}{1-S}(S_2^* - S)$ if it targets nonfinancial firms (but capitalizing banks would be the optimal strategy). In such a situation, the government may want to choose, for example, a robust strategy that aims to minimizing the maximum (excess) welfare losses due to the misallocation of public funds. Such a strategy would involve targeting both banks and firms. Note that the welfare losses due to a mixed package are proportional to $WL(A^g, N^g) \propto MRTS \times A^g + N^g$.

A robust min-max strategy solves the following problem:

$$\min_{A^g, N^g} \max_{i \in \{1,2\}} MRTS_i A^g + N^g,$$

subject to $BRE \times S = BL(1-S)A^g + N^g$. One can show that such a strategy would give rise to the mixed policy package

$$N^g = BRE \times S\left(\frac{MRTS_1 - BL\,(1-S)}{MRTS_1 - MRTS_2}\right) = BRE \times S\left(\frac{S - S_1^*}{S_2^* - S_1^*}\right)$$

and

$$\begin{aligned} A^g &= \left(\frac{BRE \times S}{BL(1-S)}\right)\left(\frac{BL(1-S) - MRTS_2}{MRTS_1 - MRTS_2}\right) \\ &= \left(\frac{BRE}{BL}\right)\left(\frac{S}{1-S}\right)\left(\frac{S_2^* - S}{S_2^* - S_1^*}\right), \end{aligned}$$

where the government targets both banks and firms as long as $S \in (S_1^*, S_2^*)$. Quite intuitively, the share of funds allocated to nonfinancial firms (banks) increases (decreases) with the size of the program S.

Second Example: Staggered Program. Assume that the government knows the threshold value S^*, but it does not know if, in the end, it wants to implement a small program $S_1 < S^*$ or a large program $S_2 > S^*$. Given Proposition 2, the small program S_1 would be optimally implement by capitalizing banks, while the larger program S_2 would be optimally implemented by targeting nonfinancial firms.

We assume that the government first implements the smaller policy package S_1, and subsequently decides whether or not it wants to expand the size of the program to S_2. Let A_1^g and N_1^g denote the government funding allocated to banks banks and firms, respectively, under policy package S_1, while A_2^g and N_2^g denote the government funding allocated to banks banks and firms, respectively, when policy package S_2 is in place. We further assume that

$$A_2^g \geq A_1^g, \quad N_2^g \geq N_1^g.$$

In words, if a certain amount of public funding is allocated to banks (firms) in the initial policy package S_1, this money cannot be taken back if the program is expanded to S_2. When designing the (robustly) optimal structure of policy package S_1, the government takes these constraints into account.

A robustly optimal strategy aims at minimizing the maximum (excess) welfare losses due to the misallocation of public funds. A robustly optimal strategy solves the problem

$$\min_{A_1^g, N_1^g, A_2^g, N_2^g} \max_{i \in \{1,2\}} MRTS \times A_i^g + N_i^g,$$

subject to

$$\begin{aligned} BRE \times S_i &= BL\,(1 - S_i)\,A_i^g + N_i^g \text{ for } i \in \{1,2\} \\ A_2^g &\geq A_1^g, \quad N_2^g \geq N_1^g. \end{aligned}$$

One can show that the robustly optimal structure of policy package S_1 is given by the equations

$$\begin{aligned} N_1^g &= BRE \times S_1 \left(\frac{\frac{1}{BL_2^*} - \frac{1}{MRTS}}{\frac{1}{BL_2^*} - \frac{1}{BL_1^*}} \right) \\ &= BRE \times S_1 \left(\frac{1 - S_1}{1 - S^*} \right) \left(\frac{S_2 - S^*}{S_2 - S_1} \right) \end{aligned}$$

and

$$\begin{aligned} A_1^g &= \frac{BRE \times S_1 - N_1^g}{BL_1^*} = \frac{BRE \times S_1^*}{BL_1^*} \left(\frac{\frac{1}{MRTS} - \frac{1}{BL_1^*}}{\frac{1}{BL_2^*} - \frac{1}{BL_1^*}} \right) \\ &= \frac{BRE \times S_1}{BL} \left(\frac{1 - S_1}{1 - S^*} \right) \left(\frac{S^* - S_1}{S_2 - S_1} \right). \end{aligned}$$

The robustly optimal structure of policy package S_2 is given by the equations

$$A_2^g = A_1^g$$

and

$$\begin{aligned} N_2^g &= BRE \times S_2 - BL_2^* A_2^g \\ &= BRE \times \left[S_2 - S_1 \left(\frac{BL_2^*}{BL_1^*} \right) \left(\frac{\frac{1}{MRT} - \frac{1}{BL_1^*}}{\frac{1}{BL_2^*} - \frac{1}{BL_1^*}} \right) \right] \\ &= BRE \times S_2 - \frac{BRE \times S_1}{BL} \left(\frac{1 - S_2}{1 - S^*} \right) \left(\frac{S^* - S_1}{S_2 - S_1} \right). \end{aligned}$$

One can show that the share of public funds allocated to nonfinancial firms (both N_1^g and N_2^g) increases with S_1 and S_2, while the share of public funds allocated to banks decreases with S_1 and S_2.

Appendix C. Calibration

C.1 Data Moments and Calibration

In calibrating the real sector of the model, we follow the RBC literature. A period is one year. We calibrate the household's utility function parameters to involve relatively modest risk aversion and a fairly inelastic labor supply: $\sigma = 2$, $\phi = 0.5$, and $\xi = 2$, and set the discount factor β to 0.98, which approximately corresponds to an annual real interest rate of 2 percent. We assign the depreciation rate δ to 0.10, a typical value in the literature. The capital share in the final goods sector, α, is set to the often-used value of 1/3. The output shares of investment and consumption are roughly 20 percent and 80 percent, respectively.

Calibration of the parameters of the financial block, while less standard, only requires values for excess returns to banks' and entrepreneurial firms' capital, their capital ratios, and bankers' monitoring costs (see Appendix C.2.1). To parameterize the steady-state (excess) rate of return on entrepreneurial capital, r^n, we first take the value of 6.5 percent, commonly used in the RBC literature, as the average return to capital in the economy, and then subtract a riskless rate of 2 percent, yielding $r^n = 4.5\%$ (see, for example, Fama and French 2002). As to the value for the entrepreneurial firms' steady-state capital ratio, N/I, the literature suggests substantial intertemporal and cross-section variation (e.g., Rajan and Zingales 1995; De Jong, Kabir, and Nguyen 2008; Graham and Leary 2011; and Graham, Leary, and Roberts 2015). We choose the value of 0.45, which is close to the post-1990 estimate for the U.S. by Graham, Leary, and Roberts (2015).

The steady-state (excess) rate of return on bank capital, r^a, is calibrated based on Albertazzi and Gambacorta (2009), who find the average after-tax return on bank equity in 1999–2003 to vary from 7 percent in the euro area to 14–15 percent in the U.K. and the U.S. (Hirtle and Stiroh 2007 report similar magnitudes

for U.S. retail banks), and on Haldane and Alessandri (2009), who find the pretax return on bank equity in the U.K. to be around 20 percent on average over the recent decades. We set r^a to 12 percent, which lies in the midrange of these estimates.

The bank's steady-state capital ratio is given by $A/(A + D - mI) = A/(I - N)$ (see Appendix D.2). Since the banks in our model have a stake in the projects they fund, the closest empirical counterpart for our bank capital is tier 1 capital, which includes banks' common stocks and retained earnings. Typical estimates (e.g., Acharya and Steffen 2014) of tier 1 capital to (non-risk-adjusted) assets vary between 4 percent and 8 percent. Our model focuses on firm loans, abstracting from other bank assets. We set $A/(I - N) = 0.08$ to account for the riskiness of corporate lending. This magnitude also corresponds to the precrisis tier 1 equity-to-asset ratio in the aggregate bank balance sheet calculated by the Federal Deposit Insurance Corporation (FDIC).

Finding an estimate for monitoring costs is not easy. Based on the estimations of Albertazzi and Gambacorta (2009) and Philippon (2015), the unit cost of financial intermediation could be 1–4 percent of a bank's total assets. As their unit cost measures include activities in addition to monitoring, that estimate provides an upper bound for the ratio of monitoring costs to assets. However, corporate lending involves more intense monitoring than many other asset classes in a bank's balance sheet. Furthermore, in our model the total operating costs of a bank are equal to the monitoring costs (since in the model there are no other operating costs). This suggests that the empirical counterpart could include (some) costs of financial intermediation not (directly) related to monitoring. Based on these observations, we choose a monitoring-cost-to-asset ratio ($mI/(I - N)$) of 1.5 percent.

C.2 Parameters of the Financial Block

C.2.1 Data Moments and Steady-State Values of Model Variables

We now define the observable financial data moments in terms of the steady state of the model variables in the financial block

(see Appendix D.2). The calibration of the parameters of the financial block of the model is based on the following observables:

- *Excess* rates of return on bank capital r^a, and on entrepreneurial capital r^n. In each period, bankers earn the gross rate of return $(1+r)(1+r^a)$ and entrepreneurs earn the rate of return $(1+r)(1+r^n)$, where $1+r=1/\beta$ is the real interest rate earned by workers in the steady state.
- Nonfinancial firms' capital ratio

$$CRF = \frac{N}{I}. \tag{C.1}$$

- Banks' capital ratio

$$CRB = \frac{A}{A+D-mI} = \frac{A}{I-N}. \tag{C.2}$$

  In the denominator, we subtract the banks' monitoring costs mI from the total amount of funds $A+D$ to obtain the amount of the banks' assets allocated to the investment projects. Note the difference between the balance sheets of nonfinancial firms and banks. The balance sheets of nonfinancial firms include funds from bankers and depositors, as well as the entrepreneurs' own capital. The grand total is I. Banks have bankers' own capital and funds from depositors, and the aggregate amount of funds is $I-N$.
- Banks' monitoring costs as a ratio of banks' assets

$$MRB = \frac{mI}{I-N}. \tag{C.3}$$

- Finally, it is useful to express the ratio of monitoring costs to output (mI/Y) with the help of these data moments, and the investment share of output $\iota = I/Y$

$$\frac{mI}{Y} = MRB\,(1-CRF)\,\iota. \tag{C.4}$$

C.2.2 Equations Linking Data Moments and Parameters of the Financial Block

Based on the equations from the main text, Appendix C.2.1 above, and the analytical solution of the steady state, given in Appendix D.2, we present equations linking the parameters of the financial block to the data moments. The calibrated financial block parameters are as follows:

- The exit rate of bankers λ^b. Equation (D.12) in Appendix D.2 implies that

$$\lambda^b = \frac{\beta}{1+r^a} = \frac{1}{(1+r^a)(1+r)}. \tag{C.5}$$

- The exit rate of entrepreneurs λ^e. Equation (D.13) in Appendix D.2 implies that

$$\lambda^e = \frac{\beta}{1+r^n} = \frac{1}{(1+r^n)(1+r)}. \tag{C.6}$$

- The (relative) difference in the success probabilities of good and bad projects $\Delta p/p_H$.

  Using the banker's incentive constraint (4b) and participation constraint (4d), together with the aggregation equation (9), all evaluated at the steady state, yields $\Delta p/p_H = mI/\left((1+r^a)A\right)$. Applying Equations (C.2) and (C.3) gives

$$\frac{\Delta p}{p_H} = \frac{MRB}{CRB\,(1+r^a)}. \tag{C.7}$$

- The elasticity of the monitoring function $\gamma/(1-\gamma)$. Inserting (C.5), (C.6), and (C.7) in (16), and recalling that $\nu = A/N$, yields $\gamma/(1-\gamma) = A\left(r^a + MRB/CRB\right)/\left(r^n N\right)$. Then using (C.1) and (C.2) gives

$$\frac{\gamma}{1-\gamma} = \frac{r^a CRB + MRB}{r^n \frac{CRF}{1-CRF}}. \tag{C.8}$$

  Note that $CRF/(1-CRF) = N/(I-N)$ is the ratio of entrepreneurial capital to non-entrepreneurial capital in

nonfinancial firms' balance sheets. Applying (C.2) and (C.3), $\gamma/(1-\gamma)$ can be re-expressed in yet another way:

$$\frac{\gamma}{1-\gamma} = \frac{r^a A + mI}{r^n N} = \frac{\text{banks' profits + banks' monitoring costs}}{\text{entrepreneurs' profits}}.$$

- Parameter of the monitoring function Γ.

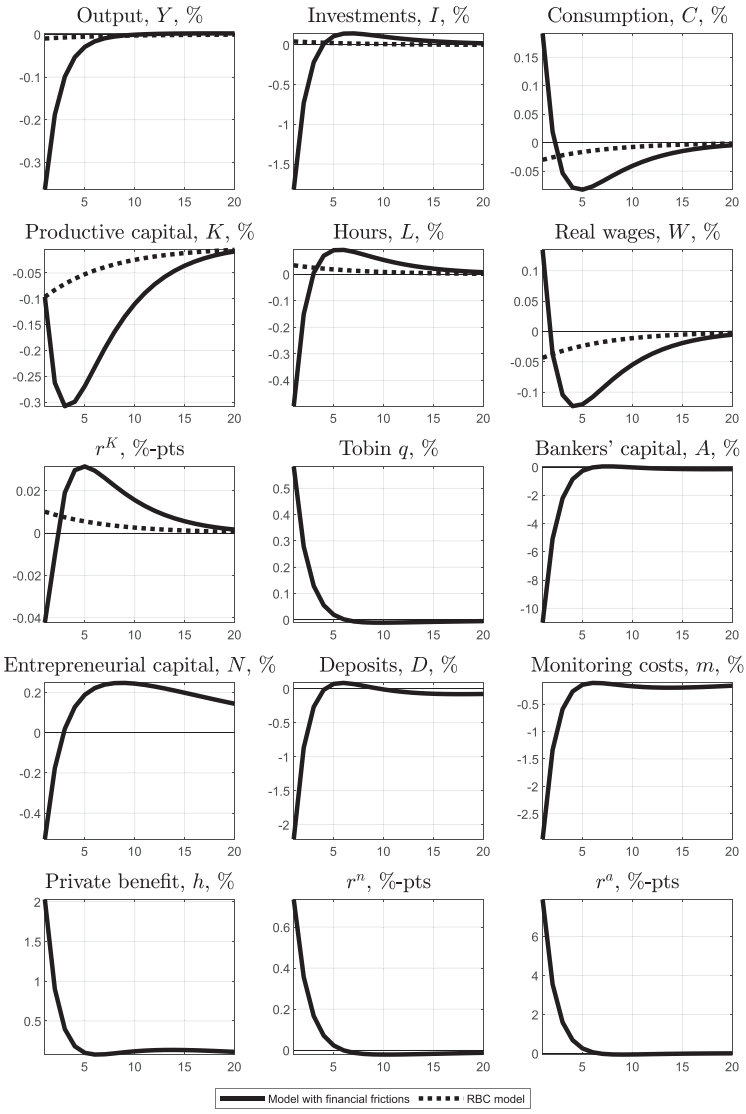
$$\Gamma = \left(\frac{1+r^n}{1+r^a}\right)\left(\frac{CRF}{CRB}\right)(1-CRF)^{\frac{\gamma}{1-\gamma}} MRB^{\frac{1}{1-\gamma}}, \quad \text{(C.9)}$$

where γ is given by (C.8). The derivation of (C.9) involves the following steps. In Appendix A.4 we define $G_t = (A_t + N_t)/I_t$. Applying (C.1) and (C.2), the steady-state version of this equation can be rewritten as $G = CRB(1-CRF) + CRF$. Using Equations (D.15), (D.25), and (D.26) in Appendix D.2, the measure G can be expressed in terms of ν and the parameters of the financial block (including Γ). Finally, applying (16), (C.5), (C.6), and (C.7), we get (C.9).

C.3 Impulse Responses

Figure C.1 portrays the impulse responses of key real- and financial-sector variables to a negative investment shock. As a benchmark, we also show the real-sector impulse responses in a standard RBC model which corresponds to our model with the exception of financial intermediation and associated frictions.

Figure C.1. Impulse Responses to a Negative Investment Shock (1 percentage point decrease in success probabilities)



Appendix D. Technical Appendix

D.1 Equilibrium

The equilibrium of the model, reproduced here for the reader's convenience, is a sequence

$$\left\{K_{t+1}, L_t, Y_t, r_{t+1}, W_t, r_t^K, C_t, I_t, q_t, \rho_t, r_t^a, r_t^n, m_t, h_t, A_{t+1}, N_{t+1}, D_t\right\}_{t=0}^{\infty}$$

that satisfies Equations (2), (3), (10), (11), (12), (13), (14), (15a,b), and

$$1 + r_{t+1} = \frac{r_{t+1}^K + q_{t+1}(1-\delta)}{q_t}, \tag{D.1}$$

$$\xi L_t^{\phi} {C_t}^{\sigma} = W_t, \tag{D.2}$$

$$Y_t = K_t^{\alpha} L_t^{1-\alpha}, \tag{D.3}$$

$$W_t = (1-\alpha)\frac{Y_t}{L_t}, \tag{D.4}$$

$$r_t^K = \alpha \frac{Y_t}{K_t}, \tag{D.5}$$

$$Y_t = C_t + I_t, \tag{D.6}$$

$$D_t = (1+m_t)\, I_t - (A_t + N_t)\,, \tag{D.7}$$

$$\rho_t = q_t - 1. \tag{D.8}$$

D.2 Steady State

We present the steady state of the model in three parts. In part A, we solve for the steady-state values of the prices and the ratios of quantities (such as $\nu = A/N$) in the financial block. In addition, we solve for the steady-state values of the moral-hazard-related variables (h and m). In part B, we solve the steady state of the real (RBC) block. Finally, in part C, we solve for the steady-state values of the quantities (levels) in the financial block.

Part A. We derive the steady-state values of financial variables in four steps:

1. The law of motion of A_t is

$$A_{t+1} = \lambda^b (1 + r_{t+1}) (1 + r_t^a) A_t \tag{D.9}$$

and the law of motion of N_t is

$$N_{t+1} = \lambda^b (1 + r_{t+1}) (1 + r_t^n) N_t. \tag{D.10}$$

Since the household's Euler equation (3) implies that in steady state

$$1 + r = \frac{1}{\beta}, \tag{D.11}$$

the steady-state versions of Equations (D.9) and (D.10) immediately yield

$$1 + r^a = \frac{\beta}{\lambda^b} \tag{D.12}$$

and

$$1 + r^n = \frac{\beta}{\lambda^e}. \tag{D.13}$$

Furthermore, the steady-state versions of (D.9) and (D.10) give

$$\frac{A}{N} \equiv \nu = \frac{\lambda^b}{\lambda^e} \frac{R^b}{R^e} = \frac{\lambda^b m}{\lambda^e h}, \tag{D.14}$$

where the last form follows since $R^b = m/(q\Delta p)$ and $R^e = h/(q\Delta p)$.

2. Denote

$$J_t = A_t + N_t$$

and recall from Appendix A.4 the definition $G_t = (A_t + N_t)/I_t = J_t/I_t$. Combining these with (D.9) and (D.10), we get

$$J_{t+1} = (1 + r_{t+1}) p_H q_t \frac{J_t}{G_t} \left(\lambda^b R_t^b + \lambda^e R_t^e\right)$$

(since $I_t = J_t/G_t$). Thus, in steady state

$$1 = (1 + r) p_H q \frac{1}{G} \left(\lambda^b R^b + \lambda^e R^e\right).$$

Combine

$$R^b = m/\left(q\Delta p\right), \quad R^e = h/\left(q\Delta p\right),$$

and (D.11) with above to obtain

$$G = \frac{1}{\beta}\frac{p_H}{\Delta p}\left(\lambda^b m + \lambda^e h\right). \tag{D.15}$$

3. Use the equilibrium relations

$$m_t = \frac{\frac{\Delta p}{p_H}}{1+\frac{\Delta p}{p_H}}\left(\gamma\rho_t + \frac{A_t}{I_t}\right) = \frac{\frac{\Delta p}{p_H}}{1+\frac{\Delta p}{p_H}}\left(\gamma\rho_t + \mu_t G_t\right) \tag{D.16}$$

and

$$\begin{aligned} m_t &= \frac{\Delta p}{p_H}\left(\left(1-\gamma\right)\rho_t + \frac{N_t}{I_t}\right) \\ &= \frac{\Delta p}{p_H}\left(\left(1-\gamma\right)\rho_t + \left(1-\mu_t\right)G_t\right), \end{aligned} \tag{D.17}$$

where

$$\mu_t = \frac{A_t}{A_t + N_t} = \frac{\nu_t}{1+\nu_t}.$$

Plug (D.15) into (D.16) and (D.17). In steady state we then have

$$m = \frac{\frac{\Delta p}{p_H}}{1+\frac{\Delta p}{p_H}}\left(\gamma\rho + \frac{\nu}{1+\nu}\frac{1}{\beta}\frac{p_H}{\Delta p}\left(\lambda^b m + \lambda^e h\right)\right) \tag{D.18}$$

and

$$h = \frac{\Delta p}{p_H}\left(\left(1-\gamma\right)\rho + \frac{1}{1+\nu}\frac{1}{\beta}\frac{p_H}{\Delta p}\left(\lambda^b m + \lambda^e h\right)\right). \tag{D.19}$$

From (D.14) we get

$$m = \frac{\lambda^e}{\lambda^b}\nu h \tag{D.20}$$

and plugging this into (D.18) and (D.19) yields

$$\frac{\lambda^e}{\lambda^b}\nu h = \frac{\frac{\Delta p}{p_H}}{1+\frac{\Delta p}{p_H}}\left(\gamma\rho + \nu\frac{1}{\beta}\frac{p_H}{\Delta p}\lambda^e h\right)$$

and

$$h = \frac{\Delta p}{p_H}\left((1-\gamma)\,\rho + \frac{1}{\beta}\frac{p_H}{\Delta p}\lambda^e h\right). \tag{D.21}$$

Solving ρ from (D.21) yields

$$\rho = \frac{p_H}{\Delta p}\left(1-\frac{\lambda^e}{\beta}\right)\left(\frac{h}{1-\gamma}\right). \tag{D.22}$$

Plugging (D.22) into (D.18) gives

$$\frac{\lambda^e}{\lambda^b}\nu h = \frac{1}{1+\frac{\Delta p}{p_H}}\left(\left(1-\frac{\lambda^e}{\beta}\right)\frac{\gamma}{1-\gamma} + \nu\frac{\lambda^e}{\beta}\right)h. \tag{D.23}$$

Evidently, h cancels out from (D.23), and the equation can be solved for ν:

$$\nu = \frac{\lambda^b}{\lambda^e}\left(\frac{1-\frac{\lambda^e}{\beta}}{1+\frac{\Delta p}{p_H}-\frac{\lambda^b}{\beta}}\right)\left(\frac{\gamma}{1-\gamma}\right), \tag{D.24}$$

4. Using the relation (D.20) together with the monitoring technology

$$h = \Gamma m^{-\frac{\gamma}{1-\gamma}} \Leftrightarrow m^\gamma b^{1-\gamma} = \Gamma^{1-\gamma}$$

we get

$$h = \left(\frac{\lambda^b}{\lambda^e}\right)^\gamma \frac{\Gamma^{1-\gamma}}{\nu^\gamma} \tag{D.25}$$

and

$$m = \left(\frac{\lambda^e}{\lambda^b}\right)^{1-\gamma}\Gamma^{1-\gamma}\nu^{1-\gamma}. \tag{D.26}$$

Given steps 1–4, we can express the steady state of prices and ratios as well as moral-hazard-related variables in the financial block in a recursive form. Real interest rate, Equation (D.11):

$$1 + r = \frac{1}{\beta}.$$

Rate of return to bank capital, Equation (D.12):

$$1 + r^a = \frac{\beta}{\lambda^b}.$$

Rate of return to entrepreneurial capital, Equation (D.13):

$$1 + r^n = \frac{\beta}{\lambda^e}.$$

Ratio of informed capital, Equation (D.24):

$$\nu = \frac{\lambda^b}{\lambda^e}\left(\frac{1 - \frac{\lambda^e}{\beta}}{1 + \frac{\Delta p}{p_H} - \frac{\lambda^b}{\beta}}\right)\left(\frac{\gamma}{1-\gamma}\right).$$

Nonverifiable revenue from a "bad" investment project, Equation (D.25):

$$h = \left(\frac{\lambda^b}{\lambda^e}\right)^{\gamma} \frac{\Gamma^{1-\gamma}}{\nu^{\gamma}}.$$

Monitoring intensity, Equation (D.26):

$$m = \left(\frac{\lambda^e}{\lambda^b}\right)^{1-\gamma} \Gamma^{1-\gamma}\nu^{1-\gamma}.$$

Ratio of informed capital and investment, Equation (D.15):

$$G = \frac{1}{\beta}\frac{p_H}{\Delta p}\left(\lambda^b m + \lambda^e h\right).$$

The net rate of return to the investment projects, Equation (D.22):

$$\rho = \frac{p_H}{\Delta p}\left(1 - \frac{\lambda^e}{\beta}\right)\left(\frac{h}{1-\gamma}\right).$$

The net rate of return to the investment project, ρ, can be further expressed as

$$\rho = \Gamma \frac{p_H}{\Delta p} \left(\frac{1 - \frac{\lambda^b}{\beta} + \frac{\Delta p}{p_H}}{\gamma} \right)^{\gamma} \left(\frac{1 - \frac{\lambda^e}{\beta}}{1 - \gamma} \right)^{1-\gamma}. \tag{D.27}$$

Part B. We now turn to the variables in the real (or RBC) block of the model. The steady state of the real block is linked to the steady state of the financial block (solved in part A above) through the price of capital, q. The steady-state version of (D.8) implies that the steady-state price of capital is given by

$$q = 1 + \rho. \tag{D.28}$$

Then the steady-state version of Equation (D.1) implies that, in steady state, the rental rate of capital is

$$r^K = q(r + \delta). \tag{D.29}$$

Next, applying the steady-state versions of Equations (2), (D.2), (D.3), (D.4), (D.5), and (D.6) allows us to solve the steady-state values of the remaining variables in the real block: Real wage,

$$W = (1 - \alpha) \left(\frac{r^K}{\alpha} \right)^{-\frac{\alpha}{1-\alpha}}, \tag{D.30}$$

physical capital stock,

$$K = \left[\left(\frac{1 - \alpha}{\xi} \right) \left(\frac{r^K}{\alpha} \right)^{-\frac{\alpha+\phi}{1-\alpha}} \left(\frac{r^K}{\alpha} - \delta \right)^{-\sigma} \right]^{\frac{1}{\phi+\sigma}}, \tag{D.31}$$

hours worked,

$$L = K \left(\frac{r^K}{\alpha} \right)^{\frac{1}{1-\alpha}}, \tag{D.32}$$

output,

$$Y = \frac{r^K K}{\alpha}, \tag{D.33}$$

investments,

$$I = \delta K, \tag{D.34}$$

and consumption,

$$C = Y - I. \tag{D.35}$$

Part C. Finally, we solve for the steady-state values of the quantities in the financial block. Using $\nu = A/N$ and $A + N = GI$ gives the steady-state values of bank capital

$$A = \frac{\nu}{1+\nu} GI \tag{D.36}$$

and entrepreneurial capital

$$N = \frac{1}{1+\nu} GI. \tag{D.37}$$

Finally, applying the steady-state version of (D.7) gives the steady-state value of deposits

$$D = (1 + m - G)I. \tag{D.38}$$

D.3 Ruling Out the Corner Solution

In this section, we study the conditions under which the no-monitoring corner solution, $m_t = 0,\ h(m_t) = \overline{h}$, can be ruled out. Assume that a firm chooses *not* to be monitored: $m_t = 0$. One may, for example, think that the firm raises outside funding directly from households, without financial intermediation by banks. Then (4a) implies that $R_t^e = \overline{h}/(\Delta p q_t)$. Furthermore, according to Equations (5a) and (5b), the maximum leverage, i_t/n_t, the firm can obtain is given by

$$\frac{i_t}{n_t} = \frac{1}{g\left(r_t^a, q_t; m_t = 0, h_t = \overline{h}\right)} = \frac{1}{\frac{p_H}{\Delta p}\overline{h} - \rho_t}.$$

Hence, the expected rate of return on entrepreneurial capital, $1+\widehat{r}_t^n$, is given by

$$1 + \widehat{r}_t^n = \frac{p_H q_t R_t^e}{g\left(r_t^a, q_t; m_t = 0, h_t = \overline{h}\right)} = \frac{\frac{p_H}{\Delta p}\overline{h}}{\frac{p_H}{\Delta p}\overline{h} - \rho_t}.$$

To rule out the corner solution, we must have

$$\widehat{r}_t^n < r_t^n, \tag{D.39}$$

where r_t^n is the expected rate of return on entrepreneurial capital if the entrepreneur chooses the interior solution that involves monitoring. In particular, the condition (D.39) should apply in the steady state, so that we get the condition

$$\overline{h} \ > \frac{\Delta p}{p_H} \frac{1 + r^n}{r^n} \rho. \tag{D.40}$$

In addition, we seek a condition that guarantees that it is socially optimal to choose the "good" project rather than the "bad" project with the maximum level of private payoffs $\overline{h}$. For this condition to hold in the steady state, we must have

$$p_H q R \ > p_L q R + \overline{h} \Leftrightarrow \overline{h} \ < \frac{\Delta p}{p_H} q. \tag{D.41}$$

When deriving the latter form of the inequality, recall the normalization $p_H R = 1$. It is possible to rule out a corner solution if and only if there exist a value $\overline{h}$ that satisfies both (D.40) and (D.41). Such a value $\overline{h}$ exists if and only if $\left(\frac{1+r^n}{r^n}\right) \rho < q = 1 + \rho$ or, equivalently,

$$r^n \ > \rho. \tag{D.42}$$

In Appendix D.4, we show that

$$\rho = r^n CRF + (r^a CRB + MRB)(1 - CRF),$$

where the data moments r^n, r^a, CRF, CRB, and MRB are defined in Section 5, or alternatively in Appendix C.2. Then one can rewrite the condition (D.42) in such a way that it only includes data moments we match,

$$r^n > \ r^a CRB + MRB. \tag{D.43}$$

Our baseline calibration satisfies this condition.

D.4 Expressing ρ in Terms of Data Moments

In this section, we show that

$$\rho = r^n CRF + (r^a CRB + MRB)(1 - CRF), \tag{D.44}$$

where ρ is the net return on the investment projects in steady state, while the data moments r^n, r^a, CRF, CRB, and MRB are defined in Section 5, or alternatively in Appendix C.2. To derive (D.44), first apply Equations (16), (D.20), and (D.22) to get

$$\rho = \left(\frac{p_H}{\Delta p}\right)\left(1 + \frac{\Delta p}{p_H} - \frac{\lambda^b}{\beta}\right)\left(\frac{m}{\gamma}\right). \tag{D.45}$$

Next note that

$$m = \left(\frac{mI}{I-N}\right)\left(\frac{I-N}{I}\right) = MRB(1 - CRF), \tag{D.46}$$

where the last form is derived using definitions (C.1) and (C.3) in Appendix C.2. Finally, plugging (C.5), (C.7), (C.8), and (D.46) into (D.45) yields (D.44).

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Monetary Policy Shocks and Inflation Inequality*

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This paper studies how monetary policy shocks influence the distribution of household-level inflation rates. We find that contractionary monetary policy shocks significantly and persistently decrease inflation dispersion in the economy. Moreover, different demographic groups are heterogeneously affected by monetary policy. Due to the different consumption baskets purchased, low- and middle-income households experience higher median inflation rates, which are at the same time more responsive to a contractionary monetary shock, leading to an overall convergence of inflation rates across income groups. The same result holds for expenditure and salary groups. The expenditures on *Energy*, *Water*, and *Gasoline* are the main drivers behind these results. These findings imply that the impact of monetary policy shocks on expenditure inequality is between 20 and 30 percent more muted once we control for differences

*We thank the anonymous referee as well as the editor Fernanda Nechio for their helpful comments. We would like to thank Florin Bilbiie, Jean-Paul Renne, and Andreas Tischbirek for their valuable comments and guidance. We are particularly indebted to Ting Lan for providing the data on the income-percentile-specific consumer price indices. We are also grateful to Philippe Bacchetta, Kenza Benhima, Aurélien Eyquem, Yuriy Gorodnichenko, Andrei Levchenko, Christina Patterson, Ricardo Reis, and fellow UNIL Ph.D. students for helpful suggestions that significantly improved the paper. Finally, we would like to thank the participants of the conferences organized by the International Association for Applied Econometrics, the Swiss Society of Economics and Statistics, the Society of Economics of the Household, the Ph.D. - Economics Virtual Seminar, the VMACS (Virtual Macro Seminar), the Berkeley GEMS, the Lausanne Macro Reading Group, the 9th Italian Congress of Econometrics and Empirical Economics, the 61st Annual Conference of the Italian Economic Association, and the 15th Economics Graduate Students Conference for precious feedback. The views expressed are those of the authors and do not necessarily reflect those of the Banca d'Italia or the Eurosystem. Author emails: lauper.chris@gmail.com and mangiante.giacomo@gmail.com.

in individual inflation rates. Overall, our empirical evidence highlights the importance of inflation heterogeneity in studying the distributional consequences that monetary policies can have.

JEL Codes: E31, E52.

1. Introduction

The relationship between monetary policy and heterogeneity has become increasingly important in macroeconomic research, both from a theoretical and an empirical point of view. Changes in interest rates do not affect households homogeneously. Renters and homeowners, savers and hand-to-mouths, high-skilled and low-skilled workers are only a few examples of different demographic groups that have been found to bear the consequences of the decisions made by the monetary authorities in completely different ways. Therefore, in the last few years, both economic researchers and central bankers have shifted their focus from aggregate to more granular effects to better understand the different channels through which monetary policy can affect individual households and firms. However, the importance of inflation heterogeneity, i.e., the different inflation rates experienced by households due to the variations in the consumption baskets they purchase, for the distributional effects of monetary policy has so far received limited attention.

This paper studies how monetary policy influences the distribution of individual inflation rates to which different households are exposed. We compute a measure of inflation heterogeneity, given by the standard deviation of individual inflation rates, and document that contractionary monetary shocks reduce both the median and the cross-sectional standard deviation of the distribution of household-specific inflation rates. We then study how the inflation rates of different demographic groups are heterogeneously affected by monetary shocks. We show that *inflation inequality*, which we define as the cross-sectional standard deviation of the decile-specific inflation rates across expenditure, salary, and income deciles, decreases after a contractionary monetary shock. The reason is that households at the bottom of the distribution are exposed to a higher inflation rate, which tends at the same time to decrease more following a monetary shock. The effect is almost entirely driven by

expenditures on *Energy*, *Water*, and *Gasoline*. The inflation rate of these sectors, even though they account for a relatively small share of the aggregate consumption bundle, is highly sensitive to changes in interest rates. Finally, taking inflation heterogeneity into account, we find that the increase in expenditure inequality is significantly more muted.

The first contribution of this paper is to evaluate how monetary policy influences the distribution of household-level inflation rates. To compute individual inflation rates, we combine item-level price data from the Bureau of Labor Statistics (BLS) with individual expenditure data from the Consumer Expenditure Survey (CEX) for the U.S. from 1980 onward. We evaluate how the different moments of the inflation rates distribution, i.e., the median and the standard deviation, react to monetary policy shocks by adopting a local projection approach à la Jordà (2005). Exogenous variations in interest rate are captured using the Romer and Romer (2004) monetary shocks series. We document that contractionary monetary policy shocks decrease the median inflation rate as well as significantly reduce the dispersion of the distribution.

The second contribution is to study whether the inflation rates of different demographic groups are heterogeneously affected by monetary policy. We demonstrate that contractionary shocks lead to a sizable decrease in inflation inequality. On the one hand, low- and middle-income households tend to experience higher inflation rates than high-income households. On the other hand, their inflation rates are more sensitive to shocks and tend to decline more in response to monetary policy tightening. The same result holds for salary and expenditure deciles, confirming the important role of endowments in the dynamics of individual inflation rates.

The third contribution is to assess which sectors are mainly responsible for the decrease in inflation dispersion. The price indices of different sectors have different sensitivity to monetary policy shocks. We document that *Energy*, *Water*, and *Gasoline* are by far the most influenced by contractionary shocks and they explain almost entirely the response of inflation dispersion to monetary shocks even though they account for only a relatively small expenditure share. Therefore, the higher responsiveness of the low- and middle-income households' inflation is driven by the larger expenditure share they devote to these categories.

The fourth contribution of the paper is to evaluate how these new findings on inflation heterogeneity influence real expenditure inequality and its response to monetary shocks. We compute two measures of real expenditure at household level: one deflating nominal expenditure by the aggregate price level (as is common in the literature, neglecting inflation heterogeneity) and one deflating each expenditure category by the relative sectoral price level. As expected, we find that assuming all households are exposed to the same inflation rate overestimates the impact of monetary policy shocks on expenditure inequality. Although the nominal expenditure of low- and middle-income households decreases more after a shock than that of high-income households, their inflation rates also decrease relatively more, partially offsetting this decrease in real terms. It is important to underline that real consumption heterogeneity is still found to increase after a monetary shock, corroborating again the evidence of the sizable distributional effects that central banks can have on the economy.

After years of relatively stable price growth, inflation rates worldwide have reached high levels in the post-COVID period. The optimal monetary policy to tackle them is again at the center of attention for academics and policymakers. However, most of the discussion focuses on stabilizing the aggregate inflation rate. The results from this paper suggest that concentrating only on the overall inflation would miss the huge heterogeneity in inflation rates to which households are exposed.

The level as well as the sensitivity of household-level inflation rates to changes in interest rates are strongly correlated with demographic characteristics. Therefore, abstracting from also considering how the individual inflation rates adjust in response to shocks would lead to systematic biases by the monetary authorities against specific demographic groups. For instance, since low-income households experience a higher inflation rate relative to high-income households, they would benefit from a more aggressive monetary policy than the one implemented by focusing only on the aggregate inflation rate. This problem may even be exacerbated by the fact that central banks usually design their policies targeting a specific subset of price indices. As we document, core measures of inflation, i.e., excluding energy and food, greatly underestimate the overall level of inflation dispersion in the economy. Finally, the empirical findings

we provide suggest that central banks should pay close attention to inflation heterogeneity, as whether it is taken into account or not has important implications for the magnitude of the distributional effects caused by the monetary authorities decisions.

Related Literature. This paper contributes to two strands of the literature. The first one is the research agenda on inflation inequality. Households are exposed to different levels of price increases given the heterogeneous consumption baskets they consume. For the U.S., Thesia, David, and Kokoski (1996), Hobijn and Lagakos (2005), Leslie and Paulson (2006), Johannsen (2014), and Orchard (2022) measure inflation inequality using the CEX data which covers the full consumption basket. More recently, Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), and Argente and Lee (2021) compute inflation inequality from scanner data which is available for a much more limited time period but provides information at a higher level of granularity. The differences in inflation rates across households are substantial over time as well as related to demographic characteristics. For instance, high-income households are exposed to lower inflation rates than low- and middle-income households. See Jaravel (2021) for a review of the growing literature on inflation inequality.

Particularly related to the results of our paper, Cravino, Lan, and Levchenko (2020) show that the inflation rate of high-income households reacts significantly less than that of middle-income households following a monetary shock. We contribute to this literature by studying how inflation dispersion across households responds to monetary policy shocks. We document that contractionary shocks decrease the cross-sectional dispersion in household inflation rates. Almost the entire effect is due to the higher sensitivity of the prices of *Energy*, *Water*, and *Gasoline* to changes in the interest rate. Combining two results from the existing literature regarding the fact that lower- and middle-income households are exposed to a higher inflation rate, as documented by Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019), and that at the same time, their inflation rate decreases relatively more following a monetary shock, as shown in Cravino, Lan, and Levchenko (2020), we find that inflation inequality across income, salary, and expenditure deciles decreases in response to a monetary shock.

The second strand is the growing literature on the distributional aspects of monetary policy. With an approach analogous to

the one we adopt, Coibion et al. (2017) document that consumption and income inequality in the U.S. increase following a contractionary monetary shock. Similar findings have also been found in other countries and in different time periods, e.g., Mumtaz and Theophilopoulou (2017) for the United Kingdom, Guerello (2018) and Samarina and Nguyen (2024) for the euro area, and Furceri, Loungani, and Zdzienicka (2018) for a panel of 32 advanced and emerging economies. A summary of the current empirical and theoretical literature on the relationship between monetary policy and inequality is provided by Colciago, Samarina, and de Haan (2019).

We show that neglecting inflation heterogeneity results in an overestimation of the impact of monetary policy shocks on expenditure inequality. In response to a contractionary monetary shock, the stronger decrease in the inflation rate of low-income households partially offsets the decrease in their nominal consumption, resulting in a more muted response in real terms. It follows that the distributional effects of monetary policy on expenditure inequality are more limited once inflation heterogeneity is taken into consideration.

Road Map. The paper is structured as follows. Section 2 describes the data set used, as well as the construction of individual inflation rates and dispersion measures. In Section 3 we discuss the empirical strategy and show the effects of monetary policy shocks on the cross-sectional inflation distribution. Section 4 studies the heterogeneous responses across different demographic groups. In Section 5 we assess the sectoral contributions to the decrease in inflation dispersion following a contractionary monetary shock. Section 6 evaluates how inflation heterogeneity dampens the response of real consumption inequality to monetary shocks. In Section 7, we perform a battery of different robustness checks to evaluate the reliability of our findings. Section 8 concludes.

2. Individual Inflation Rates

This section describes the computation of individual inflation rates at the household level by exploiting the differences in consumption patterns across households. In line with the literature on inflation inequality, we combine granular data on prices for different categories with detailed information on (individual) consumer expenditure, which allows computing the share of different goods in an

aggregate index and therefore provides weights.[1] In the following, we discuss the different steps in detail.

2.1 Inflation Data

We use data from the consumer price index (CPI) as computed by the BLS at a monthly frequency. In particular, we use the not-seasonally-adjusted *US City Average for all urban consumers* (CPI-U). The BLS collects price data on 211 different subgroups of goods and services, which it calls item strata. This is the most disaggregated level for which it publishes information on prices. However, these item strata over the period from 1980 to today undergo regular revisions, or their definition is changed. Some disappear entirely and some get newly introduced. For this reason and for data availability, we need to combine these basic price indices with more aggregate ones. We follow Hobijn and Lagakos (2005) and Johannsen (2014) in creating 21 indices, for which we get consistent inflation rates during our time sample. We call the inflation rates for subgroups of the consumer basket *inflation subindices*.[2] The construction of these inflation rates is subject to a trade-off between consistent and sufficiently long time series and finely disaggregated time series that capture as much of the difference in inflation as possible. Jaravel (2019) finds that only 20 percent of inflation inequality is captured when using 22 expenditure categories instead of 256 for the period from 2004 to 2015. In Subsection 7.1 we show that increasing the number of categories considered from 21 to 121 significantly increases the *level* of inflation dispersion across households but does not affect its *sensitivity* to monetary policy shocks.

In Table A.1 (see Appendix A) we report the mean, median, standard deviation, the 10th and the 90th percentile of the 21 inflation subindices we compute, as well as of the official CPI-U for the period 1980–2008. The observed sectoral inflation heterogeneity will be one of the key components in explaining the evolution of inflation dispersion. Households spend different shares of their overall expenditure on each category and, since these categories differ in terms of

[1] The CEX proves rich enough to provide data on expenditure, going back to 1980.

[2] The list and definitions of these subindices can be found in Appendix A.1.

price volatility and price level, this will lead to differences in terms of experienced inflation.[3] In what follows, we have to find reliable weights with which we can combine the inflation subindices to get household-level inflation rates across all items.

2.2 Expenditure Data

For the computation of expenditure weights, we use the CEX provided by the BLS. This is the same data set that is used to compute the official CPI of the U.S. The CEX is a quarterly survey of household expenditures and is divided into a diary and an interview survey. The diary survey covers small expenditures on daily items over a period of two weeks. The interview survey is more comprehensive, with detailed questioning every three months yielding up to a year of data for a single household. Since our goal is to get inflation rates that are as comprehensive as possible, we solely rely on data from the interview survey.

There are some limitations to the CEX data. The BLS removes consumption data from the 100th percentile (it is top-coded) to ensure anonymity. Additionally, since we deal with survey data, there are likely more measurement errors in the CEX compared with other data sources.[4] However, the CEX allows us to get a comprehensive picture of virtually all consumer expenditures, and it is also sufficiently large in the time dimension (starts in 1980) and along the cross-section (roughly 5,000–7,000 households each wave).

[3]The biggest limitation of using inflation subindices is that they are not individual prices. While we capture the inflation that is due to different consumption baskets, we are not able to capture inflation differences within a subindex. It is conceivable that taking the category *Food away* as an example, high-end restaurants have different price developments from low-end ones. This problem is circumvented with Nielsen scanner data. The data set reports product-level information on both prices and quantities, so it is more granular than the CEX data. However, two major limitations made the Nielsen data a nonviable solution for our analysis. First of all, the data cover only purchases in department stores, grocery stores, drug stores, convenience stores, and other similar retail outlets, which account for approximately 15 percent of total household expenditures. Moreover, the data set is available only from 2004 onward.

[4]See Bee, Meyer, and Sullivan (2015) for an assessment of the quality of our consumer data set.

Like the inflation subindices, we aggregate the expenditure data into 21 groups,[5] matching the classification of the CEX with the one from the price indices. In the next step, we aggregate the household-level expenses from monthly to yearly. By doing this, we get rid of seasonal patterns in expenditures, while at the same time "averaging out" extraordinary expenses and hence improving the quality of our data. With this approach, almost the entire variation in individual inflation rates comes from price changes, rather than from changes in consumption patterns. Hence, the variation in individual inflation rates is mainly driven by the dynamics of sectoral inflation rates, as opposed to being driven by changes in the consumption bundle, as we intend. The relevance of the substitution effects is studied in Subsection 7.1, where we compute the expenditure shares at higher frequencies.

2.3 Computation of Individual Inflation Rates

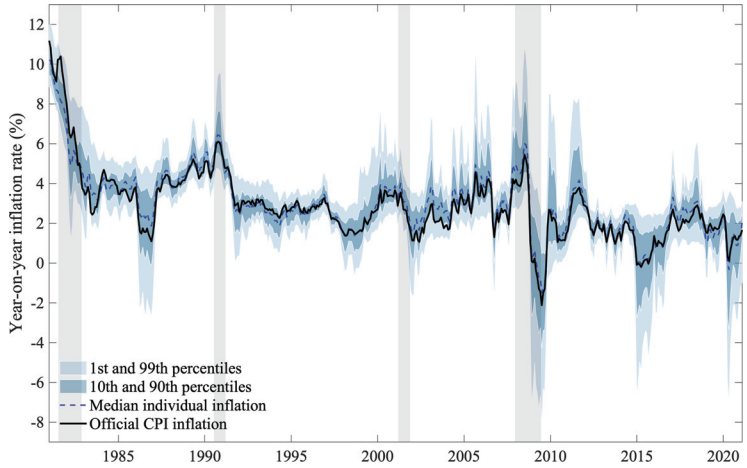
In the third step, we combine the expenditure data with the inflation data. For this, we compute consumption shares w_j^i for household i and item subgroup j, which are calculated by dividing the yearly consumption expenditure in a certain period by the total expenditure reported in the same period. In the baseline analysis, we use all 21 categories. We compute the individual inflation rate for household i as

$$\pi_{t-k,t}^i = \sum_{j \in J} w_j^i \pi_{j,t-k,t}, \tag{1}$$

where j denotes the item subgroup as defined in Section 2.2. The inflation rate of the subindex for good j in period t with base period $t-k$ is denoted by $\pi_{j,t,t-k}$. We set $k = 12$, meaning year-on-year inflation rates, which removes seasonality in the inflation subindices. Additionally, we winsorize the individual inflation rates at the 1st

[5]In computing household-level inflation rates, we have to alter the *Housing* group and omit the *Vehicle* group altogether. In particular, we follow Johannsen (2014) and we use the question on rental equivalence for the owned dwelling expenditures of the homeowners. Moreover, we exclude expenditures on new and used vehicles since in a given year the purchase of a vehicle could dominate all other expenditures. When we compute the inflation rate across deciles, vehicle purchases are included since it is less likely this category can bias the decile-level inflation rates. See Appendix A.3 and Appendix B for more details.

Figure 1. Official CPI Inflation, Cross-Sectional Distribution, and Median Individual Inflation Rate over Time



Note: This figure shows the evolution over time of the official CPI inflation as well as the median and selected percentiles (1st, 10th, 90th, and 99th) of the winsorized cross-sectional distribution in individual inflation rates. The gray shaded areas depict U.S. recessions.

and the 99th percentile. In the next step, we analyze the statistical properties of individual inflation rates.

2.4 Properties of Individual Inflation Rates

We assess the validity of the measures of individual inflation computed above by comparing the official CPI inflation rate with the median of individual inflation rates in Figure 1.[6] In the same figure, we also show different percentiles of the calculated household-specific rates of inflation.

The median of the distribution of household-specific rates of inflation closely tracks the headline value of CPI inflation. Hence, our approach gives, in an aggregate world, very similar results to the official CPI inflation rate. This result shows why for many years economic models mainly focused on the representative agent: The time

[6]Similar results are obtained for the mean of the distribution.

series of the experienced inflation for the "median household" can be considered a quite good approximation of the aggregate economy.

At the same time, the individual inflation rate percentiles in Figure 1 reveal how much information is lost when ignoring the heterogeneity across households. Not surprisingly, macroeconomic models have been expanded to include heterogeneity in consumption, wages, asset portfolio composition, and many more. However, most models still abstract from inflation differences and implicitly assume that households are exposed to the same inflation rate. Figure 1 strongly rejects this assumption.

2.5 Measures of Dispersion

To evaluate how monetary policy shocks affect inflation dispersion in the U.S., we construct three different measures of dispersion: the cross-sectional standard deviation, the difference between the 90th percentile and the 10th percentile (depicted as 90th–10th, henceforth), and the cross-sectional interquartile range (IQR). To avoid the change in the survey composition affecting our results, we calculate the variation in the inflation dispersion measures on the households present in both periods. Therefore, when we calculate the change in the cross-sectional standard deviation from t to $t+1$, we do it only for the households that are present during both periods. Sampling weights are applied throughout the analysis.

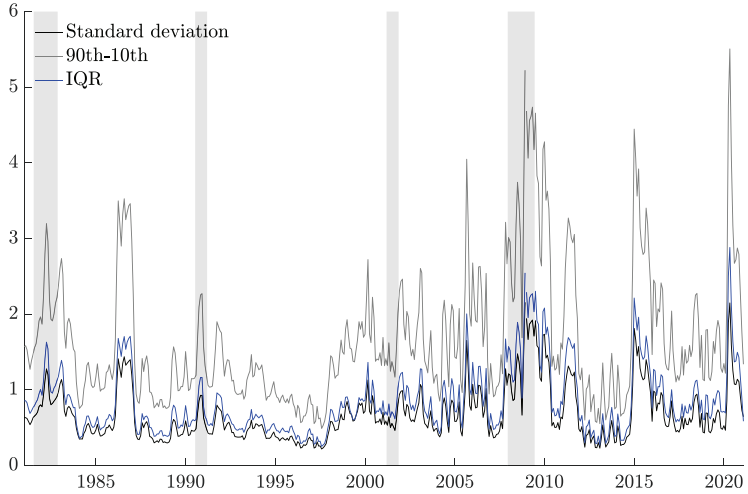
Figure 2 shows the historical evolution of the three measures of dispersion, together with U.S. recessions. The three variables are highly correlated, suggesting that a normal distribution approximates the computed individual inflation rates very well. Despite using a different time period and alternative CPI categories, the time series are comparable in magnitude to those found by Johannsen (2014). As one can notice, inflation dispersion tends to increase during U.S. recessions suggesting a sort of correlation with the business cycle in the economy.

3. The Effects on Inflation Dispersion

3.1 Methodology

To study whether and to what extent monetary policy shocks influence aggregate inflation dispersion, we adopt in the baseline

Figure 2. Historical Series of Inflation Dispersion Measures



Note: This figure shows the evolution of inflation dispersion measured using the cross-sectional standard deviation, the difference between the 90th and the 10th percentile of the cross-sectional distribution, and the IQR. All the series refer to the period 1981:M1–2020:M12. The gray shaded areas depict U.S. recessions.

specification the local projection (LP) method developed by Jordà (2005). As in Cravino, Lan, and Levchenko (2020), we estimate a series of regressions for the dependent variable over different horizons on the monetary policy shock in period t and controlling for the lags of the shock as well as of the dependent variable:

$$x_{t+h} - x_t = c_h + \beta_h e_t^{RR} + \sum_{j=1}^{J} \theta_{h,j}(x_{t+1-j} - x_{t-j}) + \sum_{i=1}^{I} \gamma_{h,i} e_{t-i} + \epsilon_{t+h}, \quad (2)$$

where x is the variable of interest and the monetary policy shocks are denoted by e_t^{RR}. In line with the literature, we include 48 lags of the shocks and 6 lags of the dependent variable as controls. The coefficient β_h for $h = 1, ..., H$ gives the response of the dependent variable

at time $t+h$ to a monetary policy shock at time t.[7] The impulse responses are computed over a horizon of 48 months using data from 1980:M1 to 2008:M12. Standard errors are corrected as in Newey and West (1987). For each impulse response, we present the one and 1.65 standard deviation confidence intervals. Unanticipated changes in the short-term interest rate are identified using the monetary policy shock series devised by Romer and Romer (2004, henceforth called R&R shocks) and extended by Coibion et al. (2017).[8]

The R&R shocks stop before 2009 so the zero lower bound period is excluded. In Appendix E we perform some additional analysis using as an alternative measure of monetary shocks the proxy from Bauer and Swanson (2022) which spans from 1988 to 2019. The main results of the paper hold considering the most recent period as well.

3.2 Analysis

We evaluate the overall effects of a contractionary monetary policy shock on inflation dispersion by estimating Equation (2) using the cross-sectional standard deviation as the baseline measure of inflation dispersion. The results are reported in Figure 3.[9]

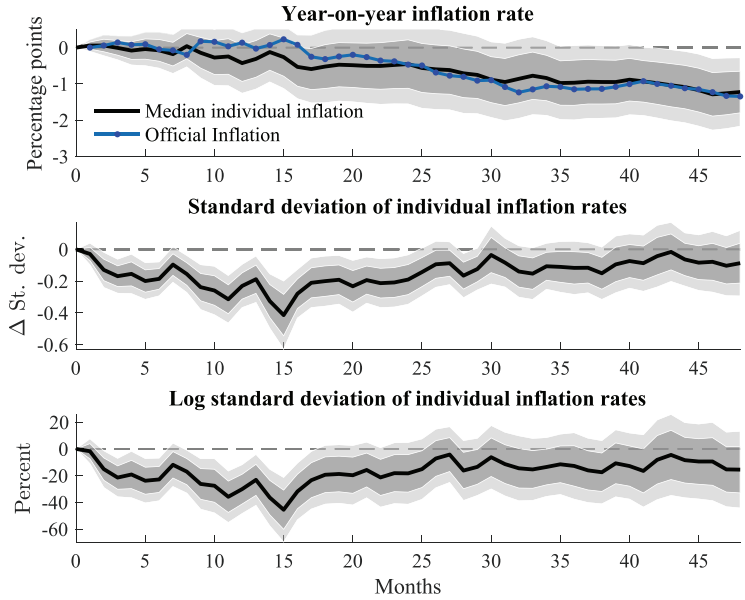
The top panel shows the responses of the annual inflation rate computed by the BLS (blue line) as well as of the median inflation rate across households (black line): following a contractionary shock, the annual rate decreases by approximately 1.5 percentage points, a magnitude in line with the literature. As one might have expected looking at Figure 1, the response of the median inflation rate closely matches the response of aggregate inflation.

[7] As an alternative specification, we also use the Romer and Romer (2004) shocks as an instrument for the change in interest rate (IV-LP) instead of directly inserting them in the LP and the results remain unchanged.

[8] Coibion (2012) shows how the Romer and Romer (2004) approach might be particularly sensitive to the period in which the Federal Reserve abandoned targeting the federal funds rate between 1979 and 1982. Therefore, in Section 7 we redo the analysis starting the sample in 1985 and showing that our results are not driven by these large monetary policy shocks in the early 80s.

[9] The responses for the difference between the 90th and the 10th percentile of the cross-sectional distribution and the IQR are highly similar. Therefore, we only report the results for the cross-sectional standard errors in this section.

Figure 3. Impulse Responses of the Year-on-Year Inflation Rate as Well as the Median and the Standard Deviation of the Individual Inflation Rate Distribution



Note: The top panel of this figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the official annual inflation rate (black line) and the median inflation rate (blue line) of the individual inflation rate distribution. The middle panel reports the impulse response using as the dependent variable the dispersion in inflation, measured by the cross-sectional standard deviation, and the bottom panel the log of the dispersion measure such that it can be interpreted as a percent change relative to the steady state. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

In the middle panel of Figure 3, we show the impulse response of our dispersion measure. Inflation dispersion decreases after a contractionary monetary policy shock and remains persistently below zero. Looking at the one and 1.65 standard deviation confidence intervals, we can easily reject the null hypothesis that the coefficients are equal to zero for the horizon considered. Therefore, the impulse response strongly suggests that monetary policy shocks lead to a decrease in the inflation dispersion in the economy.

To quantify the magnitude of the decrease in the inflation dispersion, the bottom panel computes the same impulse response but uses the log of the dispersion measure as the dependent variable, such that the magnitude can be interpreted as a percentage change relative to the steady state. Following a contractionary shock, we find that the cross-sectional standard deviation of inflation rates at the household level decreases by around 40 percent after 15 months and approximately 20 percent at the end of the horizon considered. The average inflation rate over the same time period is about 3.75 percent, so a decrease of 1.5 percentage points corresponds to a decrease in 60 percent of the average value.

4. Heterogeneity across Demographic Groups

Having shown that monetary policy shocks decrease inflation dispersion in the economy, we now evaluate whether the inflation rate of some demographic groups is more sensitive to contractionary shocks relative to other groups and how this affects the cross-sectional inflation dispersion. We focus in particular on three demographic groups: income, salary, and expenditure deciles.

4.1 Expenditure Weights

Heterogeneity in inflation rates comes from the fact that households consume different consumption baskets. As in Cravino, Lan, and Levchenko (2020), we derive the time-varying decile-specific expenditure weights following the procedure used by the BLS to compute the aggregate CPI which we describe in detail in Appendix B.[10] We report in Table A.2 (see Appendix A) the expenditure weights of the 1st, 5th, and 10th deciles of income, salary, and expenditure deciles for each of the 21 categories for the period 1980–2008.

Several interesting facts can be noticed: First, the pattern across deciles is quite similar for income, salary, and expenditures. This already anticipates that the decile-level inflation rates of these three groups will react in a consistent way to monetary policy shocks. Second, although the weight for most of the categories either decreases

[10] Appendix E shows that the results are not particularly affected by considering the simple median inflation rate for each decile.

or increases from the 1st to the 10th deciles, some categories display a U-shaped pattern, e.g., *Gasoline* and *Medical expenses*. This is consistent with the findings of Cravino, Lan, and Levchenko (2020), who document that the highest price volatility is experienced by middle-income households.

4.2 Impulse Responses by Demographic Groups

We study how the inflation rates of different demographic groups react to monetary policy shocks. We start by estimating the LP with R&R shocks using as the dependent variable the cross-sectional standard deviation of the decile-specific inflation rates across income, salary, and expenditure deciles which we define as *inflation inequality*.[11] As one can see from Figure 4, following a contractionary monetary policy shock, inflation inequality for the three groups significantly decreases.

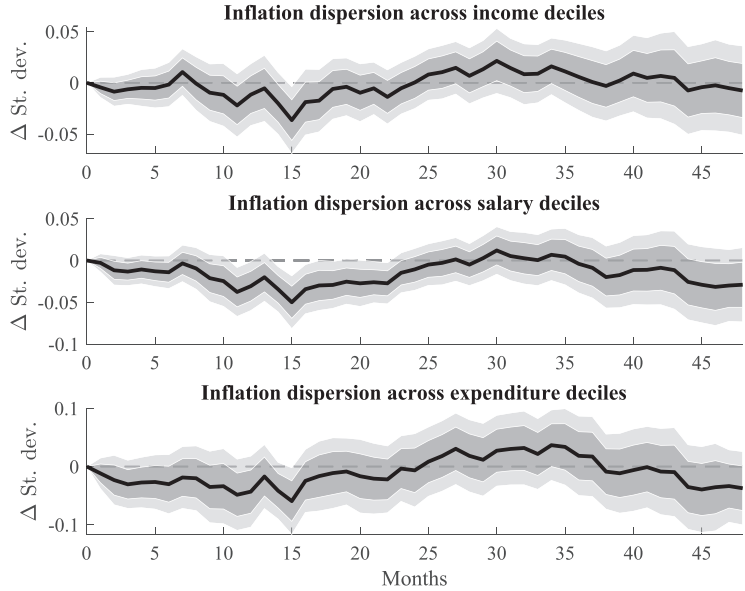
To better understand the main drivers of this result, we compare the median inflation rates of the different income, salary, and expenditure deciles with their impulse responses over time. The black lines in Figure 5 report the cross-sectional distribution of the impulse responses for the inflation rate of the different income (left panel), salary (middle panel), and expenditure deciles (right panel) 24 and 48 months after a 1 percentage point contractionary monetary policy shock.

Similar to what Cravino, Lan, and Levchenko (2020) find for income, the annual inflation rate of the households at the top of the income distribution reacts substantially less to monetary policy shocks than the one of those in the middle. The difference between middle- and high-expenditure households is economically sizable and statistically significant as tested in Appendix C. After 24 months, the annual inflation rate of the households in the top decile responds to around 40 percent less than the inflation rate of the households in the fifth decile. After 48 months, the difference is still around 25 percent.

How does this relate to inflation inequality? We report in the same panels the median inflation rates across deciles relative to the

[11] Appendix B explains in detail how the median inflation rates are computed following the same approach adopted by the BLS.

Figure 4. Impulse Responses of Inflation Dispersion across Income, Salary, and Expenditure Deciles



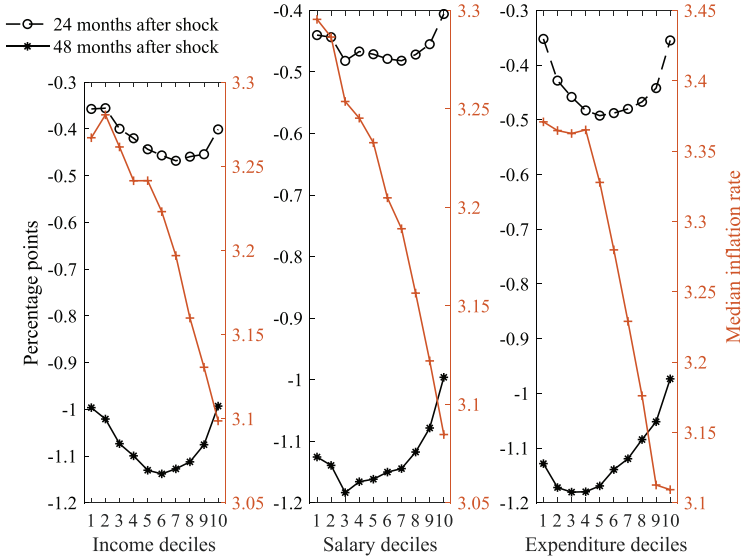
Note: The figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for inflation inequality across income (top), salary (middle), and expenditure deciles (bottom). Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

time period considered (red line, left axis).[12] One can notice how the higher the decile, the lower the median inflation rate. This result is consistent with the evidence provided by Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019) using the Nielsen scanner data.

On the one hand, given their consumption bundle, high-income households experience a lower median inflation rate than the households on the left side of the distribution. On the other hand, their inflation rate reacts significantly less to monetary policy shocks.

[12]Plotting the cumulative difference in inflation rates across deciles delivers similar results.

Figure 5. Impulse Responses of the Decile-Specific Inflation Rate across Income, Salary, and Expenditure Deciles



Note: This reports the cross-sectional distribution of the decile-specific inflation rate responses of the different income (left panel), salary (middle panel), and expenditure deciles (right panel) 24 and 48 months after a 1 percentage point contractionary monetary policy shock. The red lines refer to the median inflation rate across deciles (left axis). Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

These two results combined imply that following a contractionary shock, we observe a convergence of individual inflation rates across the distribution leading to a lower inflation inequality, as documented in Figure 4. Similar results can be found focusing on salary and expenditure deciles, as shown in the middle and right panels of Figure 5.

Our empirical analysis strongly suggests that monetary policy shocks can have significant and non-negligible distributional effects on the economy. The median inflation rate of higher-income households is lower relative to low- and middle-income deciles. At the same time, their inflation rate is less reactive to unexpected changes in the interest rate. This results in a decrease in inflation inequality following a contractionary shock.

5. Sectoral Contribution

In this section, we determine which sectors mainly drive the decrease in inflation dispersion across households. The individual inflation rates are constructed assuming there is no substitution across categories in response to a monetary policy shock.[13] Therefore, the decrease in inflation dispersion is entirely because the inflation of different sectors is heterogeneously sensitive to exogenous changes in the interest rate.[14] To evaluate which sectors are mainly responsible for the results documented in the previous sections, we compute the response of several sectoral inflation rates to a contractionary shock. The results are reported in Figure 6.

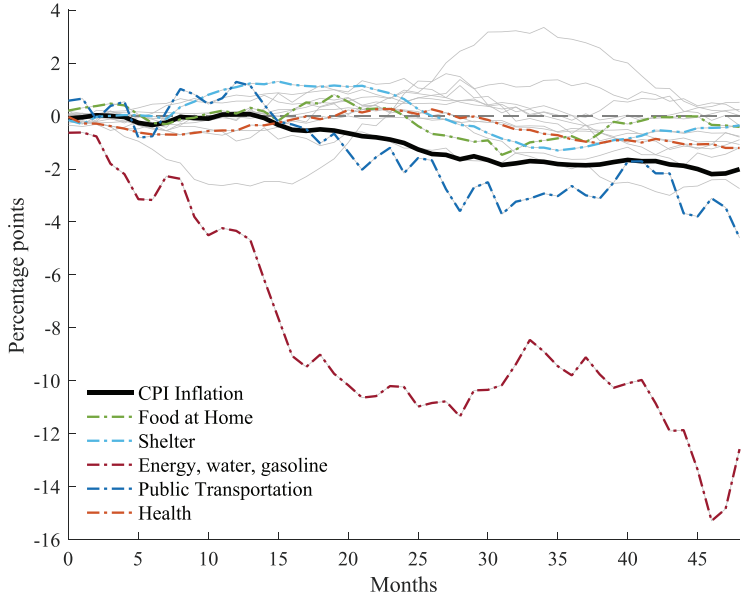
The impact of monetary shocks on the inflation rates is extremely heterogeneous across sectors, in line with the empirical evidence from Boivin, Giannoni, and Mihov (2009) and Duarte and Dias (2019). Comparing the sectoral responses to the response of aggregate CPI, it emerges that the majority of inflation rates at the sectoral level are only marginally affected by monetary policy shocks. In contrast, the inflation rates of *Public transportation* and *Energy*, *Water*, and *Gasoline* are significantly more responsive.

The fact that monetary policy shocks have a strong impact on energy prices may seem surprising. However, the result is consistent with recent empirical analysis. Del Canto et al. (2023) adopt an internal instrument vector autoregression (VAR) with Gertler and Karadi (2015)'s monetary shocks and document that the response of inflation in the *Motor fuel* category is almost 10 times larger than the response of the overall CPI, the response of inflation in the category *Fuels and utilities* is almost three times larger. Similarly, Ider et al. (2023) estimate a Bayesian proxy structural vector autoregressive (SVAR) model for the U.S. (1990–2019) and the euro area (1999–2019) and confirm that the European Central Bank and the Federal Reserve can significantly influence domestic and global energy prices. The response of the energy component of the CPI to a monetary policy shock is again about 10 times larger than the

[13]This is an assumption which we relaxed in Subsection 7.1.

[14]Note that in this empirical exercise, we take the sectoral inflation rates as given. In Appendix D, we examine the link between sectoral inflation rates and underlying shocks to pure inflation and relative prices.

Figure 6. Sectoral Inflation Rates Impulse Responses

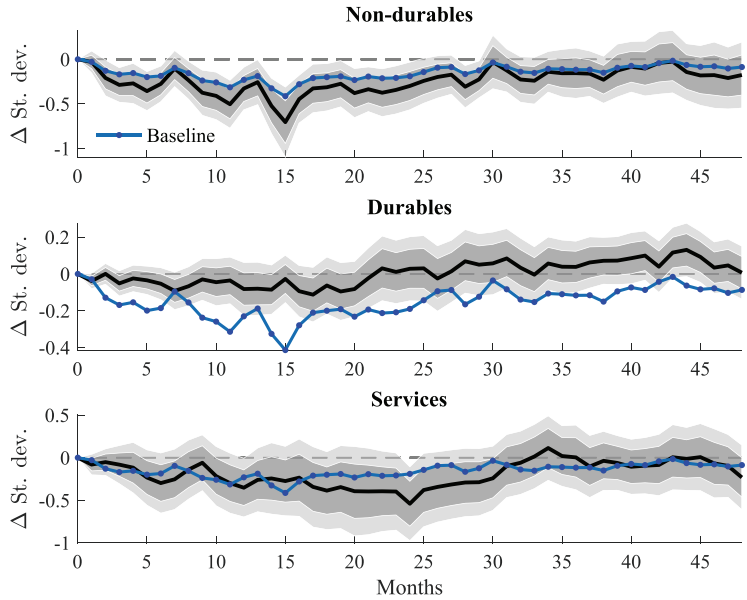


Note: This figure shows impulse responses of some of the different sectoral inflation rates that compose the official CPI inflation (thick black line) to a 1 percentage point contractionary monetary policy shock. Impulse responses are computed at a monthly frequency using data relative to the period 1980:M1–2008:M12.

response of the CPI. These magnitudes are in line with the responses we report in Figure 6. Ider et al. (2023) also examine the channels through which the Federal Reserve's monetary policy surprise may affect domestic and global energy prices. The authors find that the observed decline in the global oil price due to an exogenous increase in the interest rate stems from a decline in the energy demand, which subsequently lowers global energy prices, and thus affects the overall inflation rate.

Having shown that the sectoral inflation rates heterogeneously respond to monetary shocks, we now assess the contribution of the different sectors to the decrease in inflation dispersion. We start by computing inflation rates at the household level, considering only a subset of the overall consumption basket. In particular, we classify each category into *nondurables*, *durables*, or *services*. As before, we then derive the response of the inflation dispersion across households

Figure 7. Impulse Responses of Inflation Dispersion for Different Subcategories of Expenditure

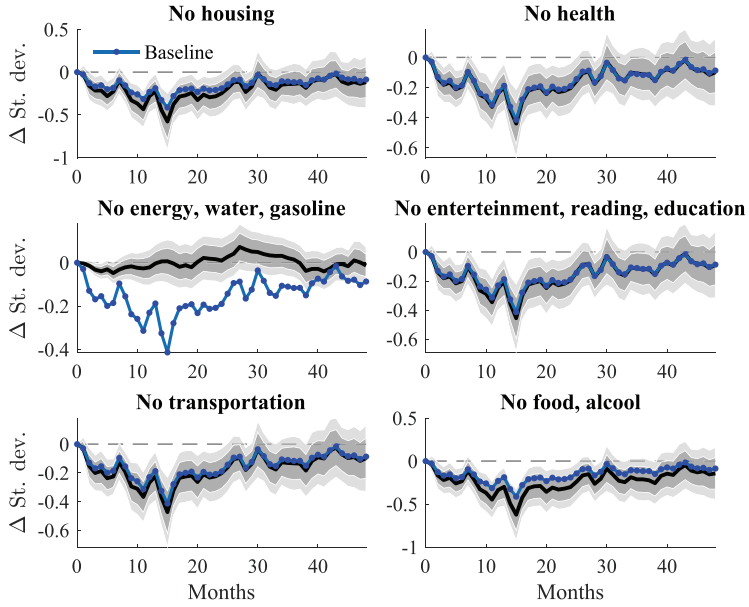


Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the dispersion in inflation, measured by the cross-sectional standard deviation. The top panel uses the standard deviation in inflation rates for nondurable categories, the middle panel for durables, and the bottom panel for services. The solid blue line refers to the baseline impulse response obtained using the baseline categories. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

for these three subcategories, defined as the cross-sectional standard deviation, to a contractionary monetary shock.

The results are reported in Figure 7. The inflation dispersions of the three subcategories decrease after a contractionary shock. However, they differ remarkably in the magnitude of their responses. The standard deviation of *nondurables* categories is more reactive whether the standard deviations of *durables* and *services* are less responsive to the shock and barely significant. The observed differences in the responses suggest that the main drivers of the decrease in inflation dispersion can be found within the *nondurables* categories.

Figure 8. Impulse Responses of Inflation Dispersion Excluding Different Categories of Expenditure



Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the dispersion in inflation, measured by the cross-sectional standard deviation. Each panel uses the standard deviation in inflation rates computing excluding expenditure categories from the consumption bundle of the households. The solid blue line refers to the baseline impulse response obtained using the baseline categories. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

Therefore, we compute the same cross-sectional standard deviation of individual inflation rates but exclude one important expenditure category at a time. The results of this exercise are shown in Figure 8. As one can notice, most expenditure categories like *Housing*, *Health expenditure*, and *Transportation*[15] have only a marginal

[15] *Housing* is defined as the sum of *Rented dwellings*, *Owned dwellings*, and *Other lodging*. *Transportation* is equal to the sum of *Public transportation* and *Other vehicle expenses*.

effect on our main results despite accounting for a significant share of the household consumption bundles.[16]

The middle left plot reports the inflation dispersion response when we exclude the categories *Energy*, *Water*, and *Gasoline*. Not surprisingly given the results shown in Figure 6, the omission of these three highly volatile categories leads to a near-complete attenuation of the observed inflation dispersion response. The significance of the *Gasoline* category in influencing the level and evolution over time of inflation inequality has been documented by Hobijn and Lagakos (2005), Cravino, Lan, and Levchenko (2020), and Orchard (2022). Building upon this prior work, we contribute by demonstrating the substantial role that this particular category plays also in transmitting monetary shocks to individual inflation rates.

To summarize, there is large heterogeneity in the contribution that each sector has to inflation dispersion. Many categories, even though being characterized by large expenditure share, have only a negligible impact. Most of the observed effects are due to the categories *Energy*, *Water*, and *Gasoline*. These categories also mainly explain the documented decrease in inflation inequality, as low- and middle-income households spend a significantly higher share of their income on them compared with high-income households, as shown in Table A.2 in Appendix A.

Conventional wisdom in monetary economics often advocates that central banks should look through fluctuations in energy and food prices. The reason is that inflation rates in these sectors are highly volatile, and price changes tend to be temporary and mostly driven by sector-specific shocks. In a seminal paper, Aoki (2001) investigates optimal monetary policy in a representative agent model with two sectors—one with perfectly flexible prices and the other with sticky prices. He shows that optimal policy involves stabilizing the price index of the sticky-price sector, i.e., the "core" CPI, thereby simultaneously stabilizing the aggregate output gap. This result is extended to a model with sticky prices in both sectors by Benigno (2004). In this framework, output gap stabilization is no longer optimal, but it remains close to optimal. Benigno (2004) also studies the optimal inflation index and shows that the central bank

[16] We report the average expenditure weights across different deciles for income, salary, and expenditures in Table A.2 in Appendix A.

should give a larger weight to the sector with stickier prices, again focusing mainly on the "core" categories of CPI.

However, stabilizing prices in the sector with stickier prices is no longer the optimal policy once heterogeneity in consumption baskets is introduced. This is shown by Lan, Li, and Li (2024), who develop a multisector, two-agent New Keynesian model with heterogeneous consumption baskets to study how optimal monetary policy differs in this framework. In the model, households' price indices have different exposures to sectoral shocks, leading to cyclical inequality in their cost of living, even under flexible prices. The difference in price indices and real wages across households distorts their labor supply and consumption decisions, giving rise to misallocation (or inequality). Therefore, optimal policy requires striking a balance between stabilizing inequality and stabilizing aggregate demand and inflation. As a result, the pursuit of "core" inflation stabilization, as suggested in Aoki (2001) and Benigno (2004), becomes suboptimal.

It becomes optimal for the central bank to tolerate some fluctuations in the aggregate output gap to reduce the inflation volatility faced by households, thereby reducing fluctuations in the cost-of-living inequality. This can be achieved by stabilizing the prices of goods produced in the sector with more flexible prices. Therefore, the central bank benefits from adopting a more aggressive stance in stabilizing inflation in the stickier-price sector.

The policy implications that we can draw from our empirical evidence support the findings of Lan, Li, and Li (2024). *Energy*, *Water*, and *Gasoline* are found to be the main drivers behind the changes in inflation heterogeneity. Therefore, monetary authorities should not only focus on stabilizing the "core" components of the CPI, but should also pay close attention to variations in the inflation rates of more flexibly priced sectors and possibly respond to them in order to minimize fluctuations in cost-of-living inequality.

6. Real Expenditure Inequality

Does the identified inflation inequality have any effect on the estimated impact of monetary shocks on real expenditure inequality? To answer this question, we follow Coibion et al. (2017) as closely as possible and compute a broad measure of household expenditure

which includes nondurables, durables, and services.[17] Few expenses are excluded since the relative subcategory price index is not easily identifiable, e.g., occupational expenses, mortgage, and property taxes.

To evaluate the role played by inflation inequality, we create two different series for real expenditure. In line with the literature, one is created by deflating each category by the aggregate CPI-U. The other one is obtained by deflating each item group by its relative price index. We then aggregate the expenditures at quarterly levels to reduce sampling error and to avoid having unusual purchases bias the analysis. We also winsorize at the bottom and top 1 percent of the distribution. Expenditure inequality across households is computed as the cross-sectional standard deviation of log levels, the Gini coefficient of levels, and the difference between the 90th percentile and the 10th percentile of log levels. Finally, all series are seasonally adjusted.

Inequality is defined as $Ineq_t^{IH}$ and $Ineq_t^{NoIH}$ respectively for when inflation heterogeneity is taken into account by deflating each category by the relative price index and for when it is neglected. As an example, the standard deviations at time t across households i are equal to $Std(logC_{i,t}^{IH})$ and $Std(logC_{i,t}^{NoIH})$ with

$$C_{i,t}^{IH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_{j,t}}, \qquad C_{i,t}^{NoIH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_t}, \tag{3}$$

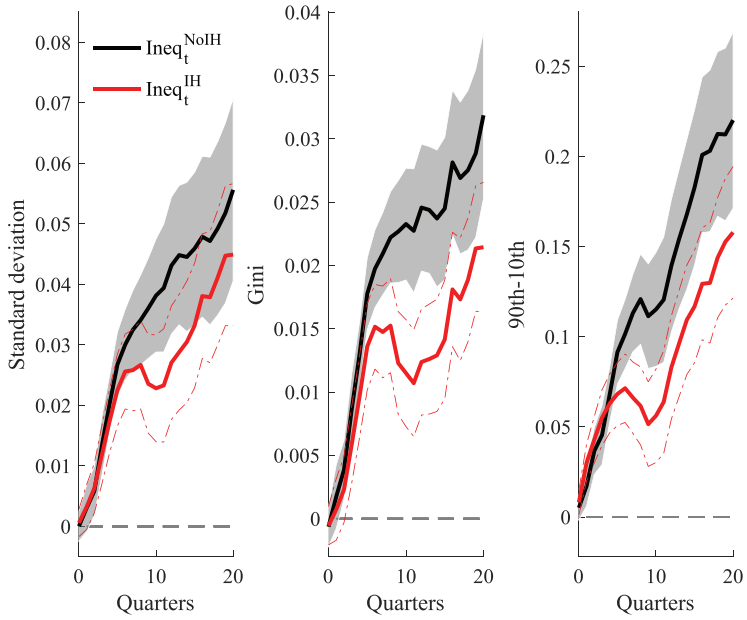
where $C_{i,j,t}$ is the nominal consumption of household i relative to category j at time t, $P_{j,t}$ is the price index of the category j at time t, and P_t is the aggregate price index.

To make our results as comparable as possible, we use the same econometric procedure adopted by Coibion et al. (2017), i.e., local projection with Romer and Romer (2004) shocks at a quarterly frequency, over the same time period, 1980:Q1–2008:Q4.[18] Since the

[17] In particular, the categories considered are *Food at Home, Food Away, Alcohol at Home, Alcohol Away, Apparel, Gasoline, Personal Care (services and durables), Reading, Tobacco, Household Furnishings and Operations, Energy, Water, Other Lodging, Public Transportation, House Expenditures (services and durables), Rental Expenditures (services and durables), Rent Paid, Health Insurance, Health Expenditures (services and durables), Education, Vehicles Purchase, Vehicle Expenditures (services and durables)*, and *Miscellaneous.*

[18] Similar results are obtained adopting our empirical analysis.

Figure 9. Impulse Responses of Expenditure Inequality



Note: This figure shows impulse responses to a 1 percentage point contractionary monetary policy shock, as well as one standard deviation confidence intervals for expenditures inequality. The horizontal axis is in quarters and inequality is measured using the cross-sectional standard deviation (left), Gini coefficient (middle), and the log difference between the 90th and 10th percentiles of the cross-sectional distribution (right). The black solid line and the dark gray shaded areas depict the impulse response obtained by deflating the expenditure categories by the aggregate CPI; the red solid line and the dashed red lines refer to the impulse obtained by deflating each category by their respective price index. Impulse responses are computed at the quarterly frequency using data for the period 1980:Q1–2008:Q4.

series is quarterly, we include as controls 20 lags for the shocks and 2 lags for the dependent variable and we compute the impulse responses over 20 quarters.

Figure 9 plots the results. The black solid lines report the impulse responses of the three measures of expenditure inequality obtained by deflating the expenditure categories by the aggregate CPI. The shape and the magnitude of the responses are very close to those obtained by Coibion et al. (2017). After a contractionary monetary policy shock, expenditure inequality persistently and significantly increases.

However, neglecting inflation heterogeneity across consumption baskets leads to an overestimation of the overall effect. As shown by the red solid lines, which report the responses of the expenditure inequality measures obtained by deflating each category by their respective price index, when the expenditure categories are properly deflated, the estimated effect of monetary policy on inequality is approximately 20 percent lower for standard deviation and 30 percent for the Gini coefficient and the 90th–10th percentile difference. It is worth mentioning that the estimated coefficients are still positive and significant, which implies that monetary policy still has redistributive effects on the economy.

This result can be explained by combining the new empirical evidence from the previous sections. Along the income distribution, a contractionary monetary shock has heterogeneous effects on nominal consumption. The nominal consumption of low- and middle-income households decreases more than that of high-income households because they are more sensitive to the monetary policy shock, e.g., they are financially constrained, they are more likely to lose their job in an economic downturn, etc. However, at the same time, the cost of their consumption basket decreases more strongly as well. Hence, the overall effect on expenditure is partially offset in real terms. This results in a more muted, but still positive and significant, increase in real expenditure inequality.

7. Robustness

To strengthen the validity of our findings in the previous sections, we show that our results are robust across a wide range of alternative specifications. First, we evaluate the importance of substitution effects. Second, we assess the sensitivity of our results to different lag specifications. Third, we perform the same analysis starting our sample in 1985:M1 to control for the Volcker disinflation period. More robustness checks can be found in Appendix E.

7.1 Substitution Effects

Throughout the paper, we conduct our analysis under the assumption that changes in prices mainly drive differences in inflation dispersion and that variations in expenditure shares play only a

marginal role. Both the inflation rate at household level as well as at the decile level are computed using expenditure weights aggregated over multiple time periods to control for seasonal effects as well as to avoid unusual purchases by the households biasing our results. The weights for the household-level inflation rate rely on the entire time series of expenditure (maximum 12 months) whereas the weights at the decile level are computed following the BLS, which updates its expenditure weight reference period approximately every 10 years and, since 2002, every 2 years (more details can be found in Appendix B).

Cravino, Lan, and Levchenko (2020) tested whether substitution effects are important for the CEX by using the difference between the Laspeyres and Paasche price index as a proxy for the substitution bias from 1987 to 2004. These authors showed that the difference between the two indices is negligible over time, demonstrating that the substitution bias must be very small.

Furthermore, using the Nielsen data, Jaravel (2019) evaluates whether the observed inflation heterogeneity along the income distribution stems from the fact that high-income households purchase different goods or whether they pay more for the same goods, for instance, because they buy from different shops. The inflation difference is then decomposed into a *between* and a *within* component. The former corresponds to the inflation difference that we would observe if households differ only in terms of the expenditure shares across categories and if they experience the same within-category inflation. Vice versa, the latter refers to the difference that would arise in case of households experience the same within-category inflation but have different expenditure shares. The between component accounts for more than 70 percent of the inflation difference.

Given the importance for our results of the assumption that inflation dispersion is mainly driven by changes in prices rather than in expenditure shares, we also test whether substitution effects are a potential source of bias. We do this through two robustness checks: First, we assess if the granularity of the expenditure categories we choose plays any role. Second, we compute our measures of inflation inequality across deciles by using annual, quarterly, and monthly expenditure shares instead of using multiple years of consumption data like the BLS.

Following the literature, in computing the individual inflation rates we adopt a rather conservative aggregation in the number of categories considered. Not only do we have data for *Food and beverage*, the most aggregate item category, but we also have data for the subcategory *Eggs*, the most disaggregate. In choosing the baseline aggregation, we face a trade-off between using as disaggregate data as possible to fully capture inflation dispersion and the quality of the price index. Many price series started significantly after 1980, especially the most disaggregated goods and services indices.

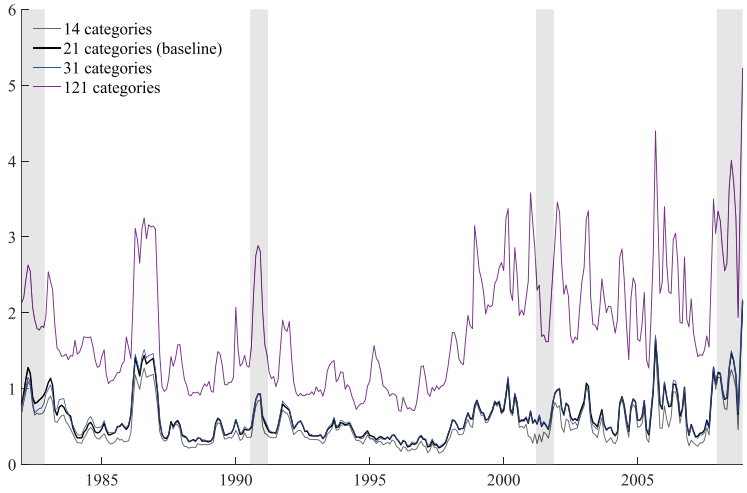
We show that the main results are unaffected by increasing or decreasing the number of categories considered. We compute the household-level inflation dispersion using 14, 31, and 121 expenditure categories.[19] The evolution over time of the dispersion measures is reported in Figure 10.

The number of categories considered significantly affects the overall level of inflation dispersion. Relative to the baseline inflation dispersion with 21 categories, the magnitude is slightly smaller with 14 categories and is slightly larger with 31. With 121 categories, the cross-sectional standard deviation is almost twice as high compared with the baseline. However, the measures of inequality are extremely positively correlated. The correlation with the baseline specification is 0.97, 0.98, and 0.86 for the measures with 14, 31, and 121 categories respectively.

In Figure 11 we compare the response from our baseline specification with 21 categories (blue line) against the three alternative aggregations. When using price indices at a slightly more granular level (middle panel, 31 categories) or an even more conservative number of categories (top panel, 14 categories), the magnitude and

[19]For this last specification some of the price indices were introduced after 1980, so it is an unbalanced panel. The 14 categories are *Food, Alcohol, Housing, Apparel, Gasoline, Other vehicle expenses, Public transportation, Medical, Entertainment, Personal care, Reading, Education, Tobacco,* and *Other expenses.* The 31 categories are *Food at home, Food away from home, Alcohol, Rental expenditures (durables), Rental expenditures (services), Rent paid, Rent equivalent, House expenditures (durables), House expenditures (services), Other house related expenses, Other lodging, Energy, Water, Phone, Household furnishings and operations, Jewelry, Clothing (durables), Clothing (services), Gasoline, Vehicle expenditure (durables), Vehicle expenditure (services), Public transportation, Medical, Entertainment, Personal care (durables), Personal care (services), Reading, Education, Tobacco,* and *Other expenses.*

Figure 10. Historical Series of Inflation Dispersion Measures

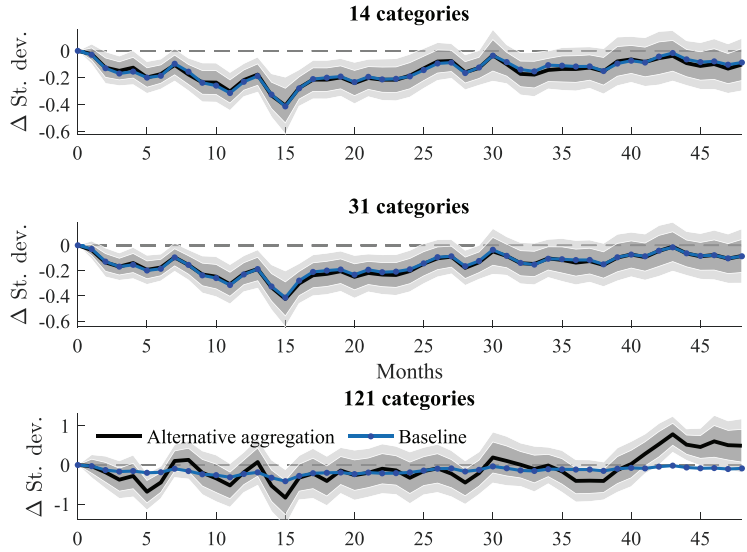


Note: The plot shows the evolution of inflation dispersion measured using the cross-sectional standard deviation computed using 14, 21, 31, and 121 expenditure categories. All the series refer to the period 1981:M1–2009:M12. The gray shaded areas depict U.S. recessions.

the shape of the responses are basically the same as that obtained in our baseline specification. Considering 121 categories, the response is still significantly and persistently negative following a contractionary shock. The magnitude of the response is almost twice as much as that of the baseline response but, since the size of the inflation dispersion measure has doubled as well, in percentage terms the results are similar. This suggests that the number of categories considered in computing individual inflation rates is important for measuring the *level* of inflation inequality but not its *sensitivity* to monetary policy shocks.

As a second test for the role of substitution effects, we compute the expenditure weights for the decile-level inflation rates at annual, quarterly, and monthly frequencies. It is important to notice that by allowing the weights to vary at a much higher frequency than the biannual frequency adopted by the BLS in the last decades, not only will our dispersion measures capture potential adjustments in

Figure 11. Impulse Responses of the Cross-Sectional Standard Deviation of Inflation (alternative aggregations)



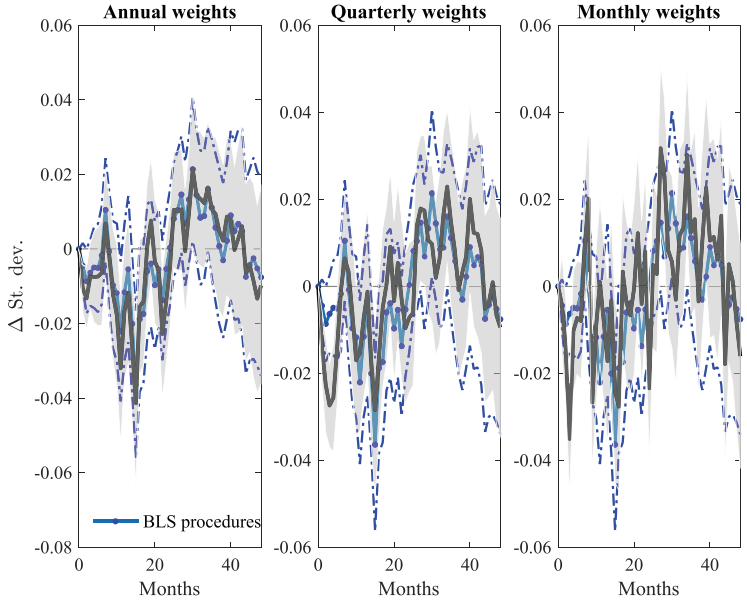
Note: This figure shows impulse responses of alternatively aggregated inflation rates to a 1 percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The solid blue line refers to the baseline impulse response obtained using the baseline categories. Impulse responses are computed at a monthly frequency using data relative to the period 1980:M1–2008:M12.

the consumption bundles due to the shocks, but measurement errors and unusual purchases will also account for a larger share.

We report in Figure 12 the response of the cross-sectional standard deviation of the median inflation rates across income deciles as well as the one standard deviation confidence interval (black line and gray area). For comparison, the blue lines refer to the impulse response of the cross-sectional standard deviation as well as the relative confidence interval computed following the BLS methodology as shown in Figure 4.

Not surprisingly, moving from annual to quarterly and especially to monthly weights makes the responses more volatile. The responses with time-varying weights are still negative and significant: inflation inequality across expenditure deciles remarkably decreases after a

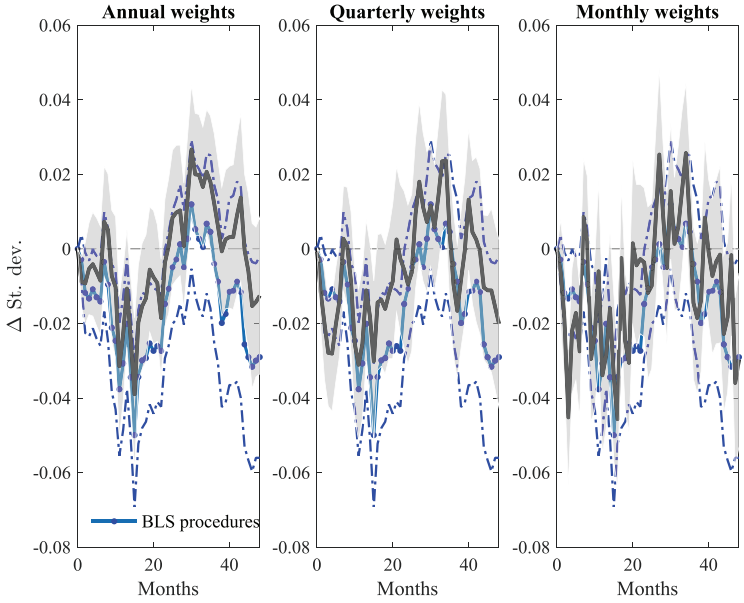
Figure 12. Impulse Responses of Inflation Inequality across Income Deciles with Time-Varying Weights



Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across income deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights; the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for nondurable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

monetary shock. The magnitude is even more negative relative to the baseline. This might suggest that substitution effects move in the same direction as our inflation heterogeneity channel: following a contractionary shock, inflation rates of the expenditure categories purchased by low- and middle-income households decrease more strongly than the other categories so their overall inflation

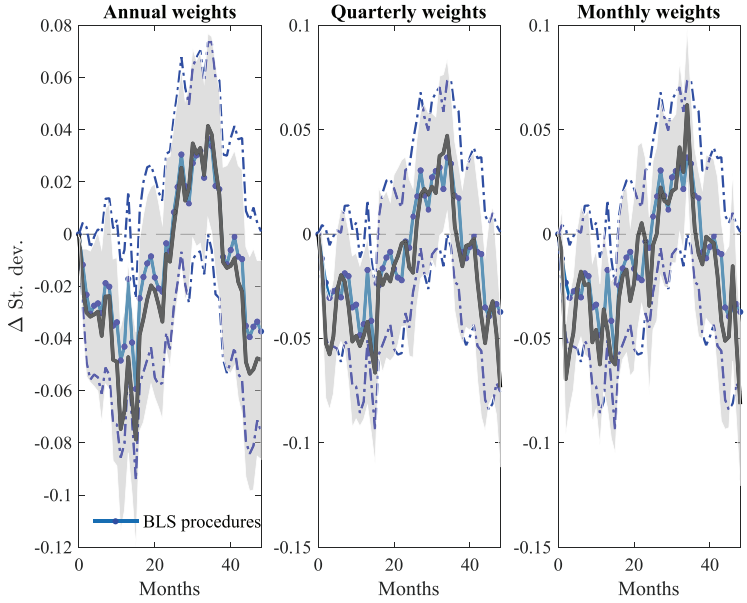
Figure 13. Impulse Responses of Inflation Inequality across Salary Deciles with Time-Varying Weights



Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across salary deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights; the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for nondurable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

rates react more. Moreover, the same households might even increase their consumption of these categories, since they are now relatively cheaper, leading to second-order effects. Similar evidence is found for the dispersions in median inflation across the salary and expenditure deciles whose responses are reported in Figure 13 and Figure 14 respectively.

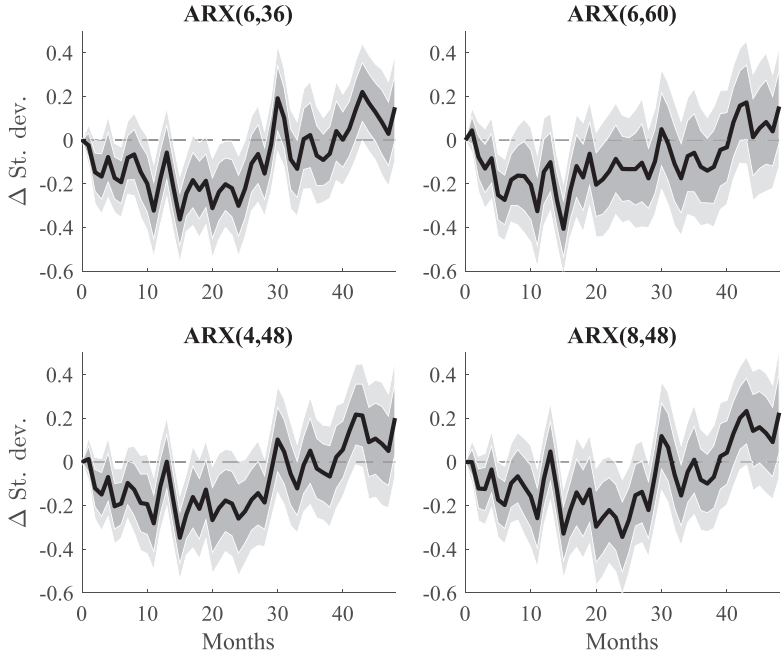
Figure 14. Impulse Responses of Inflation Inequality across Expenditure Deciles with Time-Varying Weights



Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across expenditure deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights; the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for nondurable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

Since we cannot further disentangle substitution effects from measurement errors in the survey or unrepresentative purchases made by households, we prefer to interpret these results with caution. Overall these findings confirm that substitution effects do not cancel out the impact of contractionary shocks on inflation dispersion and that heterogeneity in prices across, rather than within, expenditure categories is the main driver of our results.

Figure 15. Impulse Responses of Inflation Dispersion for Different Lag Specifications

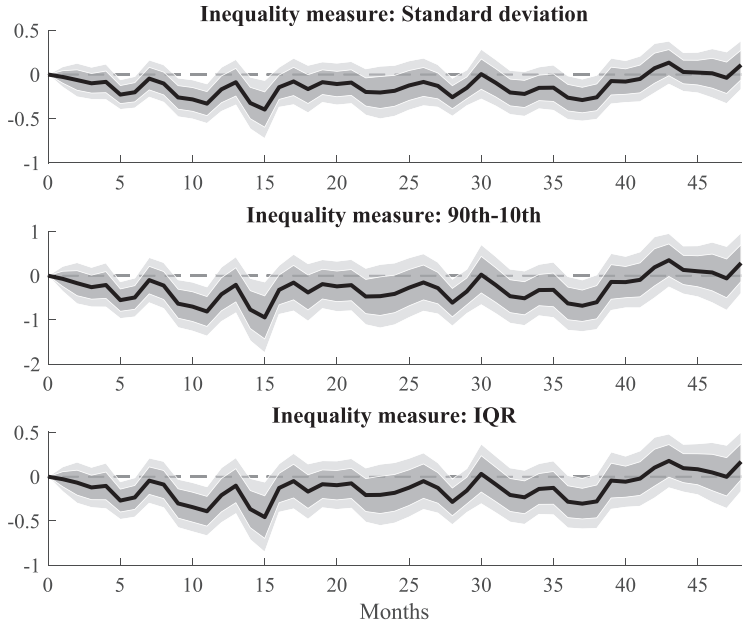


Note: This figure shows impulse responses to a 1 percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals of the cross-sectional standard deviation. The horizontal axis is in months. In an $ARX(p,r)$-model, we control for p lags of the dependent variable, and for r lags of the shock variable. Impulse responses are computed at a monthly frequency using data relative to the period 1980:M1–2008:M12.

7.2 Different Lag Specification

We reestimate Equation (2) with an alternative lag specification. In Figure 15 we run the LP regression including 36 and 60 lags for the monetary policy shocks as well as 4 and 8 lags for the cross-sectional standard deviation of the individual inflation. Similar results are also obtained for the other measures of dispersion. Increasing or reducing the number of lags has little to no effect on the impulse responses: after a contractionary monetary policy shock, inflation dispersion significantly decreases.

Figure 16. Impulse Responses of Inflation Dispersion (without Volcker period)



Note: This figure shows impulse responses to a 1 percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data relative to the period 1985:M1–2008:M12 in order to exclude the Volcker disinflation period.

7.3 Volcker Disinflation

Coibion (2012) shows how few episodes in the early 1980s can be the main drivers of the impulse responses computed using LP with R&R shocks. Since then, it has been common practice for researchers to test their results excluding the period between 1979 and 1982 in which the Federal Reserve abandoned targeting the federal funds rate. Figure 16 reports the impulse response functions obtained using the baseline specification but starting the sample in 1985:M1. In this case, the results are also robust.

8. Conclusion

Central bankers and policymakers are more and more strongly advocating the importance of the conduct of a more inclusive monetary policy where the potential negative spillovers deriving from the monetary authorities' decisions are taken into account. Similarly, macroeconomic research has shifted its focus from the aggregate effects of monetary shocks toward the different channels through which households and firms might be heterogeneously affected by it. Our results suggest that the inflation heterogeneity that arises from the different consumption baskets the agents purchase is of pivotal importance for understanding the distributional consequences of monetary policy.

This paper studies how monetary policy shocks affect the distribution of household-level inflation rates. We rely on individual expenditure data from the CEX and combine it with category-level inflation rates from the BLS to obtain household-level inflation rates. We compute different moments of the individual inflation rates distribution and we evaluate how monetary policy shocks influence the median and the cross-sectional standard deviation of the distribution. Inflation dispersion across households significantly and persistently decreases in response to a contractionary monetary policy shock.

We also evaluate how the inflation rate of different demographic groups is heterogeneously affected by monetary policy. We find that the inflation rates of low- and middle-income households are significantly more reactive to monetary shocks than those of high-income households. Since at the same time, they experience a higher median inflation rate, contractionary shocks lead to an overall convergence of inflation inequality across income groups. The same is true for expenditure and salary deciles. *Energy*, *Water*, and *Gasoline* are found to explain almost entirely the observed effects despite accounting for a relatively small expenditure share.

Finally, we demonstrate that assuming that households are exposed to the same inflation rate results in an overestimation of the impact of monetary shocks on expenditure inequality. Following a contractionary shock, low-income households experience a stronger decrease in nominal consumption relative to high-income households. However, the price of their consumption bundles decreases relatively more as well, partially offsetting the effect in real terms. Accounting for inflation heterogeneity reduces the estimated

response of expenditure inequality to monetary shocks by around 20–30 percent depending on the measure of inequality considered.

In conclusion, our research provides substantial evidence that designing optimal monetary policies as well as studying their distributional effects cannot abstract from also considering the different inflation rates to which agents are exposed. Indeed, the economic agents experience significantly different inflation rates in the long run as well as in response to shocks. Inflation heterogeneity in the economy is sizable and related to demographic characteristics. Therefore, focusing only on aggregate inflation or measures of inflation that exclude important components might lead to the implementation of systematically suboptimal policies for specific demographic groups. Finally, taking into account inflation heterogeneity is particularly relevant when it comes to assessing the impact of monetary policy on other forms of inequalities.

Appendix A. Data Sources

This appendix documents in greater detail the data sources used and the properties of the underlying data.

A.1 Price Indices

Since individual inflation rates are a weighted average of sectoral price indices, Table A.1 displays the CPI subindices used, as well as their respective statistical properties.

A.2 Consumer Expenditure Survey Data

This section provides further details about the construction of the data set we use in the empirical analysis. We download the raw data for the period 1980–2005 from the ASCII files available from the Inter-university Consortium for Political and Social Research (ICPSR), whereas from the year 2006 onward we use the data provided by the BLS. For each quarter, the interview survey is structured as follows: the expenditure data are recovered from the disaggregated MTAB files, income data are derived from the FMLY files, and additional information regarding the households can be found in the MEMB files.

Table A.1. Item-Level CPI Statistics

CPI Series (Item Code)	Mean	Std. Dev.	Min.	Max.
Food at Home (SAF11)	3.223	2.176	–2.904	10.524
Food Away from Home (SEFV)	3.598	1.751	1.422	10.675
Alcoholic Beverages (SAF116)	3.388	1.936	0.66	10.961
Rented Dwellings (SEHA)	4.028	1.706	0.694	8.938
Owned Dwellings (SEHC)	3.533	1.067	0.724	6.437
Other Lodging (SE2102-SEHB)	4.876	4.358	–9.313	19.395
Energy (SAH21)	3.744	6.739	–15.168	23.662
Water (SEHG01)	5.442	2.295	0.579	14.217
Phone (SAE2)	–0.812	1.733	–4.611	2.516
Household F&O (SAH3)	1.587	2.051	–2.295	8.545
Apparel (SAA)	1.154	2.46	–4.069	7.378
Gasoline (SETB)	3.531	17.378	–54.864	52.006
Other Vehicle Exp. (SETC-SETD-SETE-SETF)	4.397	2.235	0.208	11.936
Public Transportation (SETG)	4.867	6.313	–12.946	27.742
Medical Care (SAM)	5.723	2.347	2.447	11.778
Entertainment (SAR)	2.921	2.048	–0.407	9.391
Personal Care (SAG1)	3.335	1.798	1.028	8.904
Reading (SERG)	3.82	2.682	–0.196	11.825
Education (SAE)	6.929	2.033	4.3	13.126
Tobacco (SEGA)	7.962	6.42	–8.483	33.332
Other Expenses (SEGD)	5.588	2.397	0.972	11.893
CPI-U (SA0)	3.615	2.481	–2.119	13.764

Note: This table displays descriptive statistics about each item-level inflation rate, as measured by year-on-year changes of the respective index. The source of this data is the U.S. Bureau of Labor Statistics.

In line with the literature, we aggregate expenditures reported for the same month across different interviews. Then, we drop households that report zero expenditure on food as well as those that report negative expenditure for categories that cannot be negative according to the data codebook, such as expenditure for elderly care. Respondents younger than 25 years and older than 75 are excluded. To correct for sample breaks caused by slight changes in the questionnaire (food at home (1982:Q1–1988:Q1), food away from home (2007:Q2), and personal care services (2001:Q2)) we regress each expenditure series on a time trend and indicators for the corresponding sample breaks and then subtract the effect of the dummies from the original series. For all these transformations, we rely heavily on Coibion et al. (2017).

Finally, the CEX data started to include the imputed income in 2004. To impute income data before that year, we follow the approach adopted by Fisher, Johnson, and Smeeding (2013) and Coibion et al. (2017): for households recording a bracketed range, we use the median point of the bracket. Furthermore, we estimate the remaining income observations by regressing income on a set of observable characteristics such as age, age squared, the reference person's gender, race, education, number of weeks worked full or part time in the last 12 months, unadjusted family size, the number of children under 18, the number of people over 64, the number of earners at the annual level and with sampling weights as well as using fixed effects for the income reporting date. To account for the sampling uncertainty, we add residuals drawn randomly with replacement from the sampling distribution to the predicted values. We then trim values above the top coding threshold at the top coding value.

We then calculate expenditure shares from the cleaned expenditure data, which constitute the weights used to calculate individual inflation rates. We find substantial variation in the weights that can be explained to a large part by either income, salary, or expenditure deciles. Table A.2 shows the weights for the 1st, 5th, and 10th deciles.

A.3 Matching of Expenditure and Inflation Data

We match the expenditure categories with the respective price indices. Following Hobijn and Lagakos (2005), for the category *Other vehicle expenses*, which does not have a perfect match with the

Table A.2. Expenditure Weights for the 1st, 5th, and 10th Decile of Income, Salary, and Expenditure

	Income Deciles			Salary Deciles			Expenditure Deciles		
	1st	**5th**	**10th**	**1st**	**5th**	**10th**	**1st**	**5th**	**10th**
Food at Home	14.5	13.0	9.8	13.7	12.8	9.9	22.6	14.7	7.8
Food Away	8.1	8.2	7.7	8.8	8.3	7.7	9.3	8.5	7.2
Alcohol	1.0	1.1	1.2	1.1	1.1	1.2	1.0	1.1	1.0
Rented Dwellings	9.4	8.4	1.9	8.5	8.6	2.0	21.0	7.9	1.4
Owned Dwellings	18.8	17.4	21.4	15.5	16.2	21.5	7.4	19.8	17.7
Other Lodging	0.8	0.6	1.5	1.0	0.6	1.5	0.1	0.1	1.2
Energy	5.3	5.0	3.8	4.9	4.7	3.8	6.8	5.8	2.9
Water	0.8	0.8	0.7	0.8	0.8	0.7	0.9	1.0	0.6
Phone	2.7	2.7	2.0	2.7	2.7	2.0	4.0	3.0	1.5
Household F&O	4.3	4.5	5.1	7.8	4.7	7.0	1.2	3.0	10.6
Apparel	4.1	4.3	5.9	4.6	4.8	6.1	2.6	3.6	6.4
Gasoline	4.1	5.0	4.0	4.7	5.3	4.1	4.8	5.7	3.2
Other Vehicle Expenses	7.9	10.6	11.7	9.5	11.6	12.0	5.6	11.1	10.8
Public Transportation	1.1	1.0	1.8	1.2	1.0	1.8	0.7	0.4	2.8
Medical	5.8	6.6	4.7	5.7	5.2	4.3	4.3	5.6	5.8
Entertainment	4.2	4.8	6.9	4.8	5.3	6.9	2.6	3.9	8.9
Personal Care	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0	0.7
Reading	0.4	0.5	0.6	0.5	0.5	0.6	0.4	0.5	0.4
Education	2.5	1.0	2.7	3.2	1.3	2.8	0.2	0.4	4.3
Tobacco	1.0	1.2	0.5	1.2	1.2	0.5	2.3	1.3	0.4
Other Expenses	1.1	1.2	1.2	1.1	1.1	1.0	0.3	0.6	2.3

Note: This table displays the 1st, 5th, and 10th deciles for the weight of income, salary, and expenditure shares. While our methodology uses these shares at a monthly frequency, this table displays the average over the period 1980–2008.

Table A.3. Matching between CEX Expenditure Category and CPI

BLS Expenditure Category	CPI Series (Item Code)
Food at Home	SAF11
Food Away from Home	SEFV
Alcohol	SAF116
Owned Dwellings	SEHC
Rented Dwellings	SEHA
Other Lodging	MUUR0000SE2102-SEHB
Energy	SAH21
Water	SEHG01
Phone	SAE2
Household Furnishings and Operations	SAH3
Apparel	SAA
Gasoline	SETB
Other Vehicle Expenses	SETC-SETD-SETE-SETF
Public Transportation	SETG
Medical	SAM
Entertainment	SAR
Personal Care	SAG1
Reading	SERG
Education	SAE
Tobacco	SEGA
Other Expenses	SEGD

Note: This table displays the expenditure category from the CEX, as well as the respective category code in the CPI index series.

available CPI subcategories, we create the CPI index by combining the series that match this category (that is, SETC, SETD, SETE, and SETF). As sectoral weights, we use the average over the time period considered of the official weights provided by the BLS, as displayed in the table "Relative Importance in the CPI." Finally, since *Other lodging* changed the name, we use *Lodging away from home* until 1997 (MUUR0000SE2102) and *Lodging while out of town* (SEHB) until the end of the sample. In all cases, the CPI series we use are the not-seasonally-adjusted *US City Average for all urban consumers* series. Table A.3 displays the categories in the CEX, as well as the categories in the CPI data that were used to match the two data sets.

Appendix B. Decile-Level Expenditure Weights

Before computing the decile-level expenditure weights, some adjustments need to be performed. In line with the literature and the BLS procedure, the expenditure weight for the owners' equivalent rent of primary residence is based on the following CEX question: If someone were to rent your home today, how much do you think it would rent for monthly, unfurnished and without utilities? The homeowners' answer to this question is stored in the variable RENTEQVX in the characteristics files.

Moreover, as we mention in the main text, vehicle purchases are likely to bias the estimated expenditure shares. Indeed, they are large in size and not representative of the usual household consumption bundle. Therefore, in line with Johannsen (2014), we drop this category when computing household-level inflation rates. Following Cravino, Lan, and Levchenko (2020), we include expenditures on used cars and trucks when computing the decile-level inflation, but we reduce the spending to half to reflect only the dealer value-added.

Households are also interviewed a different number of times and for at most four consecutive quarters, which corresponds to 12 months' worth of spending information. However, this does not necessarily match the calendar year. To control for this, we compute the decile-based inflation rate closely following the BLS procedure as in Cravino, Lan, and Levchenko (2020). First, we sort households into deciles based on their annual income, salary, median, and mean expenditure. We then compute the average expenditure for each item category at every decile in the calendar year. For instance, a respondent interviewed in February will report personal consumption for January, but also for November and December of the previous year. Similar to what the BLS does for the computation of the official CPI, to account for the relative contribution of each household to the decile-mean value of a calendar year, we weight the consumption by the number of months a household reports expenditures during a calendar year (the BLS calls this variable MO_SCOPE).

We can then use the formula below to compute the average expenditure for each category j at each decile d. First, for household i at decile d, we aggregate over all the expenditures on good j during the calendar year. Second, the household total expenditure is weighted by the sampling weights, fwt, provided by BLS to make

the survey sample representative of the U.S. population. Then, the weighted household expenditure is summed up at the decile level. Finally, to obtain the monthly average income spent on good j by decile d, we divide the annual weighted household expenditure for category j by the weighted number of months household at decile d reported expenditure during the calendar year. To annualize the average category expenditure at the decile level, it is sufficient to multiply the monthly average expenditure by 12:

$$X_j^d = \frac{\sum_i fwt_i^d \sum_t c_{i,j,t}^d}{\sum_i fwt_i^d \; MO_SCOPE_i^d} \times 12, \tag{B.1}$$

where fwt_i^d is the frequency weight for household i at decile d, $c_{i,j,t}^d$ refers to the annual consumption on category j by household i at decile d, and $MO_SCOPE_i^d$ identify the number of months per year household i reported its expenditure. The decile-level expenditure weight for category d can then be computed as

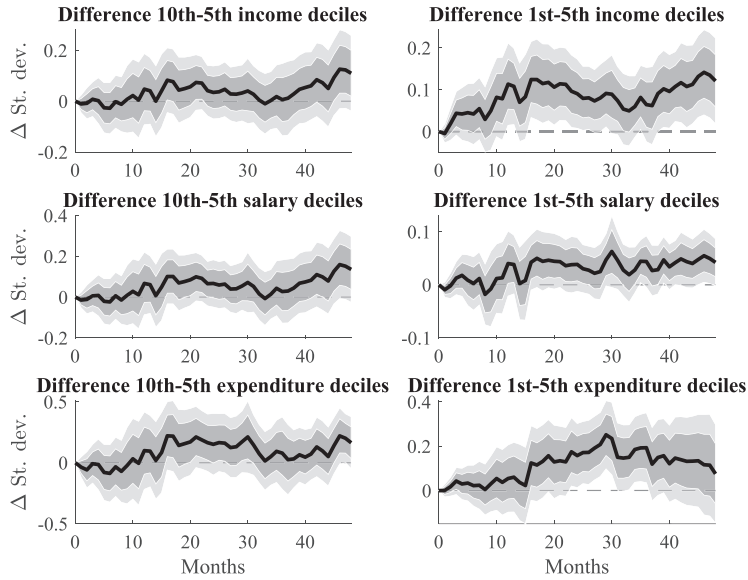
$$w_j^d = \frac{X_j^d}{\sum_j X_j^d}. \tag{B.2}$$

Appendix C. Differences in Responses across Deciles

We evaluate whether the responses of the decile-level median inflation rates to a monetary policy shock are statistically different from each other. To do so, we estimate Equation (2) using as dependent variable the difference between the inflation rate of the 10th and 1st decile of each group and the inflation rate of the 5th decile. The first column of Figure C.1 reports the responses of the difference in median inflation rate for the 10th and the 5th decile and the second column for the 1st and the 5th decile. The first row shows the responses for the differences across expenditure deciles, the second row for salary deciles, and the last row for income deciles.

As can be noticed in Figure C.1, both the median inflation rates of the 10th as well as of the 1st deciles of income, salary, and expenditures react much less to a monetary policy shock than the 5th deciles, resulting in a positive and significant response of their differences. The U-shaped response across deciles is in line with what was found by Cravino, Lan, and Levchenko (2020), who document that the

Figure C.1. Differences in Impulse Responses across Deciles



Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the difference in decile-spcific inflation rates across deciles of the demographic groups. The first column reports the responses of the difference in inflation rate for the 10th and the 5th decile, and the second column for the 1st and the 5th decile. The first row shows the responses for the difference across expenditure deciles, the second row for salary deciles, and the last row for income deciles. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

price volatility along the income distribution is hump-shaped, with the households at the top of the distribution experiencing the lowest volatility (resulting in the flattest impulse response) and middle-income households being exposed to slightly more price volatility than lower-income households.

Appendix D. Pure Inflation and Relative Goods' Prices

The present work exploits differences in sectoral inflation rates. These inflation rates are taken as given, without further analysis

of the drivers behind this data. To shed more light on the drivers behind these inflation rates, we rely on the work of Reis and Watson (2010). They use a dynamic factor model in order to derive underlying factors in the data set of sectoral inflation rates. A dynamic factor model is well suited to derive the common components in this set of correlated but distinct time series.

Applying the factor model of Reis and Watson (2010), we derive three drivers of inflation derived from sector prices.[20] First, there is a pure inflation factor ν_t, that affects all sectoral inflation rates equally. Second, they find a factor that influences relative prices, called ρ_t. This factor captures fundamental shocks that affect some price setters but not others. Third, idiosyncratic inflation stems from sectoral price changes that are uncorrelated with other sectors.

This decomposition allows us to distinguish between different underlying drivers of sectoral inflation rates. In the second step, we want to measure the importance of the three underlying factors to sectoral inflation rates. To do so, we regress sectoral inflation rates on the three factors individually and measure the importance of each factor by its respective R^2, as is displayed in the three left columns of Table D.1. Additionally, we also calculate the contribution to the R^2 of the three factors. In the three right columns, we report the difference in R^2 in a regression on all three factors, when the respective factor is removed.

As Table D.1 shows, the sectors *Food home* and *Food away* are strongly correlated with the relative price factor, while *Energy* and *Gasoline* are strongly correlated with both ρ and u. The other sectors, which are usually considered to be part of core inflation, are clearly dominated by the pure inflation factor and contribute less to changes in inflation dispersion. By construction, the pure inflation factor ν should have no or very little effect on inflation dispersion.[21]

[20]The original article by Reis and Watson (2010) is based on quarter-on-quarter inflation rates using data from the personal consumption expenditures (PCE) price index. To make this exercise comparable to the results in this paper, we use quarter-on-quarter inflation rates from (four-digit) CPI inflation rates. We also adjust the sample period to the analysis in this article, which is from 1960–99 (original paper) to 1980–2008.

[21]Note that the pure inflation factor theoretically affects all sectors' inflation rates equally, and should thus have no effect on inflation dispersion. However,

Table D.1. Regressing Sectoral Inflation Rates on Factor Data

	R^2_v	R^2_ρ	R^2_u	$Contr_v$	$Contr_\rho$	$Contr_u$
Food at Home	15	35	3	18	37	0
Food Away	61	23	5	65	26	0
Energy	12	12	13	21	13	7
Gasoline	0	12	24	19	12	19
Rented Dwellings	63	6	1	66	8	0
Owned Dwellings	34	2	7	51	14	5
Water	72	2	1	71	1	0
Medical	80	0	1	81	1	0

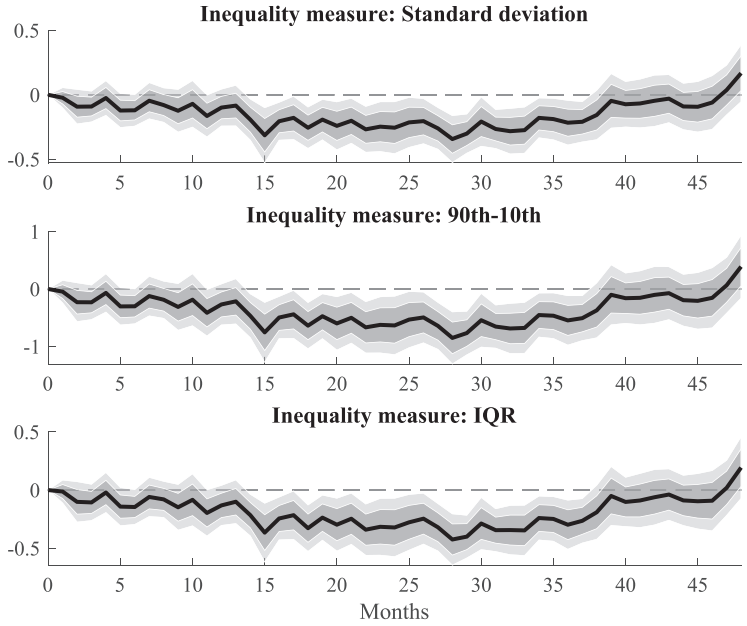
Note: This table reports the explanatory power of the pure inflation factor v, the relative price factor ρ, and the idiosyncratic factor u, as defined by Reis and Watson (2010) on sectoral inflation rates. For brevity, we only report sectors that have a median expenditure share above 5 percent according to Table A.2. The three left columns show the R^2 of a simple regression on the three factors. The three right columns report the difference in R^2 when the respective factor is removed from a regression on all three factors. The results are sorted by the contribution of the relative price factor ρ.

The results in Table D.1 show, however, that the relative price factor and the idiosyncratic factor account for a disproportionate share of the differential changes in sectoral inflation rates on which the results in this article are based.

This result is important, as it connects our findings with potential underlying drivers. Relative price changes, which are a dominant driver of aggregate inflation as shown by Reis and Watson (2010), are also driving our results. The expenditure categories *energy* and *gasoline*, which account for a higher share of the consumption bundle of low- and middle-income households, are also mainly driven by relative price changes and idiosyncratic shocks.

there are differences between the dynamic factor model and our approach both in terms of methodology and data. Also, the present paper captures the dynamics related to exogenous monetary policy shocks, while the dynamic factor model captures the overall dynamics in the data set.

Figure E.1. Impulse Responses of Inflation Dispersion (without recession periods)



Note: This figure shows impulse responses to a 1 percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data relative to the period 1980:M1–2008:M12.

Appendix E. Further Robustness Checks

As a further robustness check, Figure E.1 reports the impulse responses excluding all U.S. recession periods from the analysis (1981:M07–1982:M11, 1990:M07–1991:M03, 2001:M03–2001:M11). The results remain qualitatively unchanged relative to the baseline specification.

As a second set of checks, we assess whether our results are specific to the shock series we chose, i.e., Romer and Romer (2004). The first alternative measure of monetary shocks we use is the

high-frequency proxy proposed in Bauer and Swanson (2022). The proxy is computed from changes in future prices in a narrow window around Federal Open Market Committee announcements and orthogonalized with respect to the public information about the economic and inflation outlook. The shock series is available from 1988:M2 to 2019:M12.

The second alternative measure of monetary shocks is the series developed by Miranda-Agrippino and Ricco (2021). The authors show that monetary surprises are a combination of a true shock and information about the state of the economy that imperfectly informed agents infer from monetary policy decisions. Therefore, to remove the information content of monetary policy surprises, the surprises are regressed on a set of variables that aim to control for the central bank's superior information about the economy. The residuals are considered to be monetary policy surprises cleaned from any informational effects and are available from 1991:M1 to 2009:M12.

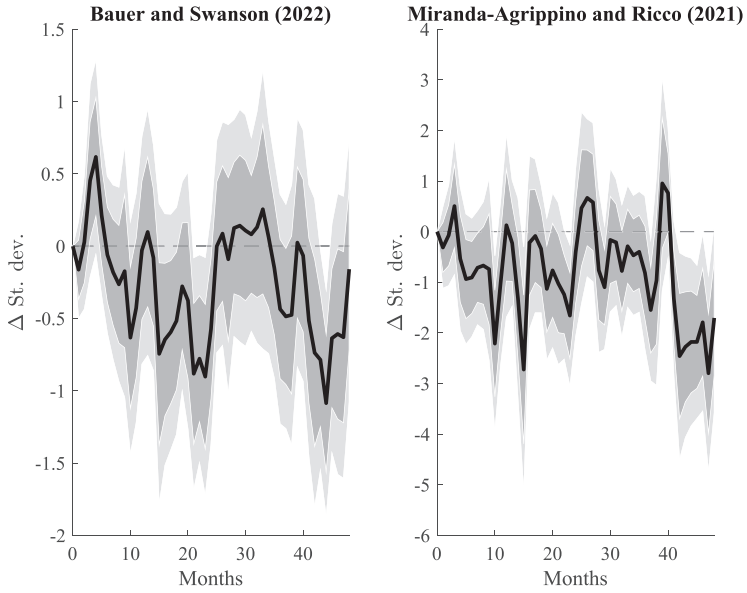
The results are presented in Figure E.2. The figure reports the responses of the cross-sectional standard deviation to the alternative contractionary shocks. All the regressions include the same controls as in the baseline specification. In both cases, inflation dispersion decreases. Overall, the results from alternative monetary policy shocks confirm our main findings and point toward a distributional role played by monetary policy in terms of inflation dispersion.

Moreover, one might be concerned that part of the inflation heterogeneity we measured is driven by differences in consumption patterns across U.S. states rather than along the income distribution. Since the BLS does not provide price indices at the state level, but only at the division level (Northeast, Midwest, South, and West), we compute the cross-sectional standard deviation of inflation for the four divisions using expenditure weights as well as price indices at the division level.[22]

The responses across U.S. divisions are reported in Figure E.3. There are some regional differences in the shape of the responses of

[22] A more limited number of price indices are available at the division level. Therefore, we used the following expenditure categories: *Food at home, Food away from home, Alcohol, Rented dwellings, Owned dwellings, Household furnishings and operations, Utility, Apparel, Private transportation, Public transportation, Gasoline, Medical, Education,* and *Miscellaneous.*

Figure E.2. Impulse Responses of Inflation Dispersion, Bauer and Swanson (2022) and Miranda-Agrippino and Ricco (2021) Monetary Shocks



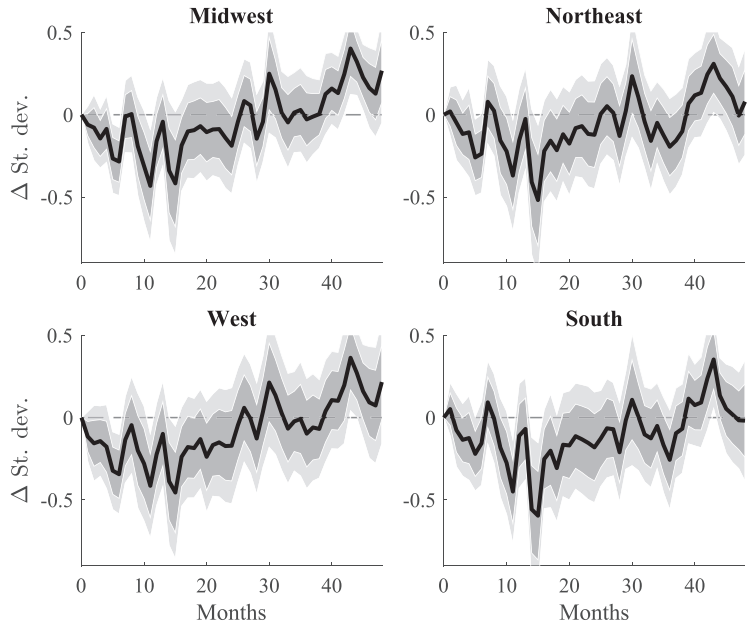
Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as the 1.65 standard deviation confidence intervals. On the left panel we use the monetary shocks computed by Bauer and Swanson (2022). On the right panel we use the monetary shocks computed by Miranda-Agrippino and Ricco (2021). The horizontal axis is in months. Impulse responses are computed at a monthly frequency.

inflation dispersion to contractionary shocks. However, the magnitude and significance of the results are comparable to the baseline specification. The decrease is more muted only for the West division.

In the main analysis, the decile-specific inflation rates are computed following the BLS procedure. The advantage of this approach is that for each decile all the individual expenditure information is combined to form the expenditure weights. In this way, outliers are less likely to bias the analysis. An alternative approach to the BLS methodology would be to simply consider the median of the individual inflation rates within each decile.

In Figure E.4 we report the responses of inflation inequality for income, salary, and expenditures to a contractionary monetary

Figure E.3. Impulse Responses of Inflation Dispersion across U.S. Divisions

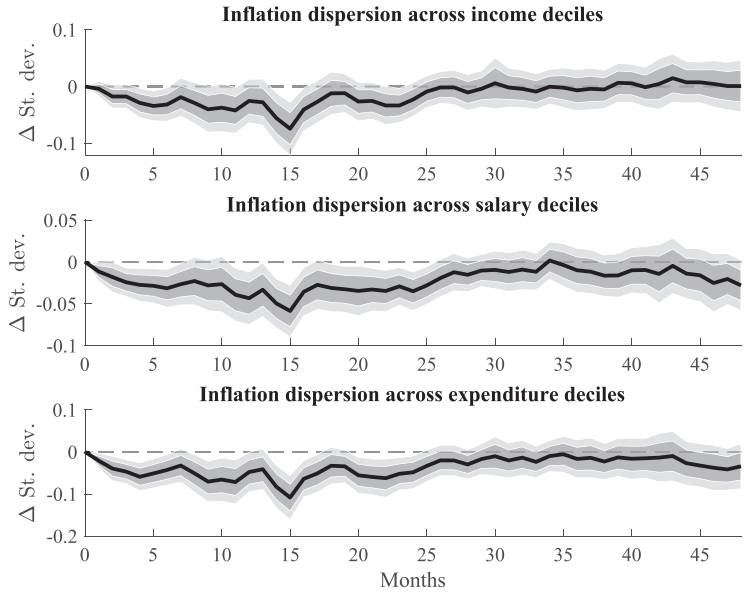


Note: This figure shows impulse responses to a 1 percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the inflation dispersion measured as the cross-sectional standard deviation for the four U.S. regions. Impulse responses are computed at a monthly frequency using data relative to the period 1980:M1–2008:M12.

shock. Inflation inequality is measured as the standard deviation of the median inflation rates across deciles. Following a monetary shock the inflation inequality responses are still negative and statistically significant, confirming the baseline results.

Finally, the baseline measure of inflation dispersion is computed using data from the interview module of the CEX but not the diary module. As the two modules of the CEX interview different households, they cannot be combined to measure inflation at the household level. However, the two modules can be jointly used to compute inflation rates for different demographic characteristics. This exercise was done by Cravino, Lan, and Levchenko (2020), who studied the differential sensitivity of inflation rates to monetary policy shocks along the income distribution.

Figure E.4. Impulse Responses of the Dispersion across the Median Inflation Rates for Income, Salary, and Expenditure Deciles



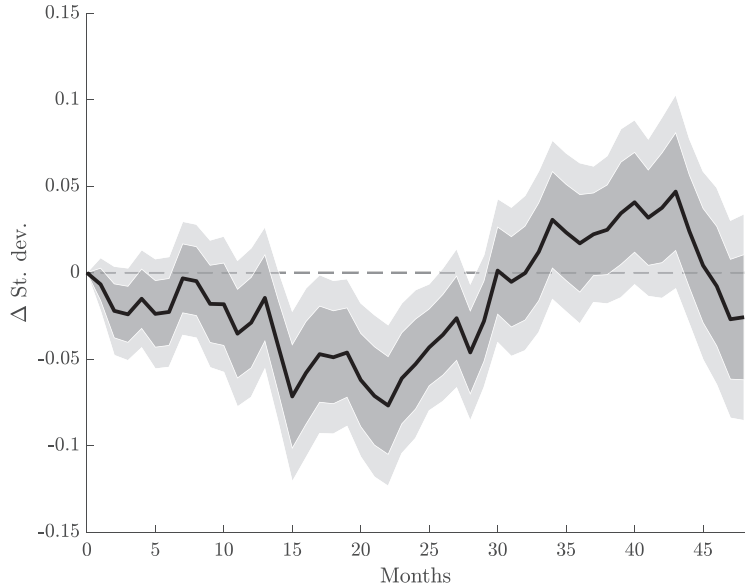
Note: This figure shows impulse responses to a 1 percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for inflation inequality across income (top), salary (middle), and expenditure deciles (bottom). Inflation inequality is measured using the cross-sectional standard deviation of the median inflation rate for each decile. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

Cravino, Lan, and Levchenko (2020) compute income-percentile-specific CPIs by combining both modules of the CEX with micro price data.[23] Using this data, we define an alternative measure of inflation inequality as the cross-sectional standard deviation in inflation rates across the income percentiles.

The response of this new measure of inflation inequality to a monetary shock is reported in Figure E.5. The shape and magnitude of the response are comparable to our baseline response. Therefore,

[23]We contacted the authors, who kindly shared their percentile-specific CPI data with us.

Figure E.5. Impulse Responses of Inflation Inequality Derived from the Income-Percentile-Specific CPI Data from Cravino, Lan, and Levchenko (2020)



Note: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as the 1.65 standard deviation confidence intervals. Inflation inequality is defined as the cross-sectional standard deviation across the income-percentile-specific CPI from Cravino, Lan, and Levchenko (2020). The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980:M1–2008:M12.

the main result of the present article is robust to include information from both the interview and the diary modules of the CEX: inflation inequality decreases following a contractionary monetary policy shock.

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A Financial Stress Index for a Small Open Economy: The Australian Case*

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We construct a financial stress index for a small open economy, Australia, which aims to provide clear and timely signals of financial market strains. Decomposing the Australian Financial Stress Index (AFSI) into foreign and domestic components, we show that foreign factors can explain about two-thirds of our index. Moreover, we find that the AFSI contains relevant and useful macroeconomic information. In particular, we find that the AFSI Granger-causes subsequent credit supply and unemployment growth. When compared with the Asian Development Bank's Australian financial stress index, we find that our measure can better capture stress episodes that affect credit provided by banks and other types of financial intermediaries. Finally, we estimate the effect of a financial stress shock, as measured by an increase in the AFSI, on the macro-observables. A financial stress shock triggers an initial increase in both money supply growth and bank loan growth, followed

*The views expressed in this paper are solely those of the authors and should not be interpreted as reflecting the views of the Board of Governors, its staff, or anyone associated with the Federal Reserve System. Views expressed in this paper are those of the authors and not necessarily those of the Reserve Bank of Australia. All remaining errors are our own. We would like to thank the Editor and the referees for their valuable feedback. We also thank the seminar participants at the Federal Reserve Board, seminar participants of the Empirical Macro reading group and the Economic Theory reading group at the University of Basel, Cynthia Doniger, Ed Lin, Zeynep Senyuz, and Michelle Wright for their comments and suggestions. Samin Abdullah provided excellent research assistance. Author emails: Pedro Gomis-Porqueras: peregomis@gmail.com, Xiaoyang Li: xiaoyang.li@deakin.edu.au, Romina Ruprecht: romina.d.ruprecht@frb.gov, Xuan Zhou: ZhouX@rba.gov.au.

by a notable decline to negative growth, before eventually stabilizing. Yet, in times of heightened levels and volatility of financial stress, the downturns in bank loan growth and retail sales growth are both more profound and prolonged.

JEL Codes: F30, G01, G15.

1. Introduction

Equity and credit markets are a cornerstone of the financial system and are critical for economic growth.[1] Although it was generally recognized that financial frictions could play an important role in economic fluctuations, the 2007–09 Global Financial Crisis (GFC) made it clear that the adverse effects of financial disruptions on economic activity could be far worse than anticipated. In particular, Ollivaud and Turner (2015) find that among 19 OECD countries that experienced a banking crisis over the period 2007–11, the median loss in potential output in 2014 is estimated to be about 5.5 percent, compared with 3.5 percent which is the loss in aggregate potential output across all OECD countries.[2] In order to prevent such losses, it may be useful to have various measures that can spot disruptions in financial markets. To identify such *abnormal* episodes, researchers gather a variety of financial data capturing increased uncertainty that private investors are facing, increased asymmetric information in financial markets, and decreased willingness to hold risky and illiquid assets.

This paper aims to develop a clear and timely measure of financial stress for a small open economy, Australia, that can serve as a warning system for investors and policymakers when monitoring financial markets. The goal of a financial stress index (FSI) is to monitor the current state of financial markets by creating a time series that has the property that increases in the index indicate

[1]We refer the readers to Levine and Zervos (1998) for more on this important nexus between financial markets and economic growth.

[2]Laeven and Valencia (2013) estimate the output loss of banking crises in advanced countries to be 32 percent of deviation from trend GDP (gross domestic product) and the fiscal costs to be 4.7 percent of GDP. Similarly, Cardarelli, Elekdag, and Lall (2009) find that recessions that were preceded by financial crises tend to be more severe. Afonso, Baxa, and Slavík (2018) provide evidence for the adverse impact of financial stress on the economy for several countries.

heightened financial stress. Since in a small open economy no single financial market is independent from the activity in other markets, within and between countries, we consider a variety of financial and macroeconomic measures. In addition, since we are considering a small open economy, we also explicitly consider external factors that directly affect domestic output and prices through trade as well as indirectly through domestic financial markets. Because of the potential for negative spillovers from financial markets to the real economy, accurately measuring financial stress is important to investors and policymakers alike. Thus, understanding the specific channels through which negative disturbances to financial markets can spill over to the rest of the economy can help to provide clear and timely signals of market strains to develop appropriate responses to address these adverse events.

Financial stress in itself is abstract and has no unique definition. In this paper, we follow the notion advocated by Hakkio and Keeton (2009). These authors define financial stress as periods with increased uncertainty about the fundamental value of financial assets, increased asymmetric information between buyers and sellers of financial assets, and a decreased willingness to hold risky or illiquid assets.[3] To construct our Australian Financial Stress Index (AFSI), we collect monthly data. The data selection for the AFSI closely follows the approaches taken in the existing literature, but we also include measures and observables that are important and relevant for small open economies.[4] The data we consider are interest rates on public and private liabilities, exchange rates, international interest rate spreads on public debt, house price growth, and inflation expectations. We aggregate this data by applying the principal component analysis (PCA) methodology to establish a single index (the AFSI) that provides a measure of financial market stress. When using the PCA approach, the underlying assumption is that financial stress moves the various data series jointly.

[3]See Illing and Liu (2006) and Balakrishnan et al. (2011) for alternative definitions and Kliesen and Smith (2010) for an overview.

[4]Kliesen, Owyang, and Vermann (2012) provide an overview of the variables included in some selected FSIs. They furthermore argue that papers constructing financial condition indices (FCIs) tend to include more information on quantities, prices, and economic indicators, whereas papers measuring FSIs tend to focus solely on prices.

Given that we are interested in a small open economy, we decompose the AFSI to determine the extent to which external factors contribute to financial stress in Australia. To do so, we follow the approach taken by Moore (2017). In particular, we regress the AFSI on a financial index for China, which is Australia's main trading partner, and an index for the United States, a global financial center. We find that foreign financial stresses can account for two-thirds of the AFSI. This finding highlights the importance of monitoring the economies and financial markets of Australia's main trading partners.

To evaluate the information content of our financial stress measure, we compare it with several stress indices for both Australia and other countries that are relevant to the domestic economy. In addition, we also consider broader measures of stress for Australia, such as economic policy uncertainty indices. We find that the AFSI is largely in line with the United States and China's financial stress measures. We also show that there are small differences between the AFSI and other indices that capture financial stress and economic uncertainty in Australia.[5] In addition, we explore whether the AFSI can better predict macroeconomic outcomes not included in the index. To do so, we run a series of Granger causality tests on various macroeconomic aggregates. We find that the AFSI Granger-causes various credit measures. We also find that when compared with the Asian Development Bank's Australian financial stress index, our measure can better capture stress episodes that affect the credit issued by different types of financial intermediaries. To summarize, the different analyses carried out in this paper highlight that the AFSI contains relevant macroeconomic information.[6] These findings then suggest that the AFSI might be able to provide clear and timely signals of financial stress in the Australian economy, which may be useful for both policymakers and investors alike.

Finally, we estimate the effect of a financial stress shock to the economy. To do so, we consider a time-varying vector autoregression

[5]These latter indicators rely on different data or capture economy-wide notions of uncertainty.

[6]We refer to Davig and Hakkio (2010), Hatzius et al. (2010), van Roye (2014), and Groen, Nattinger, and Noble (2020) for other examples where the stress index contains useful information.

(VAR) that includes macroeconomic aggregates. Our results show that the effect of an increase in financial stress depends on the level of financial stress. Moreover, a financial stress shock triggers an initial increase in both money supply growth and bank loan growth, followed by a notable decline to negative growth, before eventually stabilizing. Yet, in times of heightened levels and volatility of financial stress, the downturns in bank loan growth and retail sales growth are both more profound and prolonged. We also find that the effects of an increase in financial stress are more pronounced in the short term (one month/one quarter) than over a one-year horizon.

The remainder of this paper is structured as follows. Section 2 provides a literature review, while Section 3 describes the data and the methodology used to construct the AFSI. Section 4 compares the index with several measures of financial stress and uncertainty in Australia and abroad. Section 5 relates the index to various economic outcomes, while Section 6 concludes.

2. Literature Review

This paper connects with two strands of literature. The first one studies the effect of financial stress and financial crises on the economy, while the second quantifies and measures financial stress.

In order to measure financial stress and disruptions, financial stress indices (FSIs) and financial condition indices (FCIs) are constructed using a wide array of financial and macroeconomic variables. While early papers provide measures of financial stress as binary variables, indicating whether the economy is in a crisis or not, other work aims to construct indices that indicate the severity of financial stress. These include Illing and Liu (2006) for Canada; Hakkio and Keeton (2009) (Federal Reserve Bank of Kansas City FSI, or KCFSI), Kliesen and Smith (2010) (Federal Reserve Bank of St. Louis FSI, or STLFSI), Oet et al. (2012) (Federal Reserve Bank of Cleveland FSI, or CFSI), Hatzius et al. (2010) and Groen, Nattinger, and Noble (2020) for the United States; Cardarelli, Elekdag, and Lall (2009) (International Monetary Fund FSI, or IMF FSI) for selected advanced economies; Park and Mercado Jr. (2014) for emerging market economies; Balakrishnan et al. (2011) for 18 emerging economies; van Roye (2014) for Germany; and Hanschel and Monnin (2005) for Switzerland, among others.

In the existing literature on FSIs and FCIs, the underlying data used to construct these indices vary greatly. Kliesen, Owyang, and Vermann (2012) provide an overview of the variables included in FSIs and FCIs. The authors conclude that papers constructing FCIs tend to include more information on quantities, prices, and economic indicators, whereas papers measuring FSIs tend to focus solely on prices. The methodology to construct FSIs also varies across papers. In other words, there are several ways to combine multiple variables into a single index. For instance, Hanschel and Monnin (2005), Cardarelli, Elekdag, and Lall (2009), and Balakrishnan et al. (2011) use an equal variance weighting average to construct a single index, whereas Hakkio and Keeton (2009) and Kliesen and Smith (2010) use principal component analysis.[7] Illing and Liu (2006) use factor analysis, credit-aggregate-based weighted averages, variance equal weighted averages, and transformation of variables using the sample cumulative distribution functions (CDFs) to construct indices. Lastly, van Roye (2014) uses a dynamic approximate factor model to construct an index for Germany.

In terms of the information content of these indices, Davig and Hakkio (2010) show that financial activity tends to be lower in periods of high financial stress. Moreover, the authors also find that a financial stress shock has a larger macroeconomic impact during periods of heightened financial stress. Similarly, van Roye (2014) finds that financial stress has a negative impact on the economy once financial stress increases above a specific threshold. Hatzius et al. (2010) test several existing FSIs to see if they can improve forecasts of economic activity. They find that including the FSI together with single measures (such as the stock market index, real M2, the term spread, the federal funds rate, or the short-term credit spread) can improve forecasts. Moreover, the authors show that some FSIs can outperform the stock market as an indicator of financial stress. Also Groen, Nattinger, and Noble (2020) find that including financial stress can improve forecasts of industrial production.

This paper is also closely related to that of Hartigan and Wright (2023), who construct an FCI for Australia using data on asset prices, interest rates and spreads, credit and money, outstanding

[7]To compare the different methods, Park and Mercado Jr. (2014) use both a variance equal weighted average and principal component analysis.

debt securities, as well as indicators of leverage, banking-sector risk, financial system complexity, financial market risk, and survey indicators of businesses and consumers.[8] The authors find that more restrictive financial conditions play an important role in explaining downside risk to growth in both GDP and employment and upside risk to changes in the unemployment rate. In contrast to Hartigan and Wright (2023), we use primarily monthly price data to construct the AFSI. Using higher-frequency data allows us to pay closer attention to short-term developments in financial markets.

3. Developing the Australian Financial Stress Index

Since we are considering a small open economy, domestic output and prices are influenced by two types of factors. The first set of factors characterizes domestic financial markets, while the second reflects the external factors.[9] Conditions abroad directly affect domestic output and prices through international trade. In addition, foreign factors can indirectly impact domestic prices and output through domestic financial markets. Moreover, external conditions may influence monetary policy, ultimately affecting domestic financial conditions, output, and prices. External factors also influence the exchange rate and domestic asset prices through cross-border capital flows, affecting the terms of trade, wealth, and financing conditions. Depending on the extent of domestic financial frictions, financial markets can then also amplify the direct effects of external shocks through a feedback effect that runs from interactions between the real economy and financial markets. Explicitly considering external factors when constructing an FSI for a small open economy is the key.

Following the widely used approach in the literature, we consider the principal component analysis methodology. To do so, we collect a series of variables that capture different aspects of financial disruptions in a variety of financial markets both locally and abroad.

[8]The authors use quarterly data in an unbalanced panel from 1976 to 2020 and dynamically demean the series using a 10-year backward-looking estimate of the sample mean.

[9]These external factors include commodity prices, world demand, and global financial conditions.

3.1 Financial Measures

Symptoms of financial stress are informed by both theory and practice. These include (i) uncertainty about the fundamental value of financial assets or the behavior of investors; (ii) increased asymmetric information; and (iii) decreased willingness to hold risky or illiquid assets. Thus, data used to construct the AFSI need to capture different financial markets trading patterns and investors' expectations. In particular, we collect information for the banking sector, the equity market, government securities, international trade, and the foreign exchange market. The data contain monthly information on changes in interest rates, yield spreads, volatility of the effective exchange rate, returns and volatility in equity markets, idiosyncratic volatility of bank stock prices, housing markets, inflation expectations, and sovereign real debt spreads. We also consider Australia's major trading partners. The data considered in this paper span from January 1990 to August 2023. The corresponding data sources are listed in Table A.1, which can be found in Appendix A.

3.1.1 Banking Sector

It is well known that disruptions in the banking sector contribute significantly to periods of financial stress. This is especially relevant for Australia, where the banking sector plays a central role in the financial system. Over the past few decades, commercial banks have held the majority of assets in the Australian financial system. The banking sector is also quite concentrated, with the four largest banks (the Commonwealth Bank of Australia, National Australia Bank, Westpac, and the Australia and New Zealand Banking Group) holding over 70 percent of banking-sector-wide assets. In addition to traditional retail deposit-taking and lending activities, banks are involved in almost all other facets of financial intermediation, including business banking, trading in financial markets, stockbroking, insurance, and funds management.[10] Since Australia is a financial

[10]Additional information regarding the banking sector can be found in the various issues of the Financial Stability Review of the Reserve Bank of Australia (RBA). For instance, Table B1 in www.rba.gov.au/statistics/tables/index.html reports the asset holdings of the banking sector.

market dominated by banks, capturing the effect of financial stress on bank credit is very important.[11]

To capture the importance of the banking sector, we include various banking-sector measures. Following Hakkio and Keeton (2009), we construct the banking sector β over a two-year horizon. This measure is given by

$$\beta = \frac{cov(r, m)}{var(m)},$$

where r denotes the monthly return on the bank stock index and m denotes the monthly return of the Australian stock market index (ASX200). Using the estimates of β, we then calculate the residual return of the banking-sector aggregate stock market index. Lastly, we estimate the residual return volatility using a GARCH(1,1) process.

In addition, Hakkio and Keeton (2009), among others, emphasize that in periods of financial stress, banks are likely to experience increased uncertainty about the quality of borrowers. As a result, they are less willing to hold risky assets. This increased uncertainty can lead to sharp increases in the interbank rate and the rate of bank-accepted bills (BAB), resulting an increase in the spread of bank refinancing rates and short-term government bond yields. To capture this, we consider the *three-month TED spread* and the *three-month BAB treasury spread.* The three-month TED spread measures the spread between the Australia three-month interbank rate (BBSW) and the three-month government bond yield. The three-month BAB treasury spread measures the difference between the three-month BAB rate and the three-month government bond yield. Finally, to capture changes to banks' funding costs that are driven by changes in macroeconomic circumstances, we also consider *changes in the cash rate*, which is the key policy rate of the Reserve Bank of Australia.

[11] For instance, in her 2017 speech titled "Big Banks and Financial Stability," the then assistant governor and the current governor of the Reserve Bank of Australia, Michele Bullock, cautioned that the concentration of the banking system in four major banks in Australia does not provide financial stability benefits. (See https://www.rba.gov.au/speeches/2017/sp-ag-2017-07-21.html.)

3.1.2 Equity Market

Hakkio and Keeton (2009), among others, highlight that financial stress periods are accompanied by increased uncertainty about assets' fundamentals. This leads to sharp changes in returns and increases in volatility in equity markets. To account for these phenomena, we consider data on *S&P/ASX 200 return* and *S&P/ASX 200 return volatility*, which capture activity in the Australian equity market. Following Park and Mercado Jr. (2014), the return volatility is calculated by estimating a GARCH(1,1) process.

3.1.3 Housing Market

The Global Financial Crisis (GFC) has emphasized how disruptions in the housing can lead to financial stress. Sharp declines in the housing market can lead to increased losses for banks and investors. Thus, it is not too surprising that the housing market is a key factor when designing macroprudential policies. In order to capture financial stress arising from the housing market, we include *housing price growth* data. This series combines the growth of the hedonic home value index in eight major Australian capital cities.

3.1.4 Foreign Exchange Market

As a small open economy, it is likely that financial stresses and macroeconomic shocks experienced abroad can spill over to the Australian economy. To account for this possibility, we include data on the *effective exchange rate volatility*. To measure the effective exchange rate volatility, we take first differences of the trade weighted index of the Australian dollar.[12] We then measure the effective exchange rate volatility with a GARCH(1,1) process.

3.1.5 Inflation Expectations

In addition to changes in behavior and beliefs, agents are likely to adjust their expectations about the future during periods of financial

[12]The trade-weighted index is a weighted basket of 18 currencies. The weights are determined according to the trade balance of the respective country with Australia.

stress as Illing and Liu (2006), Kliesen, Owyang, and Vermann (2012), Abdymomunov (2013), and others point out. To capture changes in inflation expectations, we consider data on the *breakeven inflation rate*. This measure is calculated by subtracting the 10-year inflation-indexed bond yield from the 10-year nominal bond yield.[13]

3.1.6 Liquidity and Safety

During financial stress periods we observe investors shift their portfolio toward safer and more liquid assets.[14] To capture this phenomena in the Australian context, we consider data on *changes in the 5-year Commonwealth government bond yield* to measure changes medium-term expectations and *changes in the 10-year Commonwealth government bond yield* to measure changes in long-term expectations. In addition, we include data on the *term premium* to capture changes in the current monetary policy stance relative to investors' long-term expectations as in Hakkio and Keeton (2009). The term premium is calculated by subtracting the three-month Australia treasury bill yield from the 10-year nominal Commonwealth government bond yield. When monetary policy is tight relative to long-run expectations, short-term yields tend to increase relative to long-term yields, leading to an increase in the spread.

Given that we are analyzing a small open economy, we also consider the actual and perceived safety of Australian public debt relative to other foreign government debt. To measure changes in the yields of Australian safe assets relative to yields of other foreign safe assets, we include data on the *five-year real sovereign debt spread* between Australia and the United States. This is the case, as the United States is one of the most important global financial centers and one of the largest suppliers of *safe* assets. To do so, we compute the real yield of the five-year government bond yields in Australia and in the United States by subtracting the inflation rate from the nominal yields. The inflation rate measures the monthly year-on-year

[13]The time series of the 10-year inflation-indexed bond yield was discontinued in March 2023 by the Global Financial Database. This database provides a new measure of an estimated 10-year inflation-indexed bond based on the nominal 10-year bond. We use the old data series up to March 2023 and then use the new estimated series for April to August 2023.

[14]We refer to Hakkio and Keeton (2009), among others, for more on this topic.

change in the consumer price index (CPI) of both countries. To obtain CPI data for Australia for our time horizon, we combine different CPI measures. First, we take the quarterly CPI data available from the Australian Bureau of Statistics and interpolate the data based on a cubic interpolation of the values in neighboring grid points. We use this interpolated data for our Australian inflation measure from December 1989 to July 2003. From August 2003 to August 2019, we use the Monthly Inflation Gauge published by the Melbourne Institute. Lastly, for the period of September 2019 to August 2023, we use the monthly inflation data published by the RBA.[15] We then compute the spread according to the following equation:

$$y_{i,t} = AUD5Y_t - US5Y_t,$$

where y_t denotes the real sovereign debt spread in period t, $AUD5Y_t$ denotes the real five-year government bond yield in period t, and $US5Y_t$ denotes the real five-year government spread for the United States.[16]

Having described all the data, Table 1 reports descriptive statistics for all of the data series.

3.2 Methodology

Having identified several financial measures that can capture disruptions in financial markets when negative shocks hit the economy, we can construct the AFSI. Following the approach used in the literature, we consider the principal component methodology. Various authors have considered different components when constructing the financial stress index. In particular, Hakkio and Keeton (2009) use the first component, while Park and Mercado Jr. (2014) consider the first three components. In this paper we consider the first four

[15]We constructed the index both with the constructed inflation measure as described here and with the interpolated data. We didn't find any material differences between the two indices.

[16]CPI data for Australia are not available for the full sample of the index. Instead, we use quarterly CPI data from the RBA and interpolate to monthly frequency until July 2003. From 2003 onward, we use the monthly inflation gauge reported by the Melbourne Institute, pulled from Bloomberg until August 2019. From August 2019, monthly CPI data are available from the Australian Bureau of Statistics, which we use from September 2019 to August 2023.

Table 1. Descriptive Statistics

Variable	Mean	Standard Deviation
Change in Cash Target Rate	0.0071	0.2189
Change in 5-Year Government Bond Yield	–0.0002	0.0799
Change in 10-Year Government Bond Yield	–0.0010	0.0613
Term Premium	0.8601	1.0635
Inflation Expectation	2.7274	1.3880
U.S. Real Sovereign Debt Spread	1.2730	1.6835
Three-Month TED Spread	0.1889	0.2240
Three-Month BAB Spread	0.1904	0.1987
Banking-Sector Volatility	0.0318	0.0041
S&P/ASX 200 Return	0.4517	3.9123
S&P/ASX 200 Volatility	3.8411	0.8702
Effective Exchange Rate Volatility	1.5565	0.2952
Housing Price Growth	0.0039	0.0068

components. We do so as it allows us to (i) increase the share of the total variation of the variables explained by the index to 58.4 percent, and (ii) deliver a more realistic stress measure during the COVID-19 pandemic.[17]

To construct the AFSI, we first transform each of the data previously described so they have the same units. In particular, for each series we subtract the sample mean and divide by the standard deviation.[18] We then apply the principal component analysis to calculate the coefficients corresponding to these variables. The financial stress index is then constructed by adding the weighted first four components. To do so, we first multiply each component with the standardized time series. We then weigh each component

[17]Looking at the standardized time series suggests that several of the variables included in our AFSI measure showed a large change in the beginning of the pandemic. The first four components pick up some of these changes in the AFSI estimate that would otherwise be subdued when using only the first two or the first three components, respectively.

[18]In order to test for stationarity, we conduct an augmented Dickey-Fuller test. We cannot reject the unit-root null model for the equity return volatility, banking sector, and exchange rate volatility. For the transformed time series, we are able to reject the unit-root null model for all 13 variables.

Table 2. Adjusted Coefficients

Variable	Adjusted Coefficient
Change in Cash Target Rate	0.0301
Change in 5-Year Government Bond Yield	–0.554
Change in 10-Year Government Bond Yield	0.0433
Term Premium	0.0875
Inflation Expectation	0.1743
U.S. Real Sovereign Debt Spread	0.2111
Three-Month TED Spread	0.2272
Three-Month BAB Spread	0.1883
Banking-Sector Volatility	0.2156
S&P/ASX 200 Return	–0.0276
S&P/ASX 200 Volatility	0.2856
Effective Exchange Rate Volatility	0.3070
Housing Price Growth	–0.2226
Percent of Total Variation of Variables Explained by AFSI	58.4

by the eigenvalue of the respective component relative to the sum of the eigenvalues of the first four components and add them to a single index. To compute the adjusted coefficients, we scale the coefficients such that the standard deviation of the index is one. We then weigh the adjusted coefficient of each component for each variable by its eigenvalue relative to the sum of the eigenvalues of the first four components. Lastly, we add them up to obtain the adjusted coefficient corresponding to the AFSI. The resulting adjusted coefficients are reported in Table 2.

Since the coefficients are standardized, they represent the effect of a one standard deviation change of each variable on the AFSI.[19] More precisely, the coefficients in Table 2 highlight that a one standard deviation change in the exchange rate volatility has approximately 3.5 times the effect on the AFSI as a one standard deviation change in the term premium. Moreover, a one standard deviation change in the exchange rate volatility has an impact on the index that is roughly twice as large as the one implied by one standard

[19]We refer to Hakkio and Keeton (2009) for more on this topic.

Table 3. Correlation between the First Four Components and the 13 Variables

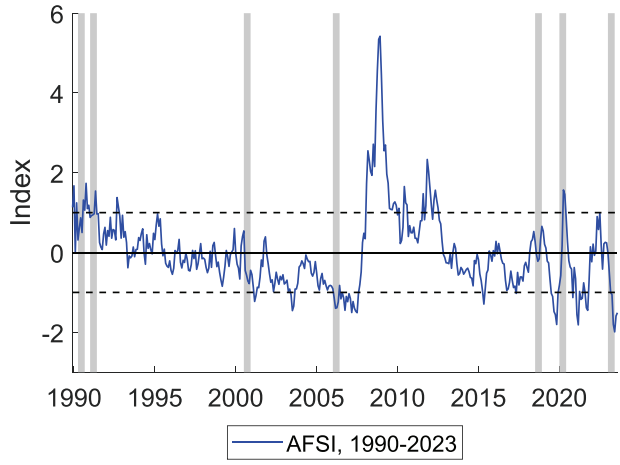
Variable	Component			
	1	2	3	4
Change in Cash Target Rate	–0.2004	0.1555	0.3094	–0.0992
Change in 5-Year Government Bond Yield	–0.6576	**0.6130**	0.1119	–0.2222
Change in 10-Year Government Bond Yield	–0.6259	**0.6324**	0.0976	–0.2129
Term Premium	–0.2653	0.3343	0.0570	0.3826
Inflation Expectation	0.0576	–0.1332	**0.7680**	0.1192
U.S. Real Sovereign Debt Spread	–0.0352	0.0685	**0.8293**	0.1279
Three-Month TED Spread	**0.7316**	0.4062	–0.0469	–0.3501
Three-Month BAB Spread	**0.7599**	0.0700	0.0971	–0.3424
Banking-Sector Volatility	0.2513	0.5499	–0.2001	0.3181
S&P/ASX 200 Return	–0.1296	–0.1422	–0.2110	0.4831
S&P/ASX 200 Volatility	0.3762	0.3498	–0.0185	**0.5512**
Effective Exchange Rate Volatility	0.5198	**0.6441**	–0.0195	0.0684
Housing Price Growth	–0.4655	0.0957	–0.4238	–0.1201

deviation in inflation expectation changes. We also find that one standard deviation change in the exchange rate, equity market, and the banking-sector volatility has the highest impact on the AFSI. In contrast, changes in medium- to long-term government bond yields have a very small and for the five-year government bond yield even a negative effect.

Next, we report the correlations between each of the first four components and the 13 variables included in the index. These are reported in Table 3.

As we can see from Table 3, the first component is most heavily correlated with the three-month TED and the three-month BAB spread. The second component correlates mostly with exchange rate volatility as well as changes in the 5-year and 10-year government bond yield. The third component is mostly correlated with inflation expectations and the real sovereign debt spread, while the fourth component correlates mostly with equity volatility. Based on these results, we identify the first component as bank funding and the second component as the exchange rate and liquidity components. Furthermore, we identify the third component as the expectations and safety and the fourth component as the equity volatility components.

Figure 1. AFSI (own calculation) for the 1990–2023 Period



Having identified the first four components, we can generate a time series for the AFSI. By construction, the average value of the index is zero and is associated with normal financial market conditions. Thus, values below zero imply low financial market stress, whereas values above zero suggest higher financial market stress periods. Moreover, larger values of the AFSI indicate greater financial stress and financial disruptions relative to other periods. Figure 1 depicts the resulting AFSI from December 1989 to August 2023. The gray bars indicate Australian recessionary periods. These correspond to two consecutive quarters of negative growth in real GDP per capita, as suggested by Restrepo-Echavarria and Reinbold (2019).[20]

The AFSI successfully captures the surge in financial stress during the GFC. Since this financial crisis, the AFSI exhibits slightly greater variability relative to the period before the GFC. The AFSI also captures the negative impact of the COVID-19 outbreak in

[20]As Restrepo-Echavarria and Reinbold (2019) highlight, Australia would not have had any recessions in recent years if real GDP is considered. However, if real GDP per capita is considered, Australia appears to have had recessions in the previous years. The authors argue that this difference stems from migration, which has been a key factor in Australia's recent trends. We follow Restrepo-Echavarria and Reinbold (2019) here and consider real GDP per capita.

Australia, starting in March 2020. The financial stress and disruptions experienced by Australian investors due to COVID-19 in April 2020 has been similar to the financial stress stemming from the Greek debt crisis in June 2010.

4. Evaluating the AFSI

Having described our index, we now analyze the properties of AFSI in terms of its external and domestic factors. We also assess the financial stress of the COVID-19 period relative to the GFC. Finally, we evaluate the relative performance of our index when compared with other stress indices.

4.1 Domestic and Foreign Factors

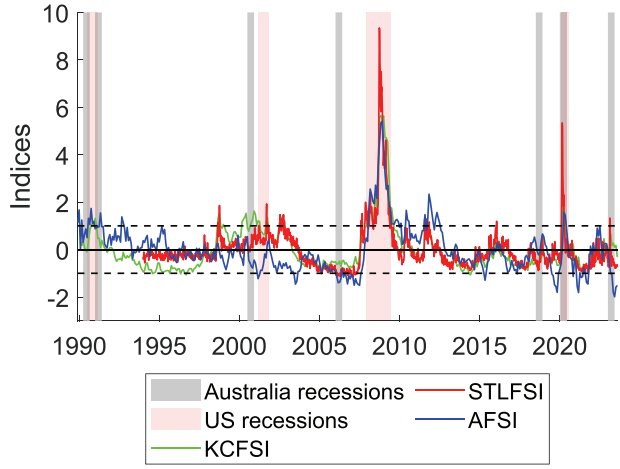
Given that the United States is a major global financial center, and that China is the largest Australian trading partner, we consider these two countries when examining the impact of foreign factors in shaping the AFSI. First, we highlight the importance of these countries for Australia by comparing the time series of the AFSI with other financial stress indices for the United States and China. We then further decompose the AFSI into domestic and external factors.

4.1.1 United States

To determine the importance of disruptions in one of the most important global financial markets, we compare the AFSI with the Kansas City Fed FSI (KCFSI) and the St. Louis Fed FSI (STLFSI).[21] Both U.S. indices apply the principal component analysis and consider just the first component. The main difference between the AFSI and

[21] The STLFSI uses data on a series of interest rates, yields spreads, and additional indicators such as different measures of volatility, inflation expectations, and data on other financial products. Similarly, the KCFSI includes data on yield spreads and volatility measures. Compared with these indices, we do not include data on corporate bond spreads. In Australia, the corporate bond market plays a smaller role in firms' financing than it does in a number of other countries. Since 1990, the share of financial intermediaries in the corporate bond market has increased significantly, making up about 60 percent of the corporate bond market (Black et al. 2012).

Figure 2. AFSI, KCFSI, and STLFSI



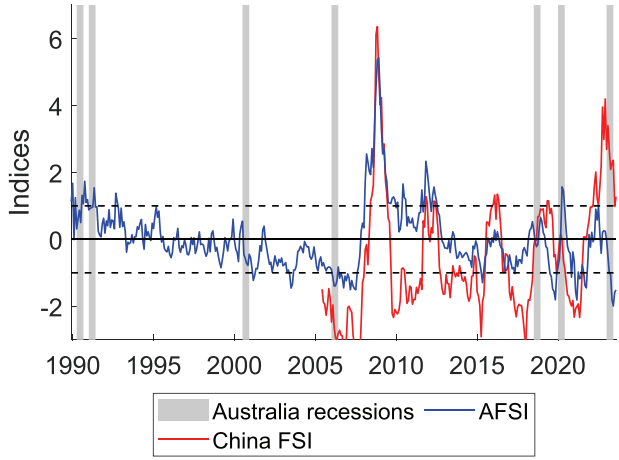
Data Source: Own calculation, Federal Reserve Economic Data (FRED).

the KCFSI/STLFSI is that we include a measure of exchange rate volatility and international public debt spreads. These are arguably important factors when considering small open economies and not global financial centers like the United States. Moreover, the STLFSI includes more information on corporate bond yields. We do not consider corporate bond yields in our measure of financial stress since the number of corporate bonds in Australia is relatively small. Lastly, the KCFSI does not include the term premium and inflation expectations.

Figure 2 compares the time series for the AFSI with the two U.S. indices. The red and gray bars indicate recessionary periods in the United States and in Australia, respectively.

Broadly speaking, the three indices comove for most of the period that spans from December 1989 to August 2023. The STLFSI shows considerably larger financial stress during the financial crises of 2007–09, when compared with the KCFSI and the AFSI. In addition, from 1998 to 2003 the AFSI shows fewer financial disruptions than the U.S. indices. However, the AFSI delivers larger values of financial stress after the financial crises of 2007–09. Lastly, the AFSI financial stress measure during the COVID-19 pandemic is slightly

Figure 3. AFSI and CHFSI



Data Source: Own calculation, Asian Development Bank.

smaller relative to the KCFSI, whereas the STLFSI is somewhat larger compared with both the AFSI and the KCFSI.

4.1.2 China

To capture potential disruptions stemming from the largest Australian trading partner, we now compare the AFSI to a Chinese financial stress index developed by the Asia Regional Integration Center of the Asian Development Bank (CHFSI).[22] Figure 3 plots the AFSI and the CHFSI, where gray bars indicate recessions in Australia.[23]

[22]The methodology of the CHFSI is based on the methodology of Park and Mercado Jr. (2014). The CHFSI considers the relative volatility of the banking sector relative to equity markets (β, as defined above), changes in equity returns, equity volatility, sovereign debt spreads between the 10-year government bond yield and the 2-year government bond yield, and changes in valuation of the domestic currency relative to the U.S. dollar (Asia Regional Integration Center 2021).

[23]Using OECD and World Bank data on nominal GDP, inflation, and population from China, we could not identify recession periods defined as two consecutive quarters of negative real GDP per capita growth for the time period from 1995 to 2023.

Table 4. Correlation of AFSI, KCFSI, STLFSI, and CHFSI

	KCFSI	STLFSI	CHFSI
AFSI	0.6310	0.7148	0.5525
AFSI(–1)	0.6145	0.6542	0.5508
Data Source: Own calculation, FRED, Asian Development Bank.			

From Figure 3, the AFSI seems to be much less correlated with the CHFSI when compared with the U.S. indices. This suggests that Australian financial markets are globally connected and less influenced by the financial conditions of its major trading partner.

4.1.3 Correlations with Foreign Series

To formally assess the comovement of the U.S. and Chinese indices with the AFSI, we calculate the corresponding correlations. In particular, Table 4 reports the correlation coefficients for our measure of the AFSI, the Australian measure obtained from the Asian Development Bank, the KCFSI, the STLFSI, and the CHFSI. We also report correlation coefficients with one lag.[24]

As we can see from Table 4, the AFSI is more correlated with financial stress in the United States relative to financial stress in China. Among the U.S. stress indices, the AFSI has the highest correlation with the STLFSI.

4.1.4 Domestic and Foreign Decomposition

An alternative way to show the importance of foreign factors in a small open economy is to decompose the AFSI into domestic and foreign components. To do so, we follow the approach taken by Moore (2017). In particular, we consider financial stress indices for the United States and China when decomposing the AFSI. As a

[24]Correlations reported in Table 4 are at monthly frequency. Thus, the weekly measures for the STLFSI are converted into monthly averages.

robustness check we also consider Japan and South Korea, which are the second and third largest Australian trade partners.[25] First, we focus on the impact of financial stress in the U.S. and China. The error term in Equation (1) represents the part of the AFSI that cannot be explained by foreign indices. Therefore, it can be interpreted as the domestic component. The first specification we consider is as follows:

$$\text{AFSI}_t = \beta_0 + \beta_1 \text{FSI}_{US,t} + \beta_2 \text{FSI}_{China,t} + \varepsilon_t. \tag{1}$$

It is of course plausible that financial stress in Australia can be transmitted from economies other than the United States and China. In a second specification, we also include indices for Japan and South Korea. Thus, we consider the following second and third specifications:

$$\text{AFSI}_t = \beta_0 + \beta_1 \text{FSI}_{US,t} + \beta_2 \text{FSI}_{China,t} + \beta_3 \text{FSI}_{SouthKorea,t} + \varepsilon_t, \tag{2}$$

$$\text{AFSI}_t = \beta_0 + \beta_1 \text{FSI}_{US,t} + \beta_2 \text{FSI}_{China,t} + \beta_3 \text{FSI}_{SouthKorea,t} + \beta_4 \text{FSI}_{Japan,t} + \varepsilon_t. \tag{3}$$

Our estimates are reported in Table 5. The data cover the period from June 2005 to August 2023. For the U.S., we use the KCFSI as a measure of financial stress in the U.S. Specification (i) estimates Equation (1); Specification (ii) estimates Equation (2). Finally, (iii) estimates Equation (3).[26]

As illustrated by Table 5, the results are similar across the different specifications. Our measure of financial stress for Australia exhibits high correlation with financial stress in the U.S. Financial stress in China, Japan, and South Korea does not contribute significantly to financial stress in Australia. However, as shown in the adjusted R^2 value and the root mean squared error (RMSE), adding these indices to the regression increases the fit of the linear regression. Focusing on Specification (ii), a one-unit increase in the

[25]The financial stress indices for Japan and South Korea were obtained from the Asian Development Bank (Asia Regional Integration Center 2021) and follow the methodology in Park and Mercado Jr. (2014).

[26]Appendix B reports additional regression results.

Table 5. Regression Results of the AFSI Decomposition

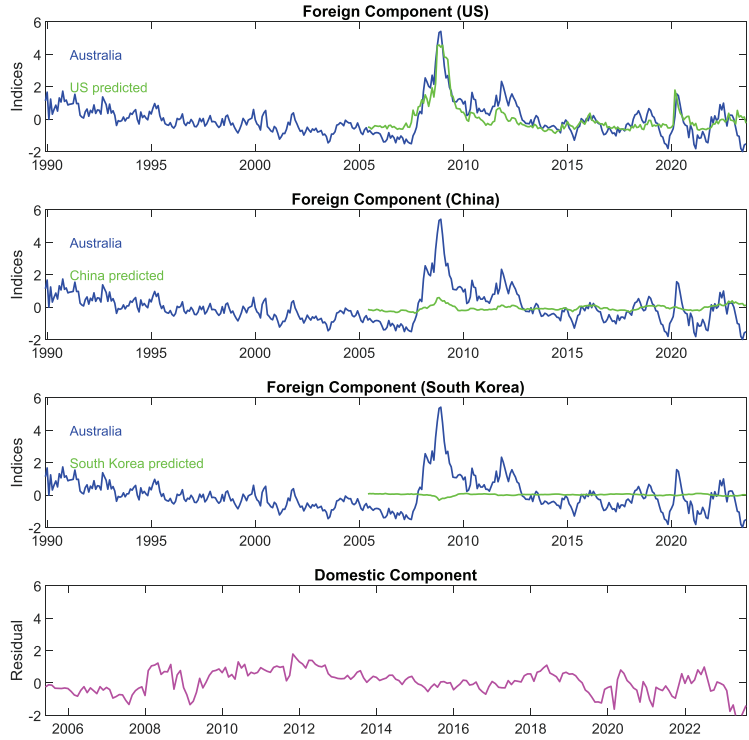
	Specification		
	(i)	**(ii)**	**(iii)**
Intercept	0.0600	0.0522	0.2277**
	(0.1407)	(0.1268)	(0.1268)
KCFSI	0.7893***	0.8109***	0.6432***
	(0.0827)	(0.1148)	(0.0951)
CHFSI	0.0733	0.0926	0.0207
	(0.0870)	(0.1422)	(0.1550)
South Korea FSI		–0.0349	–0.1067
		(0.1604)	(0.1403)
Japan FSI			0.2402**
			(0.1105)
Adjusted R^2	0.6669	0.6676	0.6635
RMSE	0.8881	0.6510	2.8417
N	219	219	219

Note: Newey-West standard errors are in parentheses. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

KCFSI leads to a 0.78-unit increase in the AFSI. Together, financial stress from abroad can explain more than half (66.7 percent) of the financial stress in Australia.

Figure 4 illustrates the results of the decomposition, using Specification (ii) in Table 5. The top panel shows the AFSI (blue) and the predicted contribution of financial stress arising from the United States, $\tilde{y_t}^1 = \beta_1 KCFSI_t$ (green). The second panel shows the AFSI (blue) and predicted contribution of financial stress emerging from China, $\tilde{y_t}^2 = \beta_2 CHFSI_t$ (green). The third panel shows the AFSI (blue) and the predicted contribution of financial stress in South Korea, $\tilde{y_t}^3 = \beta_3 FSI_{SouthKorea,t}$ (green). Finally, the bottom panel shows the domestic component, which is the residual, $y_t - \tilde{y_t}^1 - \tilde{y_t}^2 - \tilde{y_t}^3$. Figure 4 highlights the results from Table 5. Financial stress in Australia shows high correlation with the U.S. and very little correlation with financial stress in China and South Korea, respectively.

Figure 4. Foreign and Domestic Decomposition



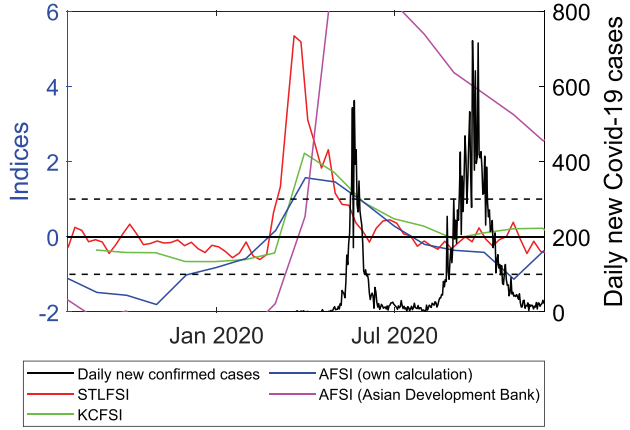
Data Source: Own calculation, FRED, Asian Development Bank.

4.2 The COVID-19 Pandemic

To capture the financial stress during the COVID-19 pandemic, we report the daily new confirmed COVID-19 cases in Australia as well as four measures of financial stress, namely the KCFSI, STLFSI, the FSI for Australia produced by the Asian Development Bank, and our measure.[27] These different indices are depicted in Figure 5 together with the number of daily confirmed cases of COVID-19 in Australia.

[27]The COVID-19 case data are obtained through the Australian Department of Health.

Figure 5. Financial Stress Indices and Daily Confirmed Cases of COVID-19



Data Source: Own calculation, FRED, Asian Development Bank, World Health Organization (WHO).

From Figure 5, all four indices show an increase in financial stress around the first wave of COVID-19. The U.S. indices as well as the AFSI peak somewhat before the peak of the first wave in Australia, with the AFSI showing a lower magnitude of financial stress relative to the U.S. indices. The index produced by the Asian Development Bank (from now on referred to as the ADB-AFSI) shows a much larger magnitude of financial stress that lasts over the first two waves of COVID-19 in Australia. Furthermore, the ADB-AFSI picks up slightly later than the AFSI and the U.S. indices.

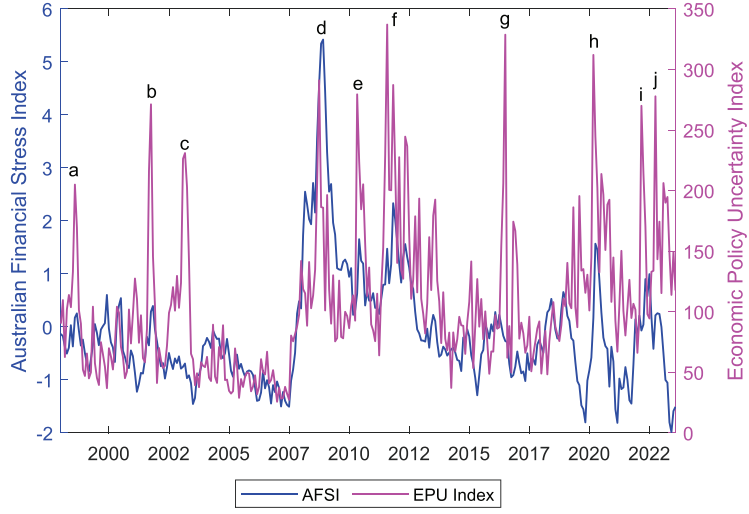
4.3 Comparison with Other Indices

4.3.1 Australian Economic Policy Uncertainty Index

As a broader alternative measure of financial stress, we now consider the Australian economic policy uncertainty (EPU) index by Baker, Bloom, and Davis (2016). Figure 6 shows the AFSI relative to the EPU index for a period from January 1998 to August 2020.[28] In

[28]The data are taken from https://www.policyuncertainty.com.

Figure 6. AFSI and Economic Policy Uncertainty Index

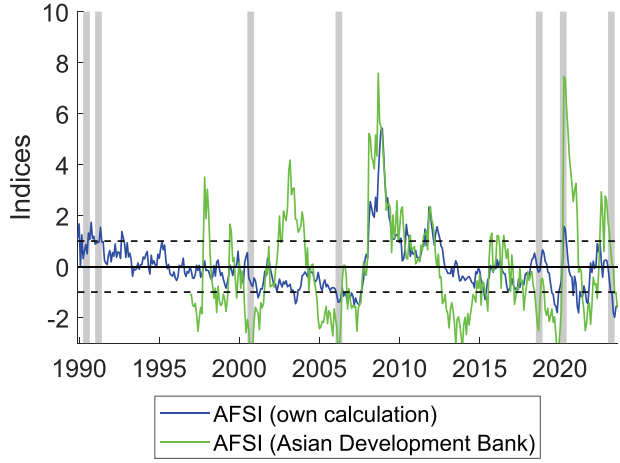


Data Source: Own calculation, www.policyuncertainty.com.

the following discussion, we also refer to Moore (2017) to identify specific Australian events. In particular, the letters (a) through (f) correspond to the following episodes of large increases of the economic policy uncertainty: (a) the close Australian election fought over goods and services tax introduction and Russian economic crisis; (b) the 9/11 attacks; (c) the invasion of Iraq; (d) the Global Financial Crisis; (e) the Greek debt crisis, mining tax, and carbon policy uncertainty; (f) the U.S. debt ceiling dispute; (g) the Brexit vote; (h) the beginning of the COVID-19 pandemic; (i) the start of the war in Ukraine; and (j) floods in Southeast Australia.

As can be seen from Figure 6, our estimate of financial stress, as measured by the AFSI, coincides with some periods of economic policy uncertainty. The strongest overlap is during the GFC. Other periods with some overlap between the two indices include the close Australian election fought over goods and services taxes (a), the Greek debt crisis and mining and carbon policy uncertainty (e) and the U.S. debt ceiling dispute (f), the start of the COVID-19 pandemic (h), and the start of the war in Ukraine (i). In these periods, the AFSI indicates higher financial stress. While there is some overlap in economic policy uncertainty and financial stress, not all

Figure 7. AFSI and AFSI-ADB by Asian Development Bank



Data Source: Own calculation, Asian Development Bank.

economic policy uncertainty episodes correspond to an increase in financial stress in Australia, such as the Brexit vote (g), the 9/11 attacks (b), or the invasion of Iraq (*c*).

4.3.2 Asian Development Bank Index

Using Park and Mercado Jr. (2014) methodology, the Asia Regional Integration Center of the Asian Development Bank tracks financial stress across several countries. In the case of Australia, the Asian Development Bank uses data on the relative volatility of the banking sector relative to equity markets (β, as defined above), changes in equity returns, equity volatility, sovereign debt spreads between the 10-year government bond yield and the 2-year government bond yield, and changes in valuation of the domestic currency relative to the U.S. dollar (Asia Regional Integration Center 2021). It is important to highlight that our measure of the Australian Financial Stress Index (AFSI) is likely to differ, since we include additional data. Figure 7 depicts the time series of these two financial stress indices. The black horizontal line indicates the mean financial stress over the time horizon and the dashed lines indicate one standard deviation.

Table 6. Correlation between AFSI-ADB and AFSI and AFSI-ADB and Lagged AFSI

	AFSI-ADB
AFSI	0.5828
AFSI(–1)	0.5617
Data Source: Own calculation, Asian Development Bank.	

As we can see from Figure 7 and Table 6, our measure displays some correlation with the measure of financial stress in Australia developed by the Asian Development Bank. It is worth noting, however, that our measure implies lower financial stress during the 2002–03 and 2016–17 periods. In contrast to our AFSI, the Asian Development Bank index suggests that the financial stress during the COVID-19 pandemic is larger than the one experienced during the Global Financial Crisis.

5. The AFSI and Macroeconomic Outcomes

One of the advantages of measuring financial stress is that it can capture disruptions in the normal functioning of financial markets that can lead to adverse real economic outcomes. This can occur in several ways. In times of increased uncertainty, firms and households may delay or reduce hiring, investment, and spending. It is not too surprising then that financial stress, as measured by the FSI, can forecast declines in economic activity.[29] We now examine the relationship between AFSI and various measures of economic activity. Finally, we also explore how AFSI shocks may affect and propagate in the economy.

5.1 Granger Causality Tests

Financial stress episodes are frequently connected with economic downturns. This is the case, as they destabilize the financial system and hinder its ability to operate smoothly. Being able to assess

[29] We refer to Apostolakis and Papadopoulos (2019) for more on this topic.

Table 7. Correlation between the AFSI, GDP per Capita Growth, Bank Credit Growth, and the Unemployment Rate

GDP per Capita (1)	Bank Credit (2)	UR_t (3)	UR_{t+18} (4)	UR_{t+36} (5)
–0.2105	–0.3385	0.0851	0.2616	0.2445

Data Source: Own calculation, Australian Bureau of Statistics, Reserve Bank of Australia.

whether the AFSI can be an early warning system and/or help improve forecasts of key macroeconomic indicators is of paramount importance. Next, we evaluate these possibilities by considering real GDP per capita growth, bank credit growth, and the unemployment rate. Before doing so, Table 7 reports the different correlations between the AFSI and these observables.

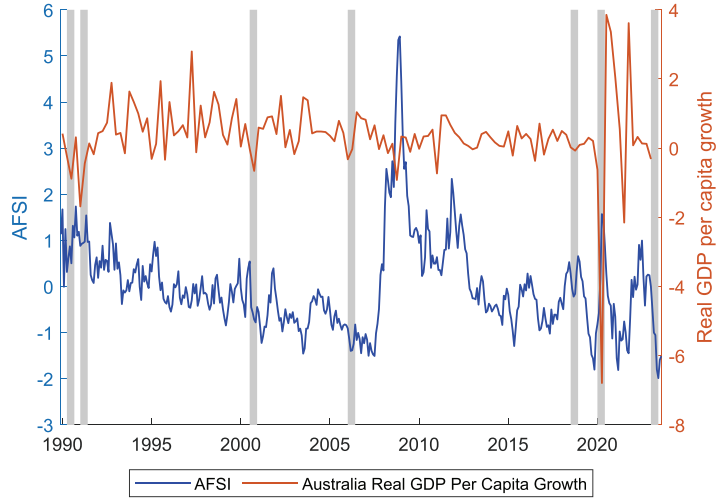
Unsurprisingly, Table 7 highlights that real GDP per capita growth is negatively correlated with our measure of financial stress. This indicates that periods of higher financial stress tend to be accompanied by lower real GDP per capita growth. Column 2 shows that the AFSI is negatively correlated with bank credit growth, indicating that bank credit growth tends to be lower in periods of financial stress. Finally, in columns 3 through 5 in Table 7, we report the correlation between the AFSI and the unemployment rate (UR) with lags of 1.5 and 3 years. The correlation is positive at all lags, indicating higher unemployment in times during and after financial stress. The correlation increases when the lag is 1.5 years relative to the contemporaneous correlation.

5.1.1 GDP

We now examine the information content of the AFSI when it comes to aggregate economic performance. Figure 8 plots real GDP per capita growth and our AFSI from January 1990 to June 2023, where the gray bars indicate recessions in Australia.[30]

[30]Since GDP is only available at a quarterly frequency, we take the mean of the values of the AFSI of each month within a quarter to create a quarterly time series of the AFSI.

Figure 8. AFSI and Real GDP per Capita Growth



Data Source: Own calculation, Australian Bureau of Statistics.

From Figure 8, our measures of higher than average financial stress periods in 1990/91, 2008, and 2020 coincide with periods of lower real GDP per capita growth. However, we also find periods of lower real GDP per capita growth where we do not see a corresponding increase in the financial stress index. Such instances are the recessionary periods in 2000/01, 2006, and 2018/19.

Next, we run a Granger causality test to determine whether including the AFSI can improve the forecasts of real GDP per capita growth relative to a forecast that only includes its past values. The null hypothesis is that the AFSI does not Granger-cause real GDP per capita growth. We fit a VAR(2) model to real GDP per capita growth and our financial stress index, where the number of lags was chosen based on the Akaike information criterion (AIC) and the maximum number of lags was set to 4. The Granger causality tests are reported in Table 8.

Our findings suggest that we cannot reject the null hypothesis that the AFSI does not Granger-cause real GDP per capita growth. Thus, our measure of the AFSI cannot improve forecasts of real GDP per capita growth relative to forecasts based on past realizations of

Table 8. Granger Causality Test for AFSI and Real GDP per Capita Growth

	F-statistic	p-value
Exclude Lagged AFSI in Real GDP per Capita Growth Equation	2.1453	0.3421
Exclude Lagged Real GDP per Capita Growth in AFSI Equation	2.0558	0.3578

real GDP per capita growth. One possible explanation for this finding is that in the case of Australia, an increase in financial stress does not always coincide with negative real GDP per capita growth, as is evident by Figure 1 in the period of the financial crisis in 2008. In addition, given that GDP data is only available at a quarterly frequency, temporary financial disruptions may not be fully captured in the quarterly data.

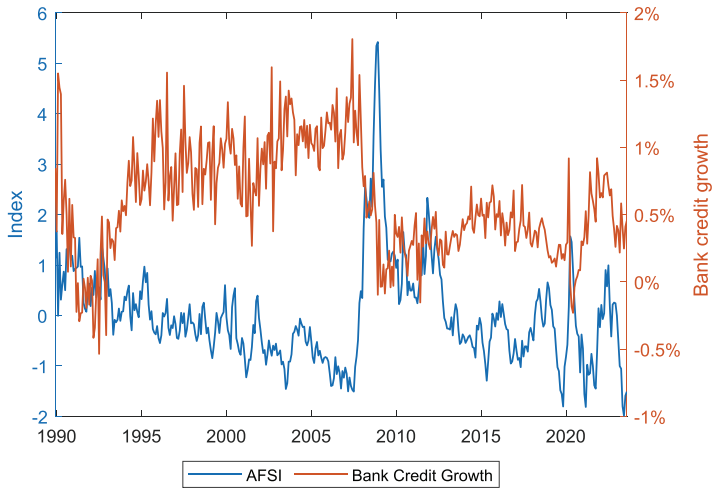
5.1.2 Loans

Another measure of economic activity that is widely used when assessing the performance of an economy is the volume of bank loans. During periods of financial stress and economic downturns, we expect bank credit growth to be lower relative to normal times. Figure 9 depicts the AFSI and monthly bank credit growth data.[31]

As we can see from Figure 9, the negative correlation is most evident in November 2008 and during the recessions of the 1990s. We, however, also observe periods without a negative correlation. For instance, during the onset of the COVID-19 pandemic, bank credit growth seems to have increased even though this was also a period of higher financial stress. One possible explanation for such

[31]For bank credit loan growth data we consider the period of December 1989 to June 2019. We use the monthly credit growth (DGFACM in Table D2 of the RBA's public credit growth data set). From August 2019 to August 2013, we use monthly credit growth including select financial businesses (variable DGFACNWM). For the missing value for July 2019, we linearly interpolate from the values of June and August 2019. Since bank credit growth data are not available for our entire time horizon, we construct this data series as previously described.

Figure 9. AFSI and Bank Credit Growth



Data Source: Own calculation, Reserve Bank of Australia.

anomaly is that the Reserve Bank of Australia implemented several relief programs in order to support bank lending.

Next, we perform the Granger causality test to determine if including financial stress, as measured by the AFSI, can improve forecasts of bank credit growth. We do so by fitting a VAR(4) model to the data, which is reported on Table 9.[32] We also report the Granger causality test results for the two separate time series.

Table 9 illustrates that we can reject the null hypothesis that the AFSI does not Granger-cause bank credit growth at the 1 percent significance level. Thus, we conclude that including the AFSI can improve forecasts of bank credit growth. Once again, this finding suggests that the AFSI captures relevant information that is key for the credit growth in an economy. Looking at bank credit growth from December 1989 to June 2019, we test the null hypothesis for both shorter periods at the 5 percent level to determine whether there are statistically significant differences in growth patterns. However, we can reject the null hypothesis at the 10 percent level for the period from December 1989 to June 2019.

[32] Again, the number of lags was selected with the AIC and the maximum number of lags was set to 4.

Table 9. Granger Causality Test for AFSI and Bank Credit Growth

	F-statistic	p-value
Bank Credit Growth: December 1989 to August 2023		
Exclude Lagged AFSI in Bank Credit Growth Equation	25.742	0.0004
Exclude Lagged Bank Credit Growth in AFSI Equation	4.2153	0.3777
Bank Credit Growth: December 1989 to June 2019		
Exclude Lagged AFSI in Bank Credit Growth Equation	21.088	0.0003
Exclude Lagged Bank Credit Growth in AFSI Equation	9.4943	0.0499
Bank Credit Growth: August 2019 to August 2023		
Exclude Lagged AFSI in Bank Credit Growth Equation	2.8001	0.0943
Exclude Lagged Bank Credit Growth in AFSI Equation	4.4083	0.0358

5.1.3 Unemployment Growth

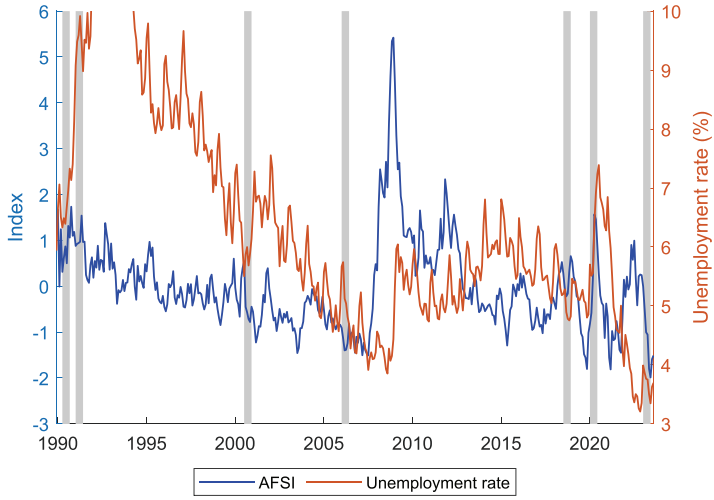
Lastly, we look how our measure of financial stress compares with changes in unemployment rate.[33] Figure 10 depicts the monthly unemployment rate in Australia together with the AFSI. Since GDP growth and unemployment tend to be negatively correlated and we have shown that our AFSI is negative correlated with GDP per capita growth, we expect a positive correlation between the AFSI and the unemployment rate.

Figure 10 implies that periods of higher unemployment tend to follow periods of financial stress with a lag. Table 10 reports the Granger causality test for our AFSI measure and the unemployment rate. To do so, we fit a VAR(25) model and test the null hypothesis that the AFSI does not Granger-cause unemployment.[34]

[33]The unemployment data are taken from the Australian Bureau of Statistics.

[34]The lag was again selected with the AIC. The maximum number of lags was set equal to 40 to account for large lags visible in the data.

Figure 10. AFSI and Unemployment Rate



Data Source: Own calculation, Australian Bureau of Statistics.

Table 10. Granger Causality Test for AFSI and Unemployment Growth

	F-statistic	p-value
Exclude Lagged AFSI in Unemployment Growth Equation	14.06	0.0028
Exclude Lagged Unemployment Growth in AFSI Equation	10.32	0.0160

Our findings suggest that we can reject the null hypothesis that the AFSI does not Granger-cause unemployment growth, suggesting that including the AFSI helps to improve the forecasts of the unemployment growth.

5.1.4 Comparison with the ADB-AFSI

To further discuss the differences between our measure of financial stress in Australia and the index from the Asian Development Bank, we run the same set of Granger causality tests for the

ADB-AFSI. These can be found in Appendix C. The AFSI generally shows stronger negative correlation with real GDP per capita growth and bank credit. Furthermore, the correlation of the unemployment rate and the ADB-AFSI is negative for all reported lags. This suggests that periods of higher financial stress are associated with lower unemployment rates at all lags, a finding that is not consistent with other FSI studies and economic theory.

Regarding Granger causality tests for the ADB-AFSI and real GDP per capita and bank credit (Tables 17–20), we find similar results to what we found for our measure. Next, we take a closer look at how well the AFSI and the ADB-AFSI can help predict different credit supply measures. To do so, we use monthly data on different credit measures from the RBA from December 1989 to June 2019.[35] Table 11 and Table 12 report the results for the Granger causality tests for the AFSI and the ADB-AFSI, respectively.

From Table 11, we can reject the null hypothesis that the AFSI does not Granger-cause loans provided by banks, nonbank financial intermediaries (NBFIs), authorized financial intermediaries (AFIs), narrow credit (both raw and seasonally adjusted), total credit (both raw and seasonally adjusted), personal credit, and business credit (seasonally adjusted). In contrast, we can only reject the null hypothesis for the ADB-AFSI for a smaller set of credit measures, including NBFI loans, total credit, personal credit, and business credit (both raw and seasonally adjusted).

These findings indicate that our measure, the AFSI, can better capture financial stress that affects credit issued by different types of financial intermediaries.[36] Arguably, capturing the effect of financial stress on bank credit is relevant since the availability of credit can affect broader aspects of the economy through loan provision to firms and households. This is even more important for Australia, where banks play such an important role.

[35]The RBA discontinued most measures of credit in June 2019. We therefore use the available data from December 1989 to June 2019. Owner-occupied and investor housing credit data only start in March 1990, so these tests include data from March 1990 to June 2019. We apply first differences to all credit-level data used here.

[36]In Appendix D we show that our index does not perform worse when using the new measures of bank credit provided by the RBA from 2003 onward.

Table 11. Granger Causality Test for the AFSI and Credit Measures

Variable	Test	F-statistic	p-value
Loans and Advances, Banks	Exclude Lagged AFSI in Bank Loans Equation Exclude Lagged Bank Loans in AFSI Equation Lags: 4	22.2488 8.3634	0.0002 0.0791
Loans and Advances, NBFIs	Exclude Lagged AFSI in NBFI Loans Equation Exclude Lagged NBFI in AFSI Equation Lags: 3	11.6075 2.9293	0.0089 0.4027
Loans and Advances, AFIs	Exclude Lagged AFSI in AFI Loans Equation Exclude Lagged AFI Loans in AFSI Equation Lags: 4	23.094 8.1393	0.0001 0.0866
Narrow Credit	Exclude Lagged AFSI in Narrow Credit Equation Exclude Lagged Narrow Credit in AFSI Equation Lags: 4	23.6589 8.5961	0.0001 0.0720
Narrow Credit, Seasonally Adjusted	Exclude Lagged AFSI in Narrow Credit Equation Exclude Lagged Narrow Credit in AFSI Equation Lags: 4	21.8975 8.3190	0.0002 0.0806
Total Credit	Exclude Lagged AFSI in Total Credit Equation Exclude Lagged Total Credit in AFSI Equation Lags: 4	36.0782 5.7090	0.0000 0.2220

(*continued*)

Table 11. (Continued)

Variable	Test	F-statistic	p-value
Total Credit, Seasonally Adjusted	Exclude Lagged AFSI in Total Credit Equation Exclude Lagged Total Credit in AFSI Equation Lags: 4	28.1110 5.1145	0.0000 0.2758
Credit, Other Personal	Exclude Lagged AFSI in Personal Credit Equation Exclude Lagged Personal Credit in AFSI Equation Lags: 1	20.8905 0.0726	0.0000 0.7876
Credit, Other Personal Seasonally Adjusted	Exclude Lagged AFSI in Personal Credit Equation Exclude Lagged Personal Credit in AFSI Equation Lags: 1	22.4004 0.1342	0.0000 0.7141
Credit, Business	Exclude Lagged AFSI in Business Credit Equation Exclude Lagged Business Credit in AFSI Equation Lags: 4	27.7112 14.2483	0.0000 0.0065
Credit, Business Seasonally Adjusted	Exclude Lagged AFSI in Business Credit Equation Exclude Lagged Business Credit in AFSI Equation Lags: 4	27.2603 8.2513	0.0000 0.0828

Table 12. Granger Causality Test for the ADB-AFSI and Credit Measures

Variable	Test	F-statistic	p-value
Loans and Advances, Banks	Exclude Lagged ADB-AFSI in Bank Loans Equation Exclude Lagged Bank Loans in ADB-AFSI Equation Lags: 4	8.0121 17.2129	0.0911 0.0018
Loans and Advances, NBFIs	Exclude Lagged ADB-AFSI in NBFI Loans Equation Exclude Lagged NBFI in ADB-AFSI Equation Lags: 1	11.2912 2.0099	0.0008 0.1563
Loans and Advances, AFIs	Exclude Lagged ADB-AFSI in AFI Loans Equation Exclude Lagged AFI Loans in ADB-AFSI Equation Lags: 4	7.6486 13.8595	0.1053 0.0078
Narrow Credit	Exclude Lagged ADB-AFSI in Narrow Credit Equation Exclude Lagged Narrow Credit in ADB-AFSI Equation Lags: 4	8.2089 14.4880	0.0842 0.0059
Narrow Credit, Seasonally Adjusted	Exclude Lagged ADB-AFSI in Narrow Credit Equation Exclude Lagged Narrow Credit in ADB-AFSI Equation Lags: 4	6.3480 12.0763	0.1746 0.0168

(*continued*)

Table 12. (Continued)

Variable	Test	F-statistic	p-value
Total Credit	Exclude Lagged ADB-AFSI in Total Credit Equation Exclude Lagged Total Credit in ADB-AFSI Equation Lags: 4	14.4971 7.7822	0.0059 0.0999
Total Credit, Seasonally Adjusted	Exclude Lagged ADB-AFSI in Total Credit Equation Exclude Lagged Total Credit in ADB-AFSI Equation Lags: 3	10.3091 3.6897	0.0161 0.2970
Credit, Other Personal	Exclude Lagged ADB-AFSI in Personal Credit Equation Exclude Lagged Personal Credit in ADB-AFSI Equation Lags: 1	9.3461 3.7708	0.0022 0.0522
Credit, Other Personal Seasonally Adjusted	Exclude Lagged ADB-AFSI in Personal Credit Equation Exclude Lagged Personal Credit in ADB-AFSI Equation Lags: 1	11.4972 3.6002	0.0007 0.0578
Credit, Business	Exclude Lagged ADB-AFSI in Business Credit Equation Exclude Lagged Business Credit in ADB-AFSI Equation Lags: 3	11.8086 6.3501	0.0081 0.0958
Credit, Business Seasonally Adjusted	Exclude Lagged ADB-AFSI in Business Credit Equation Exclude Lagged Business Credit in ADB-AFSI Equation Lags: 4	13.4456 9.3113	0.0093 0.0538

5.2 Responses to an AFSI Shock

In this section we estimate the effect of a financial stress shock, as measured by an increase in AFSI, on the unemployment rate, growth of bank loans, retail sales growth (as a proxy for the real GDP per capita growth), and the growth rate of the money supply. In order to do so, we utilize a time-varying parameter (TVP) VAR model with stochastic volatility developed by Primiceri (2005) and Nakajima (2011). The TVP-VAR model has an advantage over the constant parameter VAR models in that it does not need arbitrarily divide data into subsamples to identify the change of structure of the model. Instead, the model allows both time variation in the simultaneous relations among variables. This can occur due to variations in the structural dynamic equations relating the various macroeconomic aggregates. It also allows heteroskedasticity in the innovations, which can be driven by changes in the size of exogenous shocks or their impact on macroeconomic variables.

A TVP-VAR model is estimated using monthly data from January 1990 to August 2023. The basic structural model is given by

$$A_t Y_t = F_{1,t} Y_{1,t-1} + \ldots + F_{s,t} Y_{s,t-s} + u_t, \tag{4}$$

where Y_t is a vector that includes the AFSI, growth of broad money supply, credit growth, retail sales growth as a proxy for the real GDP per capita growth, and growth of broad money. $A_t, F_{1,t}, ...F_{s,t}$ represent 5×5 matrices of coefficients that we are going to estimate. Finally, u_t is a 5×1 structural shock where $u_t \sim N(0, \Sigma_t \Sigma_t)$. We specify the simultaneous relations of the structural shocks by recursive identification, assuming that A_t is lower-triangular. More precisely, we have the following structure:

$$\Sigma_t = \begin{pmatrix} \sigma_{1,t} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{2,t} & 0 & 0 & 0 \\ 0 & 0 & \sigma_{3,t} & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4,t} & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5,t} \end{pmatrix} \quad \text{and}$$

$$A_t = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21,t} & 1 & 0 & 0 & 0 \\ a_{31,t} & a_{32,t} & 1 & 0 & 0 \\ a_{41,t} & a_{42,t} & a_{43,t} & 1 & 0 \\ a_{51,t} & a_{52,t} & a_{53,t} & a_{54,t} & 1 \end{pmatrix}.$$

Note that Equation (4) can be rewritten as follows:

$$Y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t \quad \text{where}$$
$$X_t = I_5 \otimes (Y_{t-1}, \ldots, Y_{t-s}) \quad \text{and} \quad \varepsilon_t \sim N(0, I_5).$$

Following Primiceri (2005), let $a_t = (a_{21,t}, a_{31,t}, ..., a_{54,t})'$ be a stacked vector of the lower-triangular elements in A_t, and $h_t = (\log\sigma_{1,t}^2, ..., \log\sigma_{5,t}^2)'$. We further assume that the time-varying parameters follow a random walk process as follows: $\beta_{t+1} = \beta_t + u_{\beta t}$, $a_{t+1} = a_t + u_{at}$, $h_{t+1} = h_t + u_{ht}$, where the disturbances have the following structure:

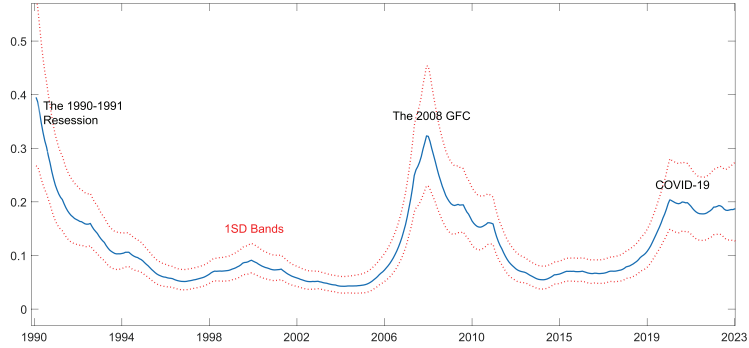
$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & O & O & O \\ O & \Sigma_\beta & O & O \\ O & O & \Sigma_a & O \\ O & O & O & \Sigma_h \end{pmatrix}\right).$$

We estimate the model using the Bayesian methods described as in Nakajima (2011) and choose the number of the VAR lags to be one.

5.2.1 Stochastic Volatility of the AFSI

First, we estimate the stochastic volatility of a financial stress shock from the period of January 1990 to August 2023. Figure 11 depicts our estimate and the associated standard deviation over time. Notably, the stochastic volatility exhibits three significant spikes, each corresponding to major economic disruptions. The initial surge is observed during the 1990–91 recession in Australia, marking a period of heightened economic uncertainty and financial stress. This spike reflects the domestic challenges Australia faced, including high interest rates and a contracting economy. The second notable increase in volatility occurred in response to the GFC

Figure 11. Posterior Estimate for Stochastic Volatility of Financial Stress Shock



in 2008. This event represented a profound and widespread shock to the global financial system, resulting in severe repercussions for financial markets worldwide, including Australia. The magnitude of this spike surpasses that of the 1990–91 recession, underscoring the global nature and severity of the GFC. The third spike, while less pronounced than the 2008 surge, was observed during and following the COVID-19 pandemic. Noteworthy in this instance is the volatility's persistence over time, suggesting a lingering uncertainty and ongoing adjustments in financial markets in response to the unprecedented global health crisis and its economic implications.

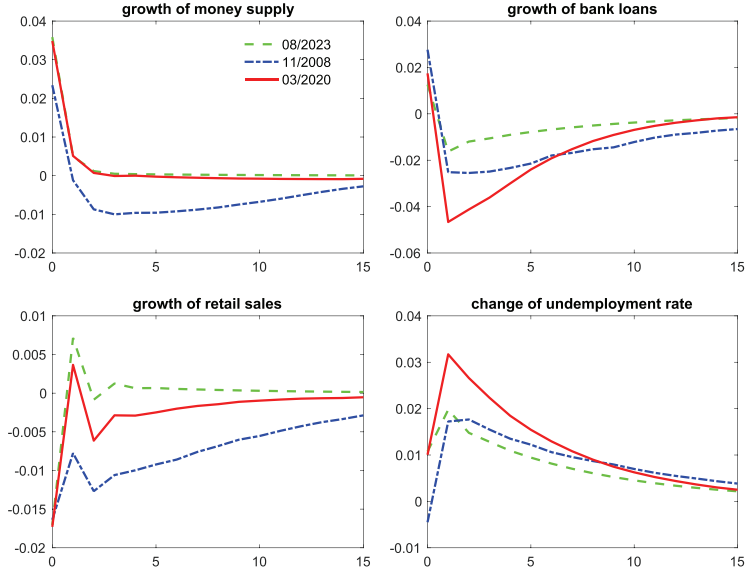
5.2.2 Impulse Responses

Next, we examine the impulse responses of macroeconomic variables to an increase of the financial stress across three periods: November 2008, March 2020, and August 2023, with the latter period characterized by notably lower financial stress.[37] This analysis, depicted in Figure 12, aims to understand the different impacts of financial shocks contingent on the prevailing levels of financial stress.

Understanding the differential impacts of financial stress shocks on essential economic indicators (such as money supply growth, bank loan growth, retail sales growth, and changes in unemployment rates) is crucial. These impacts largely hinge on the prevailing levels

[37] Our results are robust to including two or three lags.

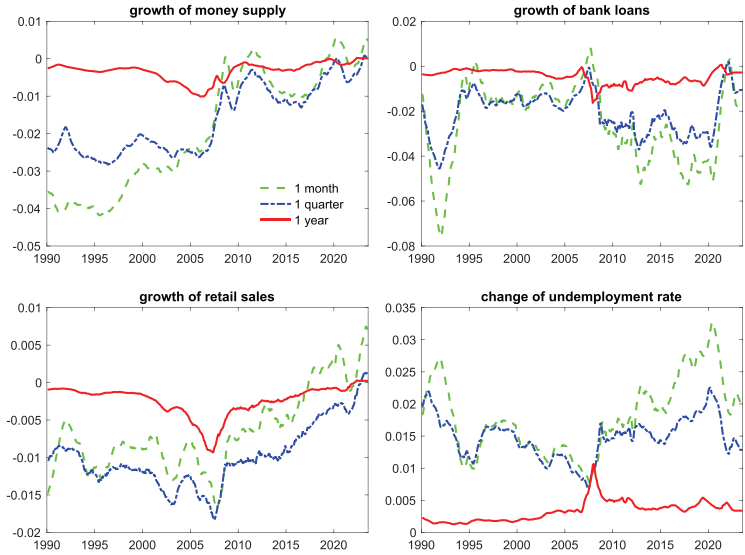
Figure 12. Impulse Responses to a Financial Stress Shock



of financial stress within the economy. Generally, a financial stress shock triggers an initial increase in both money supply growth and bank loan growth, followed by a notable decline to negative growth, before eventually stabilizing. Retail sales growth typically experiences a decline following a financial stress shock, with a subsequent period of recovery. Yet, in times of heightened levels and volatility of financial stress, the downturns in bank loan growth and retail sales growth are both more profound and prolonged. The impact on unemployment rates during periods of low financial stress, such as in August 2023, is markedly less pronounced than during more turbulent periods, like in March 2020.

Figure 13 illustrates the differential impacts on money supply growth, credit growth, retail sales growth, and changes in the unemployment rate at various intervals post-shock—specifically, one month (illustrated in green), one quarter (in blue), and one year (in red) following the event. A key observation is that the effects of an increase in financial stress are more pronounced in the short term (one month/one quarter) than over a one-year horizon. This finding

Figure 13. Time-Varying Responses to a Financial Stress Shock for the Whole Sample



underscores the critical value of higher-frequency data when analyzing a financial stress index. Moreover, the impulse responses for money supply growth, bank loan growth, and retail sales growth to a financial stress shock tend to be negative across all examined time horizons one quarter after the shock. Changes in the unemployment rate are positive across all time horizons. Yet, the intensity of these effects gradually wanes over time, leading to a negligible impact on all measured indicators a year following the initial shock. An exception is in the case of the Global Financial Crisis, where the impact can remain significant even after a year, underscoring the profound and enduring effects of major financial disturbances.

6. Conclusion

Theory and empirical findings have emphasized the strong and negative connection between stress episodes on financial markets and macroeconomic instability. Thus, it is important to continuously develop and improve tools for the timely capture of financial market

disruptions. In this spirit, in this paper we develop the Australian Financial Stress Index (AFSI) that is based on monthly data on interest rates of public and private liabilities, exchange rates, international interest rate spreads on public debt, housing price growth, and inflation expectations. We find that the first four AFSI principal components are private bank's funding cost (first component), the safe and liquid asset and exchange rate (second component), the inflation expectation and the U.S. real sovereign debt spread (third component), as well as equity volatility (fourth component). A decomposition of the AFSI into foreign and domestic factors shows that two-thirds of financial stress in Australia can be attributed to financial stresses arising from external factors. We also show that the AFSI contains relevant information that might be of interest to both investors and policymakers. In particular, we find that the AFSI can improve forecasts for various credit measures. Finally, we estimate the effect of a financial stress shock, as measured by an increase in AFSI, on the macro-observables using a TVP-VAR analysis. We find that financial stress can have nonlinear effects on important macroeconomic aggregates. In particular, an increase in financial stress has more adverse effects on bank credit growth if disruption in financial markets, as measured by the AFSI, is high. The various findings regarding the information content of the AFSI further highlight the importance and usefulness of having a measure of financial stress that policymakers can use as a timely signal of future economic activity.

Appendix A. Data Series and Sources

Table A.1. Data Series and Sources

Data Series	Data Source
Asian Development Bank FSI Australia	Asia Regional Integration Center, Asian Development Bank, https://aric.adb.org/database/fsi, accessed on September 13, 2021
ASX200 Banking Index	Global Financial Data[a]: Global Financial Data_AXBAJD
ASX200 Composite Index	Global Financial Data: Global Financial Data_AXJOD
Australia CPI	Reserve Bank of Australia: Consumer Price Inflation G1–GCPIAG
Australian GDP	Reserve Bank of Australia: Gross Domestic Product and Income H1-GGDPCVGDP (Dec. 1989–July 2003) Melbourne Institute, Monthly Inflation Gauge downloaded from Bloomberg (Aug. 2003–Aug. 2019) Australian Bureau of Statistics, Monthly CPI indicator (Sept. 2019–Aug. 2023)
Australian Three-Month Interbank Rate (BBSW)	Global Financial Data: Global Financial Data_IBAUS3D
Australian Three-Month Treasury Bill Yield	Global Financial Data: Global Financial Data_ITAUS3D
BAB Three-Month	Reserve Bank of Australia: Interest Rates and Yields – Money Market – Monthly-F1.1FIRMMBAB90
Broad Money Growth	Reserve Bank of Austrlaia: Monetary Aggregates – D3-DMABMN
Cash Rate Target	Reserve Bank of Australia: Interest Rates and Yields – Money Market – Monthly – F1.1 – FIRMMCRI
Central Bank Assets	Reserve Bank of Australia: Liabilities and Assets – detailed – A1.1 – ARBAATAW
Commonwealth Government 5-Year Bond Yield	Reserve Bank of Australia: Capital Market Yields – Government Bonds – Monthly – F2.1 – FCMYGBAG5
Commonwealth Government 10-Year Bond Yield	Reserve Bank of Australia: Capital Market Yields – Government Bonds – Monthly – F2.1 – FCMYGBAG10
Credit	Reserve Bank of Australia: Lending and Credit Aggregates – Table D2
Credit Growth	Reserve Bank of Australia: Growth in Selected Financial Aggregates – D1 DGFACM (Dec. 1989–April 2002)/ D1 – GFFACNFM (May 2002–August 2023)
Daily Confirmed COVID-19 Cases in Australia	WHO (https://covid19.who.int/region/wpro/country/au)
Economic Policy Uncertainty Index	https://www.policyuncertainty.com/, accessed on September 16, 2021

(*continued*)

Table A.1. (Continued)

Data Series	Data Source
Effective Exchange Rate	Reserve Bank of Australia: Exchange Rates – Daily and Monthly – F11 – FXRTWI
Financial Stress Index for China	Asia Regional Integration Center, Asian Development Bank, https://aric.adb.org/database/fsi, accessed on September 13, 2021
Financial Stress Index for Japan	Asia Regional Integration Center, Asian Development Bank, https://aric.adb.org/database/fsi, accessed on October 20, 2022
Financial Stress Index for South Korea	Asia Regional Integration Center, Asian Development Bank, https://aric.adb.org/database/fsi, accessed on October 20, 2022
Housing Price Growth	Sirca: Sirca_CoreLogic_Hedonic Home Value_8 Combined Capital Cities[b]
Inflation-Indexed 10-Year Bond Yield	Global Financial Data: Global Financial Data_IGAUSID (Dec. 1989–March 2023) Global Financial Data: Global Financial Data_IGAUSI10D (April 2023–Aug. 2023)
Kansas City Fed Financial Stress Index	FRED, https://fred.stlouisfed.org/series/KCFSI, accessed September 13, 2021
Population in Australia	Australian Bureau of Statistics, https://www.abs.gov.au/statistics/people/population
Retail Sales Growth	Reserve Bank of Australia: Monthly activity indicators H3-GISSRTCYP
St. Louis Fed Financial Stress Index	FRED, https://fred.stlouisfed.org/series/STLFSI4, accessed November 17, 2023
Unemployment Rate, Australia	Australian Bureau of Statistics, A84423094C
U.S. 5-Year Government Bond Yield	FRED, Federal Reserve Bank of St. Louis: 5-Year Treasury Constant Maturity Rate [DGS5], https://fred.stlouisfed.org/series/DGS5, accessed September 14, 2023
U.S. CPI	Organisation for Economic Co-operation and Development, Consumer Price Index: All Items for the United States [USACPIALLMINMEI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USACPIALLMINMEI, September 18, 2023

[a]Data from Global Financial Data were obtained by Romina Ruprecht under the purview of Federal Reserve Board licenses. The remaining coauthors, Pedro Gomis-Porqueras, Xiaoyang Li, and Xuan Zhou, did not have any unauthorized access to this data while working on this paper.
[b]Sirca data were obtained by Xiaoyang Li under the purview of Deakin University licenses. The remaining coauthors, Pedro Gomis-Porqueras, Xuan Zhou, and Romina Ruprecht, did not have any unauthorized access to this data while working on this paper.

Appendix B. Decomposition Robustness Tests

Here, we provide some robustness tests for our decomposition results. In addition to financial stress indices from the United States and China, we also include indices from Japan and South Korea (as computed by the Asian Development Bank) in our regression. Thus, we estimate the following regression:

$$\begin{aligned} \text{AFSI}_t = \beta_0 + \beta_1 \text{FSI}_{US,t} + \beta_2 \text{FSI}_{China,t} + \beta_3 \text{FSI}_{Japan,t} \\ + \beta_4 \text{FSI}_{SouthKorea,t} + \varepsilon_t, \end{aligned} \tag{5}$$

where the coefficients β_1 and β_2 measure the contribution of financial stress stemming from the United States and China, respectively, and the coefficients β_3 and β_4 measure the contribution of financial stress from Japan and South Korea, respectively. The residual ε_t can be interpreted as the component of financial stress that does not arise from the United States, China, Japan, and South Korea.

Table B.1. Regression Results of the AFSI Decomposition

	Regression				
	(i)	**(ii)**	**(iii)**	**(iv)**	**(v)**
Intercept	0.0774	0.0600	0.0522	0.2380*	0.2277**
	(0.1111)	(0.1407)	(0.1268)	(0.1452)	(0.1322)
STLFSI	0.7600***				
	(0.1033)				
KCFSI		0.7893***	0.8109***	0.5924***	0.6432***
		(0.0827)	(0.1148)	(0.0866)	(0.0951)
CHFSI	0.0789	0.0733	0.0926	–0.0305	0.0207
	(0.0751)	(0.0870)	(0.1422)	(0.1192)	(0.1550)
South Korea			–0.0349		–0.1067
FSI			(0.1604)		(0.1403)
Japan FSI				0.22306**	0.2402**
				(0.1090)	(0.1105)
Adjusted R^2	0.6499	0.6669	0.6676	0.6583	0.6635
RMSE	1.1459	0.8881	0.6510	2.9694	2.8417
No. of Observations	219	219	219	219	219

Note: Newey-West standard errors are in parentheses. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

We refer to this as the domestic component. The data cover a period from January 1995 to August 2020. Our results are reported in Table B.1. Regressions (i) and (ii) report the results using the stress indices from the U.S. and China, where (i) includes the STLFSI and (ii) includes the KCFSI as in the main text. Regression (iii) includes the stress index for Japan and Regression (iv) includes the stress index for South Korea. Regression (v) includes indices for the U.S., China, Japan, and South Korea. Specifications (ii), (iii), and (v) are presented in the main text. We replicate them here for convenience.

As Table B.1 shows, using the KCFSI instead of the STLFSI increases the adjusted R^2 and lowers the RMSE. The coefficients for the KCFSI and the CHFSI are similar across specifications.

Appendix C. Robustness Tests with the Financial Stress Index for Australia from the Asian Development Bank

In this section, we show additional comparisons for the AFSI and the ADB-AFSI. Table C.1 shows the correlations of the Australian financial stress index from the Asian Development Bank (ADB-AFSI) with real GDP per capita, bank credit, and unemployment growth including lags of 15 months and 37 months.

As discussed above in Section 5, the ADB-FSI exhibits a lower correlation with real GDP per capita growth GDP and bank credit growth compared with the AFSI. Furthermore, the ADB-AFSI shows a negative correlation with unemployment over all shown lags, suggesting that unemployment is low after a period of financial stress

Table C.1. Correlation between the ADB-AFSI, GDP per Capita Growth, Bank Credit Growth, and the Unemployment Rate

Real GDP per Capita (1)	Bank Credit (2)	UR_t (3)	UR_{t+15} (4)	UR_{t+37} (5)
–0.1317	–0.2063	–0.0512	–0.1601	–0.1058
Note: Lags: 2.				

measured by the ADB-AFSI in the same period, as well as 18 and 36 months later.

In contrast, our estimate of the AFSI exhibits negative correlation with real GDP per capita growth, as does the ADB-AFSI. However, our estimate shows a positive correlation with unemployment, suggesting that when financial stress is higher, unemployment is higher in the same period, as well as 18 and 36 months later.

Tables C.2–C.5 show Granger causality tests for the ADB-AFSI with real GDP per capita growth, bank credit, and unemployment growth. Lags were chosen based on the AIC, where the maximum number of lags was set to 4 for real GDP per capita growth, credit growth, and retail sales growth and to 40 for unemployment growth.

Based on these results, we cannot reject the null hypothesis that the ADB-AFSI does not Granger-cause unemployment growth. Therefore, including the ADB-AFSI cannot improve forecasts of the unemployment rate relative to forecasts based solely on previous values of the unemployment rate.

Table C.2. Granger Causality Test for the ADB-AFSI and Real GDP per Capita Growth

	F-statistic	**p-value**
Exclude Lagged ADB-AFSI in Real GDP per Capita Growth Equation	4.433	0.1090
Exclude Lagged Real GDP per Capita Growth in AFSI Equation	0.8819	0.6434
Note: Lags: 2.		

Table C.3. Granger Causality Test for the ADB-AFSI and Bank Credit Growth

	F-statistic	**p-value**
Exclude Lagged ADB-AFSI in Bank Credit Growth Equation	22.256	0.0002
Exclude Lagged Bank Credit Growth in AFSI Equation	6.8256	0.1454
Note: Lags: 4.		

Table C.4. Granger Causality Test for ADB-AFSI and Bank Credit Growth

	F-statistic	p-value
Bank Credit Growth: December 1989 to August 2023 (Lags: 4)		
Exclude Lagged ADB-AFSI in Bank Credit Growth Equation	22.256	0.0002
Exclude Lagged Bank Credit Growth in ADB-AFSI Equation	6.8256	0.1454
Bank Credit Growth: December 1989 to June 2019 (Lags: 4)		
Exclude Lagged AFSI in Bank Credit Growth Equation	11.268	0.0237
Exclude Lagged Bank Credit Growth in AFSI Equation	8.5839	0.0724
Bank Credit Growth: August 2019 to August 2023 (Lags: 2)		
Exclude Lagged AFSI in Bank Credit Growth Equation	9.9286	0.0070
Exclude Lagged Bank Credit Growth in AFSI Equation	5.4477	0.0656

Table C.5. Granger Causality Test for ADB-AFSI and Unemployment Growth

	F-statistic	p-value
Exclude Lagged ADB-AFSI in Unemployment Growth Equation	7.61	0.055
Exclude Lagged Unemployment Growth in AFSI Equation	1.80	0.614
Note: Lags: 27.		

Appendix D. Additional Granger Causality Tests to Compare the AFSI and the ADB-AFSI

In Section 5, we provide additional Granger causality test results for both the AFSI and the ADB-AFSI using credit data from December 1989 to June 2019. Since the RBA has changed its credit data reporting, in this appendix we report Granger causality tests using the revised credit data from the RBA, which are available from April 2003 to August 2023. Tables D.1 and D.2 report the results from the Granger causality tests. Based on these results, we conclude that the AFSI does not do worse than the ADB-AFSI for credit data starting from 2003.

Table D.1. Granger Causality Test for the AFSI and Credit Measures

Variable	Test	F-statistic	p-value
Loans and Advances, Banks Excluding Financial Businesses	Exclude Lagged AFSI in Bank Loans Equation	9.5814	0.0225
	Exclude Lagged Bank Loans in AFSI Equation Lags: 3	20.9241	0.0001
Loans and Advances, NBFIs Excluding Financial Businesses	Exclude Lagged AFSI in NBFI Loans Equation	4.5171	0.1045
	Exclude Lagged NBFI in AFSI Equation Lags: 2	0.5522	0.7588
Loans and Advances, AFI Excluding Financial Businesses	Exclude Lagged AFSI in AFI Loans Equation	7.5488	0.0060
	Exclude Lagged AFI Loans in AFSI Equation Lags: 1	16.1860	0.0001
Bills on Issue to Nonfinancial Businesses	Exclude Lagged AFSI in Bills Equation	3.7466	0.2902
	Exclude Lagged Bills in AFSI Equation Lags: 3	0.2151	0.5900
Narrow Credit Excluding Financial Businesses	Exclude Lagged AFSI in Narrow Credit Equation	8.5291	0.0363
	Exclude Lagged Narrow Credit in AFSI Equation Lags: 3	13.6634	0.0034
Narrow Credit, Seasonally Adjusted Excluding Financial Businesses	Exclude Lagged AFSI in Narrow Credit Equation	5.9286	0.0516
	Exclude Lagged Narrow Credit in AFSI Equation Lags: 2	10.3344	0.0057

(*continued*)

Table D.1. (Continued)

Variable	Test	F-statistic	p-value
Total Credit Excluding Financial Businesses	Exclude Lagged AFSI in Total Credit Equation	22.9395	0.0000
	Exclude Lagged Total Credit in AFSI Equation Lags: 1	13.6915	0.0034
Total Credit, Seasonally Adjusted Excluding Financial Businesses	Exclude Lagged AFSI in Total Credit Equation	23.3618	0.0001
	Exclude Total Credit in AFSI Equation Lags: 1	6.6152	0.1577
Credit, Nonfinancial Business	Exclude Lagged AFSI in Nonfinancial Credit Equation	15.5636	0.0014
	Exclude Nonfinancial Credit in AFSI Equation Lags: 3	21.2900	0.0001
Credit, Nonfinancial Business, Seasonally Adjusted	Exclude Lagged AFSI in Nonfinancial Credit Equation	23.0124	0.0001
	Exclude Nonfinancial Credit in AFSI Equation Lags: 4	16.1270	0.0029

Table D.2. Granger Causality Test for the ADB-AFSI and Credit Measures

Variable	Test	F-statistic	p-value
Loans and Advances, Banks Excluding Financial Businesses	Exclude Lagged ADB-AFSI in Bank Loans Equation	14.4105	0.0061
	Exclude Lagged Bank Loans in ADB-AFSI Equation Lags: 4	14.3722	0.0062
Loans and Advances, NBFIs Excluding Financial Businesses	Exclude Lagged ADB-AFSI in NBFI Loans Equation	4.6421	0.0312
	Exclude Lagged NBFI in ADB-AFSI Equation Lags: 1	0.0949	0.7580
Loans and Advances, AFIs Excluding Financial Businesses	Exclude Lagged ADB-AFSI in AFI Loans Equation	6.3308	0.0966
	Exclude Lagged AFI Loans in ADB-AFSI Equation Lags: 3	8.9647	0.0298
Bills on Issue to Nonfinancial Businesses	Exclude Lagged ADB-AFSI in Bills Equation	1.2196	0.7483
	Exclude Lagged Bills in ADB-AFSI Equation Lags: 3	1.6605	0.6457
Narrow Credit Excluding Financial Businesses	Exclude Lagged ADB-AFSI in Narrow Credit Equation	5.5836	0.1337
	Exclude Lagged Narrow Credit in ADB-AFSI Equation Lags: 3	8.6016	0.0351

(*continued*)

Table D.2. (Continued)

Variable	Test	F-statistic	p-value
Narrow Credit, Seasonally Adjusted Excluding Financial Businesses	Exclude Lagged ADB-AFSI in Narrow Credit Equation	5.3640	0.1470
	Exclude Lagged Narrow Credit in ADB-AFSI Equation Lags: 3	8.1959	0.0421
Total Credit Excluding Financial Businesses	Exclude Lagged ADB-AFSI in Total Credit Equation	24.3419	0.0001
	Exclude Lagged Total Credit in ADB-AFSI Equation Lags: 1	10.3046	0.0356
Total Credit, Seasonally Adjusted Excluding Financial Businesses	Exclude Lagged ADB-AFSI in Total Credit Equation	27.8683	0.0000
	Exclude Total Credit in ADB-AFSI Equation Lags: 4	12.3426	0.0150
Credit, Nonfinancial Business	Exclude Lagged ADB-AFSI in Nonfinancial Credit Equation	16.2134	0.0027
	Exclude Nonfinancial Credit in ADB-AFSI Equation Lags: 4	25.0822	0.0000
Credit, Nonfinancial Business, Seasonally Adjusted	Exclude Lagged ADB-AFSI in Nonfinancial Credit Equation	20.9798	0.0003
	Exclude Nonfinancial Credit in ADB-AFSI Equation Lags: 4	33.7262	0.0000

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Macroprudential Policy and Income Inequality: The Trade-Off Between Crisis Prevention and Credit Redistribution*

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Using data on 105 countries from 1990 to 2019 and a lag-augmented local projection method, we document that macroprudential policy tightening affects income inequality through two key channels: the crisis mitigation and prevention channel and the credit redistribution channel. Through the first of these, tighter regulation during credit booms reduces income inequality and mitigates the redistributive effects of financial crises, reflecting the enhanced financial sector's resilience. Through the second, it contributes to higher inequality due to its negative effect on credit growth and property prices. This has important policy

*The views expressed are those of the authors and not necessarily those of the Czech National Bank. We gratefully acknowledge comments and suggestions from the associate editor Tobias Adrian and two anonymous referees. We are also thankful to Georgina Green, Mark Joy, Stine Louise von Rüden, Mikael Juselius, David Aikman, Jan Brůha, and Adam Geršl, as well as seminar and conference participants at the 7th Annual Workshop of ESCB Research Cluster 3 on Financial Stability, Macroprudential Regulation and Microprudential Supervision. All errors and omissions remain the fault of the authors. Simona Malovaná acknowledges support from the European Regional Development Fund project "Center for Inequality and Open Society" (reg. no.: CZ.02.01.01/00/23_025/0008690), Czech Science Foundation (Project No. 24-12098S), and Charles University Research Centre Program No. 24/SSH/020. Martin Hodula acknowledges support from Institutional Research Grant No. IP100040. Jan Janků acknowledges support from the SGS project at VSB-Technical University of Ostrava (Grant No. SP2024/026). Author emails: Simona Malovaná (corresponding author): simona.malovana@cnb.cz; Jan Janků: jan.janku@cnb.cz; Martin Hodula: martin.hodula@cnb.cz

implications: the timely implementation of macroprudential regulation has preventive effects and can contribute to a more equal distribution of society's income.

JEL Codes: G01, G28, O15.

1. Introduction

Macroprudential policies have been widely implemented over the last two decades, most notably in response to the Global Financial Crisis (GFC) of 2008. Existing literature explores the impact of macroprudential policy on the financial sector and the real economy from multiple angles. Studies have established a strong link between these policies and credit dynamics (for a review, see Malovaná et al. 2021, 2025), acknowledged the ability of prudential policy to mitigate and prevent financial imbalances (Benigno et al. 2013; Galati and Moessner 2013), and evaluated its potential costs in the form of output losses (Richter, Schularick, and Shim 2019; Fidrmuc and Lind 2020).

As we move further away from the Global Financial Crisis, there is a risk that public debate will focus more on the immediate costs rather than the benefits of macroprudential policy. We are already witnessing a rising number of studies pointing to the distributional effect of monetary policy (Brunnermeier and Sannikov 2013; Auclert 2019; Albert and Gómez-Fernández 2021). Even the macroprudential policy is not a complete bystander in this debate. Using stylized models, several studies have pointed to the potential adverse effects of macroprudential borrower-based measures on income and wealth inequality (Carpantier, Olivera, and Van Kerm 2018; Tarne, Bezemer, and Theobald 2022).

In this paper, we show that changes in macroprudential policy affect income distribution across different countries. We examine this relationship in a large panel of 105 countries over the period from 1990 to 2019. We evaluate the impact on income inequality of both borrower-based measures (e.g., loan-to-value, debt-to-income, debt-service-to-income limits) and capital- and liquidity-based measures (e.g., capital buffers, liquidity requirements, or limits on credit growth). Our identification strategy accounts for the potential

endogeneity of macroprudential policy in empirical models of income inequality.

We provide empirical evidence that macroprudential policy measures can have both upward and downward effects on income inequality. We find that the direction of the effect depends heavily on the type of macroprudential policy measure used as well as on a broader set of macrofinancial conditions. This finding suggests that theoretical exploration in a stylized model could be difficult since different banking regulations under specific economic conditions can affect income distribution differently. To aid future research in this area, we empirically verify the presence of and describe the functioning of two channels through which macroprudential policy affects income inequality—the crises mitigation and prevention channel and the credit redistribution channel.

We show that through the channel of crisis mitigation and prevention, the macroprudential policy can reduce income inequality or (at least) mitigate the redistributive effect of financial crises, which are known to hit the poor harder (Lindquist 2004; Barlevy and Tsiddon 2006). More specifically, countries that have tightened macroprudential policy ex ante (before a crisis) have experienced a lesser rise in inequality following the crisis outburst. On the contrary, countries that have tightened their macroprudential policy only after a crisis outburst are found to experience a sharp rise in inequality. This contrasting evidence shows that preemptive macroprudential tightening is not associated with adverse redistribution effects, while repressive tightening is. We document similar findings when considering periods of heightened crisis probability (but without an observed crisis), which emphasizes even more the preemptive role of macroprudential policy. We find effects associated with crisis mitigation and prevention more persistent in the case of capital- and liquidity-based measures and emerging market economies. By exploring the cross-country dimension of our panel data, we find that the channel is more likely to dominate the transmission in countries with less capitalized, less developed, and more concentrated banking sectors.

While exploring the credit redistribution channel, we find that tighter macroprudential policy can lead to higher inequality through its negative effect on credit growth and house price growth. We find this channel dominant for borrower-based measures and advanced

countries. In addition, the channel is particularly strong during periods of accommodative monetary policy and in financially developed countries.

Our paper adds to at least two strands of literature. First, we contribute to the literature assessing income and wealth inequality determinants across countries (Dabla-Norris et al. 2015; Furceri and Ostry 2019). Many studies argue that financial development is an essential determinant of unequal income distribution. The literature generally agrees that financial development decreases income inequality since it improves access to credit (Demirgüç-Kunt and Levine 2009). However, at higher levels of financial development, deepening financial systems leads to a surge in top incomes (Mookerjee and Kalipioni 2010; Fouejieu et al. 2020). The finance-inequality literature has not (yet) explicitly considered the role of macroprudential policy. This might be an oversight, given that macroprudential policy significantly influences the financial sector.

Second, we add to the growing body of research that examines the financial and economic impacts of macroprudential policy. While the literature is less developed on the costs of such policies, some papers evaluate, for example, how these measures intervene with economic growth (Richter, Schularick, and Shim 2019). More studies have explored how macroprudential policies affect different population groups. For example, Peydro et al. (2020) and Acharya et al. (2022) show that macroprudential borrowing limits in the U.K. have affected low-income borrowers more than high-income borrowers. Park and Kim (2023) show that the application of loan-to-value (LTV) ceilings in South Korea has significantly widened household wealth inequality. In a paper closest to ours, Frost and van Stralen (2018) use panel regressions for 69 countries over the period 2000–13 and estimate a positive relationship between some macroprudential policy tools and income inequality. The paper provides a valuable first insight into this relationship which we extend in several dimensions. First, we focus on a broader panel of countries and cover a period that was much richer in macroprudential policy measures. Second, we aim to infer causality on the relationship, while Frost and van Stralen (2018) estimate associations. Third, we explore both the cross-country and time dimensions of the panel data in more detail.

Overall, we believe that the study assessing the potential impact of cross-country and time variations in macroprudential policy on

income distribution is highly timely and relevant to policymakers. This paper is, to our knowledge, the first to do so for such a rich panel of countries and periods and the number of implemented macroprudential policy measures.

The rest of the paper is structured as follows. Section 2 introduces data and provides a simple event study. Section 3 develops hypotheses. Section 4 describes our empirical approach and presents the main set of results. Section 5 explores the heterogeneity of our sample, and Section 6 concludes.

2. Data

When examining the impact of macroprudential policy measures on income inequality, we rely on country-level data. The data are annual in frequency and cover 105 countries for which information on income inequality is available for the period 1990–2019.[1] Table A.1 in Appendix A lists variable definitions and data sources.

2.1 Income Inequality

Our main variable to capture income inequality is the Gini index obtained from the Standardized World Income Inequality Database (SWIID), which provides the longest and widest sample of data. For each country in each year, the Gini index ranges from 0 (perfect equality) to 100 (perfect inequality). Our focus on income rather than wealth inequality stems from the fact that there are significant limitations in the availability of data on the distribution of wealth across countries (and the Gini index measuring wealth inequality), so we leave this investigation to future research. However, the Gini calculation is based on market income, which also includes nonlabor income, such as returns from financial and nonfinancial assets, so information on wealth distribution is not entirely missing.

Relying on market income to calculate the Gini index means that we track developments in income distribution before fiscal transfers and taxation. Given the strong link between fiscal measures

[1] While for some countries income inequality data can be traced further back in time, the importance of macroprudential policy before the 1990s is low to nonexistent.

and income inequality (Anderson et al. 2017), we might be concerned that institutional effects such as extraordinary public spending or fiscal transfers might pollute our estimates of the relationship between macroprudential policy and income inequality. However, we are interested in identifying the effect of macroprudential policies before such fiscal policies are typically implemented (e.g., during or after a recession). In addition, we rely on fixed-effects estimation, which should account for the fact that fiscal responses vary across countries and time and ultimately depend on the fiscal space and political forces at play (Leith and Wren-Lewis 2005).

Table 1 shows summary statistics of the Gini index for the entire period 1990–2019 and 10-year (non-overlapping) subperiods. We also consider the full sample and two subgroups according to the International Monetary Fund (IMF) country classification. To summarize, an increase in inequality can be observed in advanced economies (AE) over the years, while in emerging markets and developing countries (EMDE) inequality is relatively stable and has decreased slightly in recent years. The sample of advanced economies appears more homogeneous, while the sample of emerging markets and developing countries is very heterogeneous and includes both countries with very low inequality (Gini equal to 21.8) and countries with extreme inequality (Gini 72.3).

In the empirical analysis, we examine how the cyclical response of inequality to macroprudential policy measures. We use a broad set of controls to isolate long-term trends and employ a detrended measure of changes in the Gini index by subtracting the global trend and including the individual country trend in our regressions as a control. Details of this procedure are outlined in Section 4.

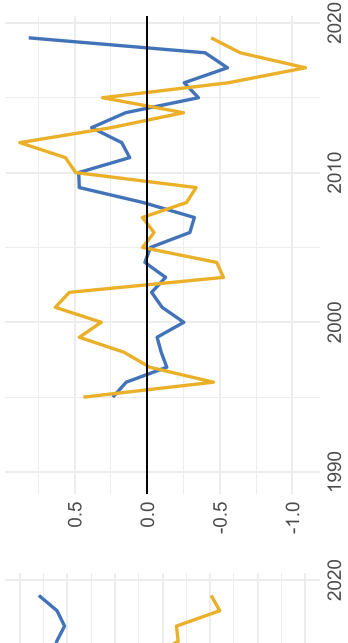
Figure 1 shows the evolution of the Gini index before and after detrending. The Gini trends upward in most advanced countries. At the same time, the development in EMDE is less straightforward, with Asia and Eastern Europe experiencing a significant increase in inequality and countries in Latin America showing a significant decrease. Dabla-Norris et al. (2015) demonstrate that rising income inequality in most advanced economies and some emerging markets has been driven primarily by the growing income share of the top 10 percent. The crisis has exacerbated these effects (Organisation for Economic Co-operation and Development 2014), which is well visible from the right-hand graph, showing a surge in inequality during the

Table 1. Summary Statistics of the Gini Index Over 1990–2019

	Level			Annual Growth Rate (%)			Cumulative Change (First Difference)		
	Mean	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**
Entire Period									
All Countries	45.49	21.8	72.3	0.11	–3.96	8.04	1.51	–9.50	13.50
AE	45.94	28.7	56.3	0.31	–3.07	6.35	3.14	–4.80	9.40
EMDE	45.23	21.8	72.3	0.01	–3.96	8.04	0.69	–9.50	13.50
1990–1999									
All Countries	44.75	23.1	68.4	0.38	–1.58	8.04	0.92	–1.30	11.40
AE	44.33	28.7	54.1	0.62	–1.58	6.35	1.55	–0.80	8.00
EMDE	45.00	23.1	68.4	0.26	–1.30	8.04	0.61	–1.30	11.40
2000–2009									
All Countries	45.82	22.5	72.3	0.08	–2.75	3.98	0.33	–4.80	5.90
AE	46.24	30.8	55.1	0.32	–2.75	3.28	0.83	–3.50	5.90
EMDE	45.61	22.5	72.3	–0.04	–2.23	3.98	0.08	–4.80	5.40
2010–2019									
All Countries	45.86	21.8	72.1	–0.12	–3.96	2.86	–0.27	–6.20	3.40
AE	47.25	30.5	56.3	–0.01	–3.07	2.47	0.28	–4.70	3.40
EMDE	44.99	21.8	72.1	–0.17	–3.96	2.86	–0.55	–6.20	2.90

Note: The table shows summary statistics for the market Gini index in different transformations (level, annual growth rate, and cumulative first difference). Each statistic is calculated as an average (minimum, maximum) across countries and periods in the sample group. The list of countries in each group is reported in Table A.2 in Appendix A.

Figure 1. Gini Index and Its Detrended Version



Note: The detrended Gini index is calculated as the Gini index minus the global trend, experessed as a percentage of the global trend.

post-GFC period in advanced countries. In some emerging markets and developing countries, the story is somewhat different. For example, the increase in inequality in China and South Africa appears to be primarily explained by the shift of income from the upper middle class to the upper class. In countries with falling inequality, such as Peru and Brazil, rising incomes can be seen for those at the bottom and middle of the income distribution.[2]

In addition to the Gini index, we consider income share groups. By focusing on changes to income shares of individual income groups, we address the fact that the Gini index captures changes around the median of the income distribution and can somewhat underestimate the effect of bottom and top income groups. Moreover, international data sources on income inequality are known for underrepresenting the top income groups.

2.2 Macroprudential Policy Measures

To capture macroprudential policy in individual countries, we rely on the Integrated Macroprudential Policy (iMaPP) database maintained by the IMF and introduced in Alam et al. (2019). From the database, we collect dummy-type indicators of tightening and loosening actions of various macroprudential policy instruments. The indices count the number of tightening (positive integer) and loosening (negative integer) actions in a given year. For example, a value of 3 means that the policy was tightened three times that year. The indices are based on the effective date, which is more widely available than the announcement date.

We categorize the instruments included in the database into two main groups—capital- and liquidity-based measures (CLBM) and borrower-based measures (BBM; Table A.3).[3] Generally, both types of instruments aim to enhance the financial sector's resilience and prevent and reduce excessive risk-taking and leverage among economic agents. However, their focus and transmission channels

[2]Figures A.1 and A.2 in the appendix show the heterogeneity of the Gini index across countries and time. Figure A.1 shows the broad distribution of the Gini index for EMDE, and Figure A.2 shows how the average inequality in AE has surpassed the inequality in EMDE over the years.

[3]We do not consider changes to reserve requirements as macroprudential instruments.

Table 2. Number of Macroprudential Policy Actions Over 1990–2019

	BBM		CLBM	
	No. of Events	**No. of Countries**	**No. of Events**	**No. of Countries**
All Countries	285	61	1,296	105
Advanced Economies	151	29	539	35
Emerging Markets and Developing Economies	134	32	757	70
Africa	2	1	62	12
Asia and Pacific	103	14	267	21
Europe	136	31	664	41
Middle and South America	9	5	152	15
Middle East and Central Asia	20	8	120	14
North America	15	2	31	2
1990–1999	7	6	67	39
2000–2009	87	30	233	72
2010–2019	191	49	996	96

Note: The table shows the total number of macroprudential policy actions in our sample. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). The number of events is calculated as a sum of the absolute value of the iMaPP indices, which can take both positive (macroprudential policy tightening) and negative (macroprudential policy easing) values. For example, a value of 3 means that the policy was tightened three times that year. The list of countries in each group is reported in Table A.2 in Appendix A.

differ. Capital- and liquidity-based measures are primarily aimed at banks and tasked to increase their resilience by building capital buffers to cover losses during unforeseen events. If crises hurt primarily the poor, then capital regulation should reduce income inequality. Borrower-based measures limit borrowing relative to the property value and borrower's income. Similarly to capital- and liquidity-based measures, borrower-based measures are also intended to reduce systemic risk. However, they can prevent riskier (poorer) borrowers from entering the credit market, reducing their future income.

Table 2 summarizes number of macroprudential policy measures implemented in all countries and individual geographic regions. As

can be seen, capital- and liquidity-based measures change more frequently than borrower-based measures. On average, we record 5 changes to borrower-based measures per country and 12 changes to capital- and liquidity-based measures per country. The number of borrower-based actions is almost equal in advanced economies as well as emerging markets and developing countries, while the capital- and liquidity-based measures change more frequently in emerging markets and developing countries.

Figures A.3 and A.4 in Appendix A provide a more detailed breakdown of policy actions taken in a given year by policy instrument. While the Global Financial Crisis and the implementation of the Basel III Accords have led to more frequent use of policy tools (Figure A.3), we do not observe a structural shift in the type of instruments used (Figure A.4), in line with observations made by Cerutti, Claessens, and Laeven (2017) and Alam et al. (2019).[4]

2.3 Control Variables

The control variables in our study come from the extensive literature on the determinants of income inequality (Dabla-Norris et al. 2015; Furceri and Ostry 2019) and studies that deal with the finance-inequality relationship (de Haan and Sturm 2017; Chiu and Lee 2019). In particular, we control for several macrofinancial variables and demographic factors.[5] We consider control variables in differences rather than levels, given that we focus on the cyclical development of income inequality. Summary statistics of our control variables are shown in Table A.4 in Appendix A.

First, we consider the real output gap and consumer price inflation to control for business cycle fluctuations and monetary conditions. Economists generally agree that cyclical fluctuations ultimately affect the distribution of earnings, with recessions hitting the poor hardest (Lindquist 2004; Barlevy and Tsiddon 2006). In the case of inflation, literature commonly assumes that low-income households are more vulnerable to rising inflation (Albanesi 2007). In

[4]These statements hold even when we group the sample countries into advanced and emerging economies and evaluate the use of macroprudential policy tools over time.

[5]Since our model specification includes country and time fixed effects, we do not control for time-invariant variables.

addition, we directly control for crisis periods by including a binary crisis dummy from Laeven and Valencia (2020).

Second, we control for trade and fiscal policy factors. Specifically, we represent a country's level of trade openness using the sum of exports and imports as a share of gross domestic product (GDP). Looking at it through standard Heckscher-Ohlin trade theory, trade openness increases income, but empirical estimates are inconclusive (Roine, Vlachos, and Waldenström 2009). We also control for government activity, as our measure of inequality is calculated from market income, i.e., before taxes and transfers. To this purpose, we include the ratio of central government expenditures as a share of GDP. Higher government spending is expected to help the poor primarily, but the strength of the effect can differ across countries with different levels of institutional development (Fatás and Mihov 2001; Bastagli, Coady, and Gupta 2012).

Third, we include two demographic factors that are commonly present in models characterizing income inequality. We consider a change in the human capital index based on years of schooling and returns to education. Differences in labor skills are expected to be a strong determinant of wage gaps. We also include population growth to filter out changes in income inequality that may have been driven by significant demographic changes in each country.

Finally, we need to control for the country's financial development, even if its impact on inequality is ambiguous. While financial development could expand the economic wealth of disadvantaged groups (Becker and Tomes 1986), it could also improve the financial services of those who already have access to the financial system, thereby disproportionately helping the wealthy (Greenwood and Jovanovic 1990). We follow Furceri and Ostry (2019) and approximate the level of financial development using domestic credit to the private sector as a share of GDP.

2.4 Event Analysis

To get a first insight into the evolution of the Gini index around policy events, we explore the *unconditional* relationship between macroprudential policy actions and the Gini using a simple event-study approach. We divide the period 1990–2019 into event windows, with macroprudential policy tightening occurring in the middle of

these windows, and examine the path of inequality before and after this event. In this exercise, we express the Gini index as a percentage change relative to its average level five years before the tightening and then take the average across all macroprudential actions.

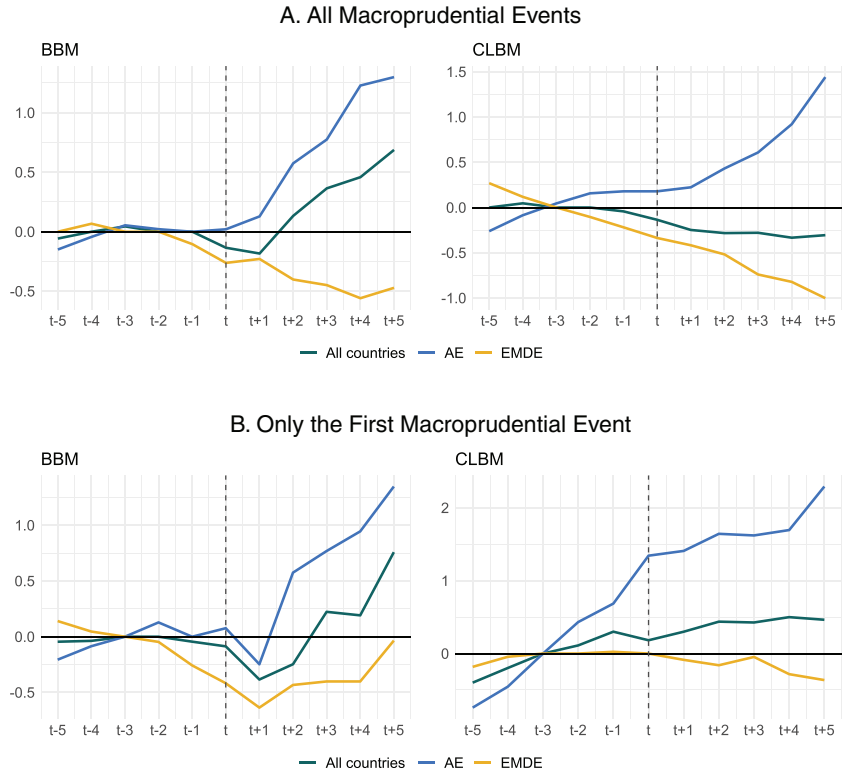
The results are depicted in Figure 2, panel A. The left-hand graph shows a clear structural break after the tightening of borrower-based measures. While income inequality increases significantly in advanced economies compared with the period before the events, it declines in emerging markets and developing countries. The results tracking the change in the Gini index after the tightening of capital- and liquidity-based measures are less indicative. While we see income inequality rising again in advanced economies and falling in emerging markets and developing countries, the two start to diverge a few years before the event.

Several factors can cause this. First, capital- and liquidity-based measures are tightened more frequently than borrower-based measures, meaning that the five-year period before each event is likely to include one or more additional changes to capital- and liquidity-based measures with a potential impact on income inequality. To account for this, we consider only the first macroprudential policy tightening in each country (Figure 2, panel B), but the picture remains roughly the same. Second, it can reflect that the macroprudential indices are based on the effective date of the policy, which can differ from the announcement date. Changes in capital requirements are usually known for at least several months before the regulation becomes effective so that the affected banks can build up capital buffers gradually. Third, at this stage, we do not yet control for the impact of long-run trends and other factors that may affect income inequality. At most, these unconditional results suggest an economically meaningful link between macroprudential policy and income inequality. In addition, they emphasize the need to carefully control for other factors, which we discuss earlier in this section.

3. Hypotheses

Our hypotheses are based on the idea that macroprudential policy affects income inequality through two main channels: (i) the credit redistribution channel and (ii) the crisis mitigation and prevention channel. To date, the income redistribution channel has

Figure 2. Average Path of Gini Index after the Macroprudential Policy Tightening



Note: The graphs show the evolution of the Gini index five years before and after each macroprudential policy tightening in all 105 countries. The Gini index is expressed as a percentage change relative to its average level five years before the tightening. The average is taken across all macroprudential events. We record a total of 219 dates of borrower-based measures (BBM) tightening and 697 dates of capital- and liquidity-based measures (CLBM) tightening.

been described in the context of monetary policy (Brunnermeier and Sannikov 2013; Auclert 2019; Albert and Gómez-Fernández 2021). However, macroprudential policy can also have a disproportionate effect on income and welfare, resulting from its impact on the provision of bank credit. For example, borrower-based macroprudential measures, such as loan-to-value (LTV), loan-to-income (LTI), and debt-service-to-income (DSTI) limits, directly restrict the amount of

credit available to some borrowers to decrease the riskiness of banks' credit portfolios and increase their resilience. The consequence of the reduced ability of households to purchase property can thus result in both an increase in wealth inequality (e.g., the property cannot be used as an inflation shield) and income inequality (e.g., the property cannot generate rental income). For example, Peydro et al. (2020) show that macroprudential borrowing limits affect low-income borrowers more than high-income borrowers. This leads to our first testable hypothesis.

Hypothesis 1. *Under the credit redistribution channel, macroprudential policy increases income inequality.*

Macroprudential measures aim to reduce the probability of financial and subsequent economic crises, which have redistributive effects of their own. The primary mechanism by which crises (recessionary episodes) could increase inequality is their impact on the labor market. For example, in the Global Financial Crisis, higher unemployment was found to be a significant driver of rising market income inequality in Europe and the U.S. (Jenkins et al. 2012; Vacas-Soriano and Fernández-Macías 2018). Recessions are also known to depress the wages of less-skilled workers (Castaneda, Diaz-Gimenez, and Rios-Rull 2003; Guvenen, Ozkan, and Song 2014), leading to increased wage inequality. Bridges, Green, and Joy (2021) show that rapid credit growth in the run-up to a recession significantly amplifies the effects of unemployment and income inequality that follow. Thus, if macroprudential policy successfully mitigates the probability and impact of crises, we should be able to identify less pronounced growth in inequality in countries with active macroprudential policy in precrisis periods. This leads to our second hypothesis.

Hypothesis 2. *Under the crisis mitigation and prevention channel, macroprudential policy decreases income inequality.*

Of course, both channels can operate simultaneously, and which one turns out to be dominant is an empirical question. For example, the relative dominance of both channels can be conditional on individual country- and time-specific characteristics. This argument is supported by the fact that literature finds different effects of macroprudential policy across countries (Cerutti, Claessens, and Laeven 2017; Akinci and Olmstead-Rumsey 2018). Furthermore,

studies show that the financial sector affects income inequality differently in advanced economies and emerging markets (Cihak and Sahay 2020) or bank-based and market-based financial sectors (Brei, Ferri, and Gambacorta 2018). Given the limited evidence on the use and effectiveness of macroprudential policy in different periods, our third hypothesis is based on the cross-sectional aspect of our panel data set.

Hypothesis 3. *The crisis mitigation and prevention channel is more likely to dominate in countries with riskier banking-sector characteristics.*

Our empirical tests will focus on these hypotheses and also provide additional tests to check whether the macroprudential policy is indeed an important force explaining a portion of the dynamics of income inequality.

4. Effects of Macroprudential Regulation

Our primary objective is to determine whether changes to macroprudential policy help to predict changes in income inequality. We employ the local projections method developed by Jordà (2005), in which impulse responses are derived from separate regressions for each forecast horizon $t + h$, conditional on a given set of variables at time t. In other words, local projections are estimated for each period of interest h rather than extrapolating into increasingly distant horizons from a given model as it is done with VAR models. The estimated parameters from each regression are used to calculate an impulse response function at a given horizon. The regression model is

$$GI^{gap}_{i,t+h} = \beta^h MaPP_{i,t} + \gamma^h GI^{cs_trend}_{i,t} + \sum_{j=1}^{2} \delta^h_j Z_{i,t-j} + \alpha^h_i + \alpha^h_t + \epsilon_{i,t}, \quad (1)$$

where $GI^{gap}_{i,t+h}$ is the detrended Gini index, net of and expressed as a percentage of the global trend; $GI^{cs_trend}_{i,t}$ is a country-specific trend of the Gini index; $Z_{i,t}$ is a vector of control variables described in

more detail in Subsection 2.3;[6] α_i^h and α_t^h are country and time fixed effects. As proposed by Montiel Olea and Plagborg-Møller (2021), we include lags of the dependent variable among the controls to augment local projections. In our baseline analysis, we consider three lags of all control variables, but we assess the sensitivity of the estimates when using up to five lags.[7]

Following Bridges, Green, and Joy (2021), we introduce two Gini index trends—global and country-specific. This is a rather conservative approach which, however, should help shield estimated effects from the impact of long-term structural developments and attenuate the size of any cyclical effects that we estimate. We calculate the global trend across countries and years separately for AE and EMDE due to significant differences in Gini trends between the two (Dabla-Norris et al. 2015). We estimate both trends using the Hamilton (2018) method.

The main parameter of interest is β associated with $MaPP_{i,t}$, the macroprudential policy index. This index takes a positive value for tightening actions, a negative value for loosening actions, and zero for no change. The magnitude of the index reflects the number of actions taken during one year.

β measures the change in the cyclical component of pretax Gini (as a percent of the trend) from period t to $t+h$ due to changes in the macroprudential policy index. For example, $GI_{i,t+5}^{gap}$ represents the percentage point deviation in the cyclical component of the Gini index (in percentage of trend) in the fifth year after a macroprudential policy measure that occurred in period t in country i. The interpretation of the coefficient estimates takes into account the deviation in the macroprudential policy index resulting from tightening,

[6]Our control variables, which include both macrofinancial and demographic factors, typically appear in the literature with some lagged effect on inequality (Bridges, Green, and Joy 2021; Pereira da Silva et al. 2022), which we account for in our estimation framework.

[7]In the lag selection process, we followed the suggestion in Montiel Olea and Plagborg-Møller (2021) and adopted a conservative stance, favoring more lags over fewer. This approach generally entails minimal asymptotic efficiency costs and has a negligible impact on finite samples. However, as stated in Montiel Olea and Plagborg-Møller (2021), one should always prioritize the inclusion of sufficient control variables over pinpointing the exact number of necessary lags, ensuring that the model adheres to the conditional mean independence condition, which is more critical than the precise number of lags.

especially since most actions in our sample involve tightening. The robustness of the macroprudential policy variable's specification will be analyzed later in the paper.

Identification. To solve the identification problem, one can follow three strategies. The first option is an event-study setup where a researcher would focus on a specific change in macroprudential policy in one country and track the development of income distribution around that change. Using this strategy, Beck, Levine, and Levkov (2010) assess the impact of bank deregulation on income distribution in the United States. The downside of this approach is that one obtains a single country's evidence that may not be transferable across countries. The second option would be to use the instrumental variables approach, which would ensure that analyzed changes in macroprudential policy are not highly correlated with macrofinancial sources of income inequality. Delis, Hasan, and Kazakis (2014) provide evidence on the effect of liberalization of banking systems on income inequality, using an index of supervisory power to instrument for changes in the explanatory variable. While this approach allows tracking the impact of macroprudential policy across countries, one runs into difficulties in considering an appropriate instrument. The third option (adopted in this paper) builds on a narrative identification approach used to identify shocks to the macroprudential policy that are (i) exogenous with respect to the current and lagged real variables, (ii) uncorrelated with other shocks, and (iii) preferably unexpected.

For the narrative identification, we follow Richter, Schularick, and Shim (2019) who quantify the effects of changes in loan-to-value limits on output and inflation. First, we check whether the stated objectives of macroprudential policy actions in individual countries reflect in any way the current state of the real economy. The IMF's iMaPP database provides a description of each policy action taken from official press release announcement and regulatory documents. This information makes it possible to understand the rationale behind each policy action. Capital-based macroprudential measures are usually aimed primarily at banks tasked to increase their resilience by building up capital buffers to cover losses during unforeseen events. By design, they do not have a stated economic objective, and we do not consider those that might. Based on that, we do not consider changes in the reserve requirements

as capital- and liquidity-based measures, as they are generally difficult to attribute unambiguously to macroprudential or monetary policy across countries. For example, the objectives of the 2007 and 2008 changes to the reserve requirements in Ukraine and Saudi Arabia were to "restrain (control) the inflationary pressures," according to the official reports. The official communication of other countries states that the reserve requirements has also been used for "monetary policy purposes" (e.g., in Slovakia, Croatia, El Salvador, Switzerland, and others).[8] Borrower-based macroprudential measures pose a challenge to the narrative identification approach because they limit borrowing relative to property values and the income of households. However, Richter, Schularick, and Shim (2019) show that the dominant share of borrower-based policy actions has a stated financial objective unrelated to real economic developments. Specifically, they reviewed a total of 92 LTV actions, finding only three actions with a stated objective linked to the real economy. Unlike monetary policy, macroprudential policy does not respond to the real economy, which makes it easier to identify.

To support our narrative identification approach, we test for the exogeneity of our macroprudential policy variable using a procedure suggested by Stock and Watson (2018) for local projection equations. Specifically, we examine the correlation between leads and lags of the macroprudential policy variable and the residuals of Equation (1). The results, presented in Appendix B, largely indicate that the macroprudential policy measures are exogenous.[9]

One remaining concern, which the narrative identification approach cannot fully address, is that factors influencing policy decisions might also be correlated with changes in income inequality.

[8]The distinction between macroprudential policies and monetary policies, such as changes in reserve requirements, is crucial. By excluding measures ambiguously attributed to or directly tied with monetary policy objectives, like inflation control, we aim to minimize the risk of erroneously attributing effects to macroprudential policy that might actually originate from monetary policy actions. This is essential, considering that monetary policy can independently influence income inequality, potentially confounding the effects of macroprudential measures.

[9]In an additional, unreported analysis, we compared the estimates of the relationship between macroprudential policy and income inequality both with and without the inclusion of control variables (details available upon request). Given that these variables do not significantly alter the estimated relationship, we infer that the error term is orthogonal.

Failing to account for these factors could results in the so-called omitted variable bias. For example, the macroeconomic environment can simultaneously determine both elements of Equation (1). To minimize the bias, we consider numerous control variables described in detail in Subsection 2.3 and use the lag-augmented local projection method which includes lagged values of the response variable among the set of controls (Montiel Olea and Plagborg-Møller 2021).[10]

4.1 Baseline Results

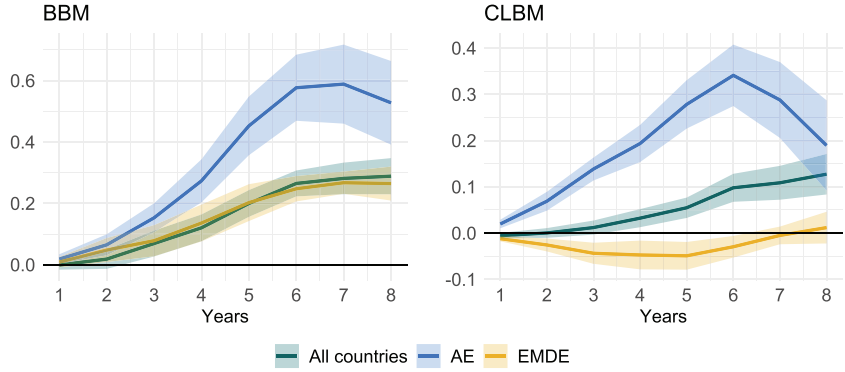
Figure 3 shows the baseline model estimates for the full sample, advanced countries, and emerging market and developing countries. The accompanying regression tables (C.1 and C.2) are included in Appendix C. The sample split is motivated by a number of studies showing a differential impact of macroprudential policy on the real economy and the financial sector between advanced economies and emerging markets (Cerutti, Claessens, and Laeven 2017; Akinci and Olmstead-Rumsey 2018; Fidrmuc and Lind 2020). Furthermore, Cihak and Sahay (2020) document important cross-country differences in the relationship between financial development and income inequality.

A bird's-eye view of the results suggests two facts: (i) macroprudential policy actions have a significant effect on income distribution, and (ii) the direction and magnitude of the effect are conditional on the type of macroprudential policy used and broad country characteristics. Estimates using the full sample of countries suggest that a one-point increase (tightening) in the borrower-based index (BBM) does not have an immediate effect on income inequality but has a longer-term effect, raising the detrended Gini index by about 0.2 percentage point (pp) after five years and about 0.3 pp after eight years.[11] Estimates further show that this effect is predominantly

[10]To further strengthen the robustness of our results, we employ the inverse-probability-weighted regression adjustment (IPWRA) estimator as an alternative means of estimation. This approach provides a different identification strategy, safeguarding the estimated effects from potential sampling bias. More details are available in Subsection 4.5, where the results are shown to remain robust.

[11]The long-term effect is mostly expected since macroprudential policy first affects the distribution of credit and the new distribution has a lagged effect on

Figure 3. Response of Income Inequality to a Change in Macroprudential Policy



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Country subsamples are for advanced economies (AE) and emerging markets and developing economies (EMDE). Shaded areas refer to one-standard-deviation confidence bounds. We estimate all models with a full set of control variables and robust standard errors.

driven by advanced economies where the cyclical component of income inequality rises by nearly 0.6 pp after six to seven years. These findings suggest that the tightening of borrower-based measures affects income inequality predominantly via the credit redistribution channel (Hypothesis 1).

We obtain somewhat mixed estimates when considering the tightening of capital- and liquidity-based measures. Increasing the CLBM index by one unit (tightening) raises income inequality by 0.1 pp after six years when using a full sample of countries. However, this effect is entirely driven by advanced economies, whereas in emerging markets and developing countries, an increase in the

inequality. Moreover, in the case of BBM instruments, wealth inequality is largely affected first, which affects income inequality after a certain period. Thus, we expect a peak in the impact after several years, with any significant effect with a certain lag.

CLBM index by one unit is associated with a reduction in inequality. The documented increase in inequality in advanced economies would be representative of the credit redistribution channel, while the decrease in inequality in emerging markets and developing countries would validate the crisis mitigation and prevention channel, ceteris paribus. In other words, the results suggest that, in the face of global events like the Global Financial Crisis, emerging and developing countries might experience a smaller increase in inequality compared with scenarios without macroprudential policy intervention.[12] At this stage, we cannot reject or confirm Hypothesis 2 concerning the effect of capital- and liquidity-based measures on income inequality, as further validation is needed.

Overall, the baseline model estimates confirm a significant link between macroprudential policy and income inequality, while it highlights important differences between advanced economies and emerging markets. So far, the findings support the idea, suggested by Bourguignon (2005), that banking regulation may not work the same way in emerging markets as it does in advanced economies.

While the baseline model provides a useful insight into the aggregate effects of macroprudential policy on income inequality, it prevents us from exploring deeper into the reasons behind these results. We argue that there might be two channels through which macroprudential policy affects income inequality: the crises mitigation and prevention channel and the credit redistribution channel. The next sections will look into whether these two channels actually influence income inequality.

4.2 Crises Mitigation and Prevention Channel

The macroprudential policy can affect income inequality by building capacity in the financial sector to mitigate the adverse effects of a crisis (crisis mitigation) and directly preventing materialization of financial risks (crisis prevention).

[12]This result may also reflect the observation that emerging markets have employed macroprudential policy more extensively compared with advanced economies (Cerutti, Claessens, and Laeven 2017).

Crisis Mitigation Channel. To empirically verify the presence of the crisis mitigation channel, we estimate the effect of macroprudential policy on income inequality around periods where we observe a financial crisis. We consider the effects of ex ante macroprudential policy (before a crisis outburst) and ex post policy (after a crisis outburst). To facilitate tracking of our identification procedure, Table C.3 in Appendix C displays the number of countries and observations used in each model specification. We proceed as follows.

First, we define the financial crisis periods based on the database by Laeven and Valencia (2020). Second, we estimate two model specifications and compare the outcomes. Model 1 (yellow color) is estimated on a set of countries that have experienced a financial crisis (54 countries out of 93 in the whole sample). We use a six-year time window around each crisis outbreak to estimate the model. For instance, for a country that experienced a crisis during 2008–09, we evaluate the impact of macroprudential policies implemented three years prior to the crisis (2005–07) on the trajectory of income inequality both during the crisis and for the three years following it (2008–12).[13] Among the 54 countries that experienced a financial crisis, 11 had implemented borrower-based measures and 22 had implemented capital- and liquidity-based measures within the three years leading up to the crisis outbreak. The remaining countries (43 in the case of BBM and 32 in the case of CLBM) serve as a counterfactual. Therefore, Model 1 is designed to estimate the effects of preemptive macroprudential policy (implemented before a crisis) on the subsequent trajectory of income inequality.

Model 2 (blue color) assesses the effects of macroprudential policy actions taken during or after a crisis outbreak. Consequently, it is estimated using data from the years of the crisis and the three years following, deliberately excluding any preemptive macroprudential actions. Among the 54 countries experiencing a crisis, 22 recorded borrower-based policy tightening actions and 40 recorded capital- and liquidity-based policy tightening after a crisis outbreak, with the remaining 32 (14) serving as a counterfactual. Model 2

[13]We also explored shorter and longer periods around the crisis (up to five years) and found that they yield qualitatively similar estimates.

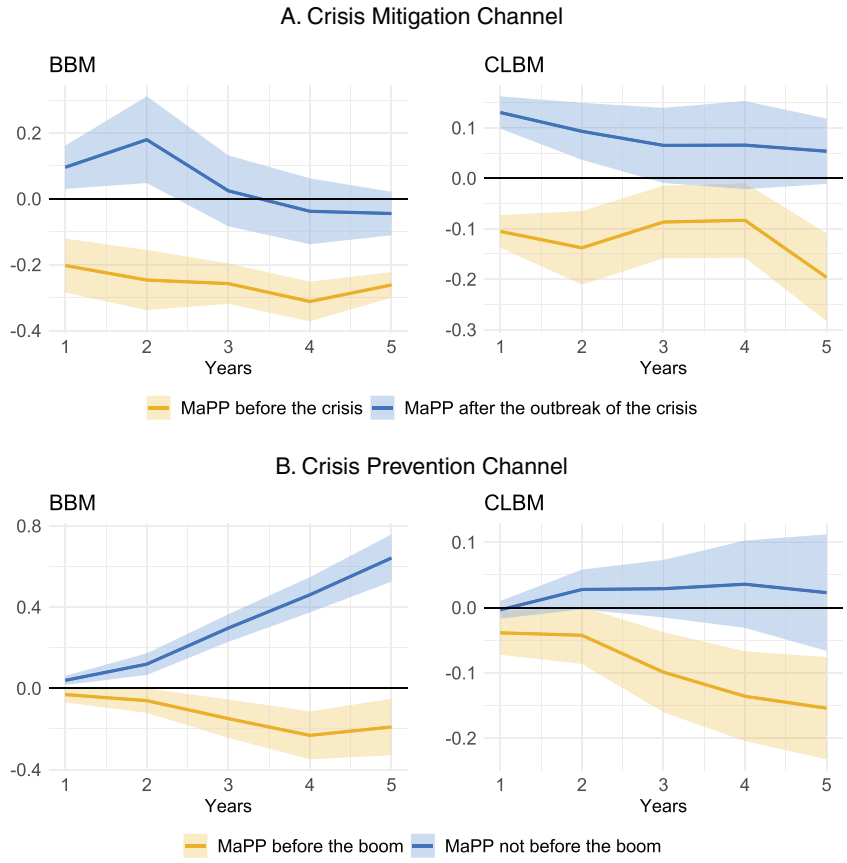
aims to explain the impact of restrictive macroprudential measures implemented in the wake of a crisis.[14]

Figure 4, panel A depicts the estimates of the two models. They show that macroprudential policy reduces income inequality when tightened before a financial crisis (relative to a counterfactual with no preemptive macroprudential policy). This evidence is consistent with the crisis mitigation channel under which macroprudential policy can reduce the adverse impact on inequality following a crisis outburst by building the financial-sector resilience in the precrisis period. On the contrary, when the macroprudential policy was tightened only after the crisis outburst, we document an increase in income inequality relative to a situation with no tightening policy actions. Both effects are comparable between borrower-based measures and capital- and liquidity-based measures. Due to a limited number of observations, which result from our strict identification procedure, we cannot confidently estimate the model separately for advanced and emerging economies.

Crisis Prevention Channel. Macroprudential policy that acts preemptively can contribute to lowering the probability of a crisis. Therefore, we extend our analysis to study the crisis prevention channel, i.e., we track the impact of macroprudential policy on income inequality during the periods with a high probability of crisis (the boom periods). Of course, it is challenging to estimate the probability of a crisis, even more so in a cross-section of countries from around the world. Previous studies show that several early warning signals, particularly rapid growth in aggregate credit and asset prices, help predict the arrival of financial crises (Schularick and Taylor 2012; Babecký et al. 2014; Drehmann and Juselius 2014; Geršl and Jašová 2018; Greenwood et al. 2022). Importantly, Schularick and Taylor (2012) show that financial crises can be predicted by elevated bank loan growth over the previous five years.

[14]Despite expectations that a financial crisis would typically reduce credit provision to the economy, the aftermath of the Global Financial Crisis of 2008 did not see a decrease in policy tightening events for most sample countries, marking it as the primary crisis event in our sample (Figure A.3). Utilizing the iMaPP database for an overview of policy actions, we identify three primary reasons for tightening macroprudential policy during or after a crisis: (i) to strengthen financial resilience, (ii) to prevent excessive risk-taking, and (iii) to address already emerging risks.

Figure 4. Crises, Macroprudential Policy, and Income Inequality



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the five years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. In the regression, we exclude two control variables: the dummy variable for the financial crisis and the credit-to-GDP ratio. We estimate robust standard errors.

Greenwood et al. (2022) show that when home price growth is in the top tercile and household credit growth is in the top quintile, the probability of a crisis beginning within three years is roughly 40 percent.

We consider four specifications to define boom periods. In our baseline model, we characterize boom periods as instances when the growth of real credit exceeds the growth of real output by more than 2 pp over at least three consecutive years. This misalignment between credit and output growth suggests a buildup of financial vulnerabilities, as pointed out by Drehmann and Juselius (2014). Second, we identify boom periods when a country's real credit growth is in the top quintile (Schularick and Taylor 2012; Greenwood et al. 2022). Third, we use the change in credit-to-GDP growth instead of credit growth for each country. Fourth, boom periods are determined by estimating the likelihood of a crisis and identifying those periods with a heightened probability of crisis (Engle and Ruan 2019).[15]

Table 3 presents summary statistics of the variables for our data sample. For example, the cumulative difference between credit and output growth averages about 7 pp three years prior to all observed crises, in contrast to a difference of less than 3 pp during "normal" times.[16] Similar patterns are observed across other boom variables. Notably, the estimated crisis probability significantly increases during the precrisis period compared with other times, supporting the accuracy of our boom period identification.

To test for the presence of the crisis prevention channel, we use a similar setup as for the crisis mitigation channel. Model 1 (yellow color) measures the impact of macroprudential policies tightened three years before the identified credit boom on income inequality during the boom and in the following three years. For our baseline definition of boom periods, which is the difference between real credit growth and real output growth, 73 out of the 93 countries in our sample were found to have experienced a credit boom

[15]We estimated a logit model with the crisis dummy serving as the dependent variable, and a set of macrofinancial variables along with country fixed effects as predictors. The estimates from this logit model are presented in Table C.4.

[16]We explored other combinations (up to a 5 pp difference lasting for up to five consecutive years). The results remain consistent across shorter periods with larger differences and longer periods with smaller differences, highlighting the significance of the cumulative effect.

Table 3. Periods of High Vulnerabilities and Probability of Crisis

	Obs.	Ctrs.	Three Years Before Crisis			Crisis			All Other Periods		
			Mean	25%	75%	Mean	25%	75%	Mean	25%	75%
All Countries											
Credit Growth – GDP Growth	1,574	93	7.14	3.03	10.04	–1.22	–7.58	4.33	2.70	–2.52	7.12
Real GDP Growth	1,861	93	3.24	1.69	5.77	–0.38	–2.79	2.21	2.89	1.15	4.62
Real Credit Growth	1,574	93	13.27	7.93	17.43	–0.34	–7.22	3.68	7.38	0.78	12.43
ΔCredit-to-GDP Ratio	1,581	93	4.50	1.76	8.76	–0.48	–4.83	3.71	0.81	–1.20	2.86
Prob. of Crises (Estim.)	1,574	93	12.69	3.39	14.64	41.19	18.87	60.84	5.79	0.00	7.26
AE											
Credit Growth – GDP Growth	615	34	6.49	2.93	8.68	–0.63	–3.97	4.25	0.44	–3.20	3.96
Real GDP Growth	662	34	2.66	1.75	3.48	–1.02	–3.23	1.16	2.17	0.89	3.26
Real Credit Growth	615	34	12.01	7.91	14.74	–0.36	–5.26	3.26	3.79	–0.79	7.08
ΔCredit-to-GDP Ratio	618	34	5.19	3.23	9.62	0.13	–5.25	5.34	0.28	–2.98	3.08
Prob. of Crises (Estim.)	615	34	8.88	3.62	12.63	37.81	19.15	55.17	11.40	0.00	16.72
EMDE											
Credit Growth – GDP Growth	959	59	8.39	3.30	15.28	–2.16	–11.13	6.11	3.88	–1.89	9.70
Real GDP Growth	1,199	59	3.94	1.25	7.60	0.31	–2.04	3.48	3.22	1.33	5.07
Real Credit Growth	959	59	15.69	8.15	28.41	–0.32	–11.65	5.88	9.27	1.92	15.34
ΔCredit-to-GDP Ratio	963	59	3.24	1.15	5.94	–1.42	–4.68	1.09	1.09	–0.53	2.67
Prob. of Crises (Estim.)	959	59	19.98	2.18	32.91	46.51	17.63	68.55	2.84	0.00	1.01

Note: The table shows summary statistics for selected variables during three years before a financial crisis outburst, during the crisis period, and during non-crises periods. The financial crisis periods are taken from the Laeven and Valencia (2020) database. In order to maximize data coverage, variables were collected from different sources. The credit variable is domestic credit to the private sector from the World Bank's World Development Indicators (WDI); GDP is the real GDP from the Penn World Table (PWT). Probability of crises is estimated using a logit model. The period used for calculation of the indicators is the same as in regression analysis (1990–2019).

(see Table C.3 in Appendix C). Of these, 23 tightened borrower-based measures and 53 tightened capital- and liquidity-based measures before the boom. The remaining 50 (20) countries that did not implement BBM (CLBM) provide a counterfactual. Model 2 (blue color) is calculated using data from the 73 countries that experienced a credit boom but did not implement any macroprudential policy measure before these boom periods.

Figure 4, panel B depicts the baseline results using the difference between real credit growth and real output growth for boom identification. Estimates show that when macroprudential policy measures are tightened before the boom period, income inequality decreases by about 0.1 to 0.2 pp over the course of five years. The response is slightly stronger in the case of borrower-based measures. Estimates from Model 2 are largely consistent with our baseline findings, though there are small differences because countries without boom periods were not included in the sample. This model shows that income inequality in these countries increases, aligning with the mechanisms of the credit redistribution channel or repressive policy measures.

Additionally, we added an interaction term to the crisis prevention models to distinguish between countries that had a credit boom without a following financial crisis and those that experienced a crisis after the boom. The results are displayed in Figure C.1 in Appendix C. By examining the impact of tightening macroprudential policies before the boom, we found that inequality decreased in cases without a subsequent crisis, or showed a less significant increase or no change when a crisis did occur. This suggests that when preventative macroprudential policies successfully reduce financial risks, they help lower inequality. However, when these measures fail to prevent a crisis, the crisis has a smaller impact on income redistribution compared with situations where no preventative actions were taken.

Results for the three alternative definitions of boom periods, shown in Figures C.2 and C.3 in Appendix C, are consistent. Implementing macroprudential tightening measures before a boom reduces income inequality compared with scenarios without these policies. Quantitatively, these alternative definitions show a decrease in inequality of between –0.3 and –0.5 pp over five years, which closely matches our baseline estimates. Overall, our results strongly support the effectiveness of the crisis prevention channel.

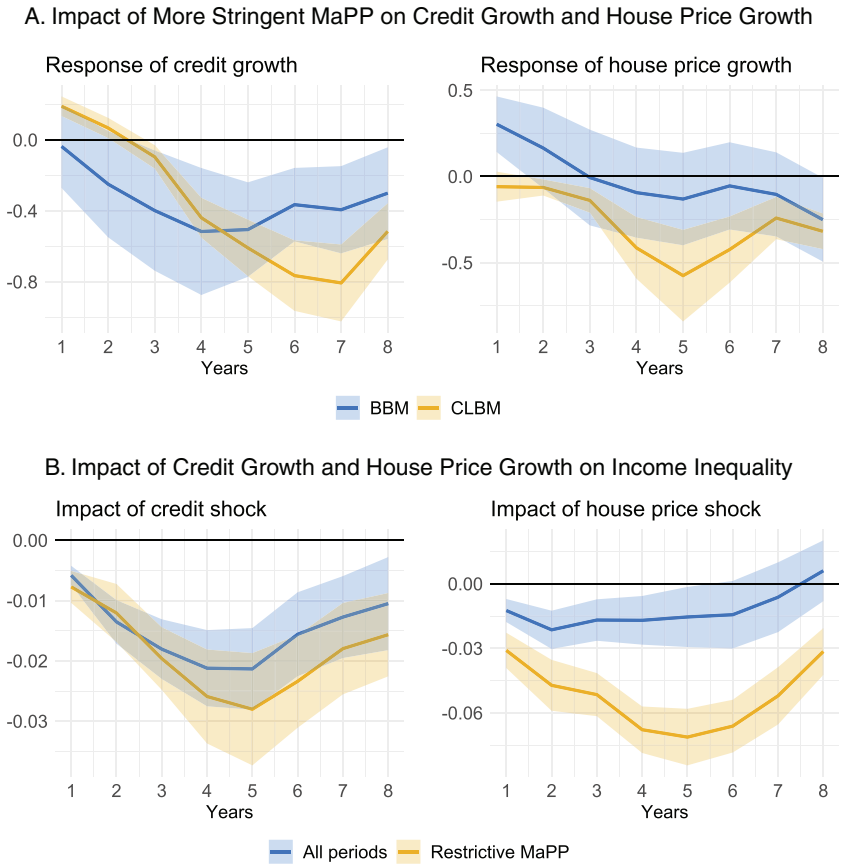
4.3 Credit Redistribution Channel

Access to credit is an important factor influencing borrowers' future income and contributing to a reduction in income inequality (Mookerjee and Kalipioni 2010; Agnello, Mallick, and Sousa 2012). Delis, Fringuellotti, and Ongena (2020) show that loan application acceptance increases recipients' income five years later by more than 10 percent compared with denied applicants. Given that macroprudential policy can affect both credit growth (Malovaná et al. 2021, 2025) and house price growth (Vandenbussche, Vogel, and Detragiache 2015; Akinci and Olmstead-Rumsey 2018), we focus our identification of the credit redistribution channel around these two variables and estimate a system of two equations.

First, we estimate the impact of macroprudential policy on credit growth and house price growth, confirming that this impact is mainly negative (Figure 5, panel A) and economically material. Following a tightening of capital- and liquidity-based measures, credit growth decreases by 0.5 to 0.8 pp (depending on the type of macroprudential measure) and house price growth by 0.1 to 0.5 pp relative to their pre-event levels. Second, we estimate the impact of credit growth and house price growth on income inequality. To capture the credit reduction due to macroprudential policy tightening, we estimate the response for all periods and then only for periods where we observe the restrictive macroprudential policy. The results in Figure 5, panel B show that a reduction in credit and house price growth increases income inequality. At the same time, we observe a significant amplification during periods of more restrictive macroprudential policy.

Altogether, the system of two equations shows that a more stringent macroprudential policy can lead to higher inequality via its negative effect on credit and house price growth. In pursuing financial stability, macroprudential policy "targets" riskier exposures, usually loans provided to lower-income households. Hence, the negative impact on credit is expected to affect low-income households disproportionately more than high-income households (Peydro et al. 2020). Similarly, the decrease in house prices will affect more households with lower income, as these have a relatively higher share of real estate wealth while households with higher income have a relatively larger share of financial wealth (Benjamin, Chinloy, and Jud 2004; El-Attar and Poschke 2011). The decline in house prices affects potential income from real estate wealth (e.g., rental income, income

Figure 5. Credit Redistribution, Macroprudential Policy, and Income Inequality



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). In the first stage, we estimate the impact of a unit change in the macroprudential policy index on credit and house price growth (panel A). We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). In the second stage, we estimate the impact of a 1 pp change in credit and house price growth on the detrended Gini index. Solid lines display the coefficients of (noncumulative) responses over the eight years following the unit shock. Shaded areas refer to one-standard-deviation confidence bounds. From our set of control variables, we exclude the credit-to-GDP ratio. We estimate robust standard errors.

from sale), contributing to higher income inequality. A further analysis using microlevel (household-level) data would be desirable to understand the mechanisms behind the identified channel better.

4.4 Economic Significance

Before turning to the robustness analysis and other considerations, we briefly discuss the economic magnitude of our estimates. Although our sample is largely heterogeneous and country experiences may differ, we still find it helpful to provide some back-of-the-envelope calculations of average effects to understand the economic significance. Since our dependent variable GI^{gap} is the cyclical component of the Gini index, expressed as a percentage of the global trend GI^{g_trend}, we recalculate the impact on the Gini index as follows:

$$\frac{\partial GI}{\partial MaPP} = \frac{\partial GI^{gap}}{\partial MaPP} \times \frac{1}{100} \times GI^{g_trend}. \tag{2}$$

The value of $\frac{\partial GI^{gap}}{\partial MaPP}$, denoted β^h in Equation (1), is the estimated impact of macroprudential policy on detrended Gini index. For the baseline, these values are taken from Tables C.1 and C.2 in Appendix C. The value of GI^{g_trend} is calculated directly from data. The effect $\frac{\partial GI}{\partial MaPP}$ represents an absolute change in the Gini index in response to a one-unit increase in the macroprudential policy index. To understand the overall magnitude during the analyzed period, we multiplied $\frac{\partial GI}{\partial MaPP}$ by an average number of tightening actions. Recalculated effects of the baseline model are presented in Table 4.

Economically, the identified effects are material. Following a tightening of borrower-based measures, an average advanced economy in our sample records an increase of the Gini index by 0.127 after four years. To put it even more into perspective, the effect of one average tightening of borrower-based measures would account for 4 percent of the total increase in inequality, other factors held constant. We calculate this number based on the average increase in the Gini index of 3.14 in advanced economies between 1990 and 2019 (see Table 1). The lagged impact of macroprudential policy on inequality is consistent with the literature examining inequality, as is the lag we attribute to the effect of the two channels we describe above. Considering the average number of BBM tightening actions in each country over the analyzed period (2.97 for AE; see

Table 4. Economic Significance—Baseline Model

	Average Global Trend	Average No. of Actions	Average Change in Gini Index in Response to One Action		Average Change in Gini Index in Response to the Average No. of Actions	
			4Y	8Y	4Y	8Y
	(1)	(2)	(3)	(4)	(5)	(6)
BBM						
All Countries	45.804	2.054	*0.055*	*0.132*	*0.113*	*0.272*
AE	46.663	2.971	*0.127*	*0.246*	*0.378*	*0.732*
EMDE	45.309	1.525	*0.062*	*0.120*	*0.094*	*0.183*
CLBM						
All Countries	45.804	10.796	*0.015*	*0.058*	*0.158*	*0.628*
AE	46.663	13.118	*0.091*	*0.089*	*1.188*	*1.163*
EMDE	45.309	9.458	–0.021	0.005	–0.201	0.051

Note: The table shows a back-of-the-envelope calculation of changes in the Gini index in response to the tightening of the macroprudential measures. The effects are calculated using regression coefficients from Tables C.1 and C.2. For example, the average change in the Gini index in advanced economies four years after the introduction or tightening of borrower-based measures (column 3) is calculated as $0.273/100 \times 46.663 = 0.127$. If we multiply this number by the average number of borrower-based measures introduced during the analyzed period, we get 0.378 (column 5). Effects statistically significant at the 10 percent level are in italics.

Table 5. Economic Significance—Crisis Prevention and Mitigation Channel

	Average Global Trend	Average Change in Gini Index in Response to One Action		
		1Y	3Y	5Y
	(1)	(2)	(3)	(4)
BBM				
Before the Crisis	45.82	*–0.093*	*–0.048*	*–0.118*
After the Outbreak of the Crisis	46.07	0.044	0.060	0.011
Before the Boom	45.63	–0.014	–0.018	–0.068
Not Before the Boom	45.75	*0.018*	*–0.002*	*0.136*
CLBM				
Before the Crisis	45.82	*–0.040*	–0.120	*–0.090*
After the Outbreak of the Crisis	46.07	*0.030*	–0.021	0.025
Before the Boom	45.63	–0.045	–0.087	*–0.070*
Not Before the Boom	45.75	0.013	0.293	0.010

Note: Similarly to Table 4, this table shows a back-of-the-envelope calculation of changes in the Gini index in response to the tightening of the macroprudential measures. The effects are calculated using regression coefficients from the two identified channels—crisis prevention and mitigation channel—as depicted in Figure 4 (full regression results are available upon request). Effects statistically significant at the 10 percent level are in italics.

column 2), the overall Gini response to these policies is 0.378 four years after their tightening. Looking at the effect of capital- and liquidity-based measures, the average increase in the Gini index in advanced economies after single CLBM tightening accounts for 0.091 after four years. Considering these measures have been tightened more frequently, the overall impact amounts to 1.188 after four years. In emerging markets and developing countries, the impact of capital- and liquidity-based measures is insignificant, while borrower-based measures reduce the Gini index over the four-year horizon by 0.094, taking into account the average number of actions.

In Table 5, we focus on the economic significance behind the crisis prevention and mitigation channel. Following the tightening of borrower-based measures (a one-unit increase in the index) before

Table 6. Share of Macroprudential Measures Taken Before the Crisis (boom) and During the Crisis (%)

	Before the Crisis		After the Outbreak of the Crisis		Before the Boom	
	BBM	**CLBM**	**BBM**	**CLBM**	**BBM**	**CLBM**
All Countries	2.62	1.79	13.61	9.56	10.47	5.58
AE	3.96	1.12	12.87	10.31	10.89	3.36
EMDE	1.11	2.33	14.44	8.96	10.00	7.35

Note: The table shows the percentage share of macroprudential tightening actions introduced during certain periods—three years before the crisis or credit boom and after the outbreak of the crisis, which includes the crisis period and three years after that.

the crisis period, the Gini index is reduced by 0.09 after one year, 0.05 after three years, and 0.12 after five years. This contrasts with the documented increase in inequality by up to 0.06 when the policy was introduced after the crisis outbreak. Furthermore, the downward economic effect on income inequality following a preemptive macroprudential policy is comparable in size to the upward economic effect documented in the baseline model. This is because countries have a rather short history of using macroprudential policy preemptively (Table 6). While only about 15 percent of all macroprudential policy actions were taken ahead of a boom (6 percent before an observed crisis), about 39 percent was used after a crisis outburst and the rest during "normal" times.

We have also recalculated the economic magnitude of the credit redistribution channel, only to find that it is much smaller than the crisis prevention and mitigation channel. Specifically, we find that the average change in the Gini index following a one-unit increase in the macroprudential policy index is less than 0.01 units after five years for both borrower-based and capital- and liquidity-based measures.[17] However, given that most macroprudential policy actions

[17]The estimation of the economic significance of the credit redistribution channel is as follows. First, we multiply estimated coefficients from the two-equation model and then apply the recalculation back to Gini index with the trend as in Equation (2). The results are available upon request.

took place during the "normal" times, the effect basically compounds over time. Taken together with all the repressive macroprudential actions introduced during or shortly after the outbreak of the crisis, the overall impact on income inequality is positive. In fact, this is exactly what we observe in the baseline results.

4.5 Robustness

To evaluate the robustness of our results, we explore several alternative specifications and tests. First, we show how important it is to include fixed effects, control variables, and trend. Second, we consider time subsamples, differentiating between periods before and after the Global Financial Crisis. Third, we demonstrate that our results are robust to using a continuous macroprudential indicator instead of the dummy-type index. Fourth, we propose a different identification strategy to control for potential endogeneity bias. Fifth, we use alternative measures of income inequality to address the critique of the Gini index and support our baseline results. Sixth, we rerun our estimation for a sample without low-income countries where the relevance of macroprudential policy is generally low. Such countries can also be more prone to data errors. We also focus on capital-based measures, excluding liquidity-based ones from the macroprudential policy index. Last, we consider alternative specifications of the macroprudential policy dummy.

Different Specifications. Tables D.1 and D.2 in Appendix D summarize the baseline model estimates with and without country fixed effects and control variables. Estimates show that regardless of considering borrower- or capital- and liquidity-based measures, including country fixed effects is crucial to uncover the cyclical change in inequality following macroprudential policy actions. Further, tables show that including the macrofinancial controls highly reduces the size of the estimated coefficient. For instance, with control variables, the estimated impact of borrower-based measures on the detrended Gini index is reduced from 0.4 in year 5 to 0.2 (Table D.1).

Time Subsamples: Before and After the Global Financial Crisis. Figure D.1 in Appendix D shows estimates for two different time periods, separated by the start of the Global Financial Crisis in 2008. We divided the data this way because the crisis may have

triggered significant structural changes, and because macroprudential policy became much more common afterward, especially after the Basel III Accords were introduced. Despite these factors, the estimates are very similar to our baseline findings in both direction and magnitude. We found that tightening borrower-based measures tends to increase inequality in both advanced economies and emerging markets, while the effects of capital- and liquidity-based measures vary.

Continuous Measure. So far, our estimation of the relationship between macroprudential policy and income inequality was based on dummy-type indices that fail to account for the intensity of the policy taken. For example, a change in the loan-to-value limit from 100 to 90 would be treated the same as a change from 100 to 80. While this represents an important weakness of the macroprudential policy index, dummy-coding each policy action as a 0/1 indicator allows for much richer cross-country comparison, which would not be possible if all measures were intensity-adjusted. Nevertheless, we can use an intensity-adjusted measure for one specific policy instrument—the loan-to-value limit—for which we have data. We follow Alam et al. (2019) and consider the LTV limit of 100 as the baseline (neutral) regulatory setting. We then calculate the distance of an observed LTV limit in the country i and year t to the baseline level of LTV.

Table D.3 in Appendix D shows that the response to a 5 pp increase in the distance to LTV is a 0.28 pp increase in the detrended Gini index after five years which increases to 0.35 pp after seven years.[18] The effect of changes to the intensity-adjusted LTV measure is surprisingly fairly close to the effect estimated using a dummy-type borrower-based index which includes more types of policy actions (changes to debt-service-to-income limits or debt-to-income limits).

Inverse-Probability-Weighted Regression Adjustment (IPWRA) Estimator. We took special care to ensure that our results did not suffer from endogeneity problems (see Section 4.1). Nevertheless, we propose another empirical exercise to reassure our readers. Specifically, we use the IPWRA estimator, which combines the advantages of the inverse-probability-weighted estimator and

[18]Malovaná et al. (2025) show that a five-point change to the LTV limit is the most common regulatory action.

the local projection method. Richter, Schularick, and Shim (2019) use the same identification strategy to estimate the effect of LTV tightening on financial variables.

The estimation has two stages. In the first stage, we estimate the probability of a tightening of macroprudential measures based on prevailing macrofinancial conditions:

$$log\left(\frac{P[d_{i,t}=1|Z_{i,t-1}]}{P[d_{i,t}=0|Z_{i,t-1}]}\right)=\beta Z_{i,t-1}+\alpha_i+\epsilon_{i,t}, \tag{3}$$

where $d_{i,t}$ is a binary indicator equal to one if macroprudential policy was tightened and zero otherwise;[19] $Z_{i,t-1}$ is a vector of macrofinancial variables (output gap, CPI inflation, credit-to-GDP ratio, and unemployment); and α_i are country fixed effects.

Next, we use the inverse of the estimated probability of a tightening $\hat{p}_{i,t}$ to calculate weights $w_{i,t}=d_{i,t}/\hat{p}_{i,t}+(1-d_{i,t})/(1-\hat{p}_{i,t})$ that enter the second stage of the regression. Such a weighting scheme puts more weight on those difficult-to-predict observations. In other words, we place more weight on those macroprudential measures that appear to be a surprise given the observed economic and financial environment and less on those that could be predicted. In the second stage, we run the same model specification as in our baseline Equation (1) using weighted least squares. Further details on the methodology can be found in Jordà, Schularick, and Taylor (2016) and Jordà and Taylor (2016).

Table D.4 and Figure D.2 in Appendix D present the first- and second-stage results, respectively. The shape of the impulse responses is similar to the baseline results, suggesting that potential endogeneity is likely limited in our case. The only notable difference is a somewhat faster decay of the responses at the longer horizon. This is especially true for the tightening of capital- and liquidity-based measures.

Alternative Measures of Inequality. The literature on income inequality discusses the potential shortcomings of the Gini index. For example, Allison (1978) suggests that for a typically shaped income distribution, the Gini index tends to be most sensitive to changes around the middle of the distribution and the least

[19] We estimate the model separately for borrower-based measures and capital- and liquidity-based measures.

sensitive to changes among the very rich and very poor. Atkinson and Bourguignon (2015) add that a country with a lower Gini index does not always experience more equal income distribution than a country with a higher Gini index because the Lorenz curves of the two countries may intersect. Other studies then advise using alternative measures of income inequality to overcome these potential shortcomings (Palma 2006; Zenga 2007; Cobham and Sumner 2014).[20] To address the literature, we use income shares as an alternative to the Gini index. The income shares are percentages of the national income received by a segment of the population. However, data coverage for these additional measures is limited compared with the Gini index (only about 40 percent of the baseline data set). Figure D.3 in Appendix D shows the results.

Two main findings stand out. First, the sum of impulse response functions for the top and bottom 50 percent income shares roughly match the direction of impulse response functions in the baseline model with the Gini index. This is not surprising because the Gini index captures mainly average changes in the middle of the income distribution. After borrower-based measures tighten, the inequality measured by income shares also increases (increase in the income share of top 50 percent and decrease in the income share of bottom 50 percent), even though at a longer horizon and more so for advanced economies. On the other hand, after capital- and liquidity-based measures tighten, inequality increases in advanced economies and decreases in emerging markets and developing countries. Altogether, the shifts in income shares in response to macroprudential policy actions are consistent with changes in the detrended Gini index.

Second, the impact of macroprudential policy on the top 20 percent income shares seems to be stronger than on the top 50 percent. However, it is generally stronger for the bottom 50 percent than for the bottom 20 percent. Nevertheless, the distributional effects for top and bottom 20 percent income shares are only slightly different from the top and bottom 50 percent. Thus, we believe that

[20]On the other hand, Gastwirth (2017) shows that the Gini index is not overly sensitive to changes in the middle of the distribution and remains a useful tool for measuring inequality.

our results with the detrended Gini should fairly reflect the changes across the income distribution.

Excluding Low-Income Countries and Liquidity-Based Measures. So far, we have included all emerging markets and developing economies for which we have available data, meaning that we also retain some low-income developing countries. Therefore, we next check how the regression results change if we exclude those countries. In addition, we consider an even narrower sample, excluding countries that switched from low-income to middle-income status during the analyzed period. The division of countries into individual groups is shown in Table A.2 in Appendix A. The comparison of regression results is then depicted in Figure D.4 in Appendix D. The response of income inequality to both groups of macroprudential measures (BBM and CLBM) is almost identical for the full sample of EMDE and the sample without low-income countries. This is not surprising given that the low-income countries implemented only a handful of macroprudential measures (see Table D.5). The impact estimated for a sample of countries excluding also switching low-income countries is more pronounced but retains the same direction.

Next, we test the effect of a subset of macroprudential measures. Specifically, we exclude liquidity instruments from the set of capital- and liquidity-based macroprudential measures. As such, we analyze the impact of "pure" capital-based measures comprising countercyclical capital buffer, capital conservation buffer, leverage ratio, and other capital requirements (risk weights, systemic risk buffer, minimum requirements). As shown in Figure D.5 in Appendix D, the shape of the response and the strength of the impact of "pure" capital-based measures on income inequality remains very similar in all regions compared with the full set of capital- and liquidity-based measures. In advanced economies, the response is slightly weaker and decays more quickly, reflecting that capital requirements have only recently been implemented in most advanced economies.

Alternative Specifications of the Macroprudential Policy Index. In the baseline model, the macroprudential policy index takes a positive value for tightening actions, a negative value for loosening actions, and zero for no change. The size of the index then reflects the number of actions taken during one year and the related results then inform on the effect of each additional macroprudential

policy action on inequality, regardless of whether they have been implemented all in one year or subsequently in different years.

Alternatively, we redefine the index as a binary indicator, giving a value of one for any year where at least one macroprudential measure was tightened and zero otherwise. This approach focuses on when measures were implemented, ignoring how often they occurred. The results, shown in Figure D.6, panel A, reveal stronger effects, although the overall trend remains the same. This suggests that the combined impact of multiple measures in a single year has a greater effect on inequality than individual actions in our original analysis.

Further, we introduced an interaction dummy variable to the model with binary macroprudential indicator differentiating between countries that implemented multiple measures for extended periods and those with fewer measures or similar measures spread over longer periods. As such, we can assesses the intensity and duration of policy actions. As shown in Figure D.6, panel B, significant differences emerge specifically for borrower-based measures, with countries implementing more intensive macroprudential policies experiencing lesser increases in inequality. These results hold even when using our baseline definition of the macroprudential policy index.

Frequency of Macroprudential Policy Actions. Next, we estimate the effect of macroprudential policy depending on the frequency of macroprudential policy use. Some papers show that economies that have been actively using (macro)prudential policy tend to benefit from financial development more than economies where this policy was less active (Agénor et al. 2018; Hodula and Ngo 2022). We define the more frequent use as the top quartile of the entire distribution, i.e., we focus the analysis on the top 25 percent of countries with the most frequent use of the macroprudential policy. Figure D.7 in Appendix D shows that the effect in countries with more frequent macroprudential actions is generally pushed downward, as it is less positive for borrower-based measures and more negative for capital- and liquidity-based measures. A higher frequency of macroprudential policy is expected to boost resilience and lower the riskiness of the financial sector. This would suggest that it aids the strength of the crisis mitigation and prevention channel.

5. On the Relative Dominance of the Crisis Prevention and Mitigation Channel and the Credit Redistribution Channel

In this section, we check whether the relative dominance of the crisis prevention and mitigation channel and the credit redistribution channel is conditional on certain time or cross-sectional (country) characteristics. The main difference from the baseline specification in Equation (1) is that we differentiate the impact of macroprudential policy across countries and periods by including interaction terms with respective dummy variables $d_{i,t}$. Formally,

$$GI_{i,t+h}^{gap} = \beta^h MaPP_{i,t} \times d_{i,t} + \gamma^h GI_{i,t}^{cs_trend} + \sum_{j=1}^{2} \delta_j^h Z_{i,t-j} + \alpha_i^h + \alpha_t^h + \epsilon_{i,t}, \quad (4)$$

where $d_{i,t}$ is a binary indicator that takes value one when a certain characteristic crosses a selected threshold (median or quartile values) and zero otherwise. Note that we create the dummy variable at the country level, meaning that the threshold value is defined for each country. As such, each country will switch between the two states. Previously defined terms remain the same. Parameter β^h gives us a state-dependent effect of macroprudential policy on income inequality.

5.1 Accommodative Monetary Policy

Recent studies suggest that prolonged low interest rates have increased income and wealth inequality (Berisha, Meszavos and Olson 2018; Auclert 2019). Accommodative monetary policy affects household balance sheets due to variations in asset portfolio compositions (Inui, Sudou, and Yamada 2017; Samarina and Nguyen 2024). Higher equity prices, benefiting high-income households who own the majority of financial assets, increase wealth inequality (Bernanke 2020). An unexpected expansionary monetary policy can also increase income inequality by decreasing the labor share of income for low-skilled workers while increasing it for high-skilled workers (Dolado, Motyovszki, and Pappa 2021). We, nonetheless,

acknowledge that studies present a mixed view on monetary policy's effects on income inequality (Colciago, Samarina, and de Haan 2019). Some studies argue that accommodative monetary policies might reduce inequality by aiding debtors with lower incomes through unexpected inflation (Colciago, Samarina, and de Haan 2019), reduced debt service burdens (Samarina and Nguyen 2024), or lower unemployment (Ampudia Fraile et al. 2018).

Based on our data, however, we clearly show that a decrease in interest rates contributes to an increase in income inequality (see Figure C.4 in Appendix C), and this effect is further amplified during periods of negative changes in interest rates (i.e., periods of monetary policy easing). At the same time, the low interest rates environment (LIRE) can contribute to the buildup of financial imbalances.[21] It is thus not surprising that the LIRE period coincides with the increased use of macroprudential policy around the world. This motivated us to estimate the impact of macroprudential policy on income inequality in periods of interest rates decreases (monetary policy is getting more accommodative) and periods of low interest rates (monetary policy is already accommodative).[22]

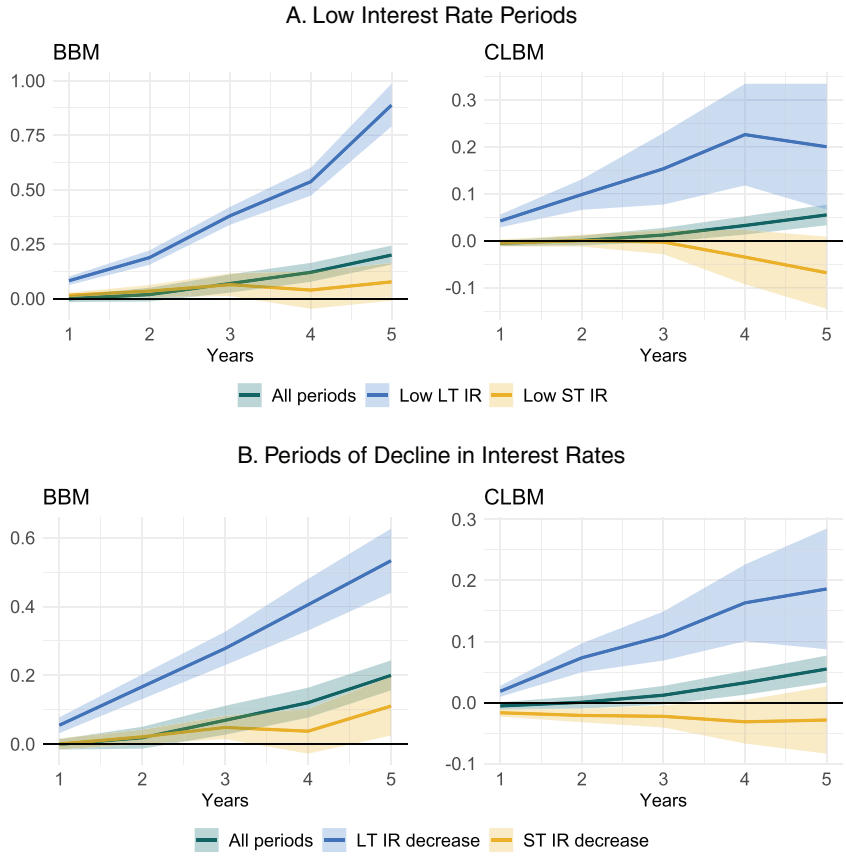
Figure 6 shows that macroprudential policy tightening increases income inequality in periods of accommodative monetary policy. The positive effect of the macroprudential policy when interest rates are low is more than 50 percent stronger than the baseline effect. These results suggest that the credit redistribution channel is likely to dominate during periods of accommodative monetary policy. The possible mechanism can be as follows: Accommodative monetary policy boosts the incomes of higher-income households relative to lower-income households, while stringent macroprudential policy restricts the incomes of lower-income households relative to higher-income households (e.g., by cutting off riskier, lower-income households from the credit market).[23]

[21]Malovaná et al. (2023) review literature on the potential adverse effects of a prolonged period of low interest rates on financial stability.

[22]Low interest rate periods are defined as interest rates being below the first quartile.

[23]We recognize the distinction between the pre- and post-GFC periods of low interest rates, noting that the latter period also involved unconventional monetary policies (Cukierman 2013). Despite these differences, our analysis, as illustrated in Figure D.1, shows that the impacts on inequality were not significantly different

Figure 6. Low or Falling Interest Rates, Macroprudential Policy, and Income Inequality



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (4). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the five years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. Low interest rate periods are defined as interest rates below the first quartile (panel A). We estimate all models with a full set of control variables and robust standard errors.

5.2 Financial-Sector Characteristics

Banking-Sector Capital Resilience. Recent studies have established a strong empirical link between indicators of poor financial conditions (low level of capitalization in particular) and significant tail risks to GDP (Adrian, Boyarchenko, and Giannone 2019; Aikman et al. 2019). Considering that the macroprudential policy aims to build the financial sector's resilience, we test the sensitivity of its impact on income inequality conditional on banking-sector resilience, expressed by the value of the regulatory capital ratio (measured as regulatory capital to total risk-weighted assets).

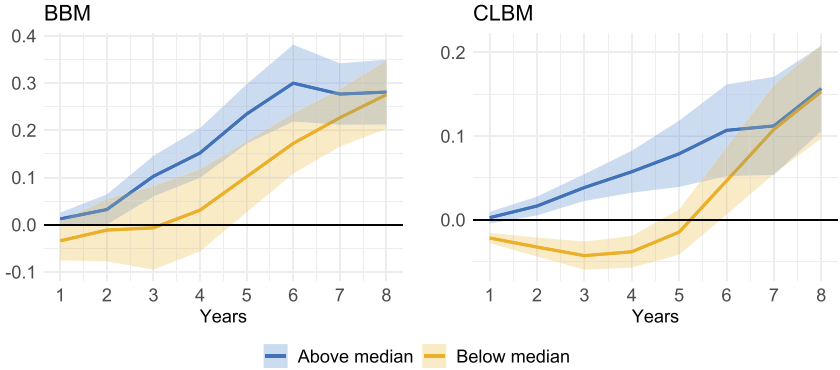
Figure 7 highlights important differences between countries with below- and above-median values of regulatory capital ratio. In relatively less capitalized countries (below median), capital- and liquidity-based regulation decreases income inequality, which points to a more prominent role of the crisis prevention and mitigation channel. To reiterate, an increase in capital requirements through additional macroprudential policy measure seems to be more effective in reducing the crises probability for weakly capitalized banking sector.

As for the borrower-based measures, we continue to find a positive impact on income inequality but significantly weaker in countries with a below-median regulatory capital ratio. Specifically, the increase in income inequality following borrower-based measures tightening is about 50 percent lower in countries with less capitalized banking sectors. Thus, while the credit redistribution channel is still dominant in the case of borrower-based measures, it can be substantially weaker in these countries. The strength of the crisis prevention and mitigation channel in such countries becomes well visible even though we are focusing on below/above median values.

Banking-Sector Competition. Next, we explore the impact of macroprudential policy on income inequality in countries differentiated by the level of banking-sector competition, proxied by

across these periods. To provide a comprehensive understanding, we interpret the effects discussed here as those associated with an environment of accommodative monetary policy, which includes both traditional low interest rates and unconventional policies like quantitative easing (QE). It is likely that QE influences inequality in the same direction as low interest rates, as demonstrated, for example, in De Luigi et al. (2023).

Figure 7. Banking-Sector Resilience, Macroprudential Policy, and Income Inequality



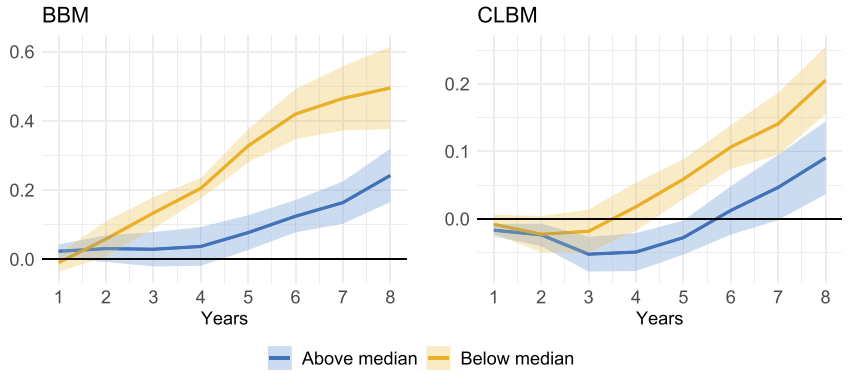
Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (4). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. We measure the regulatory capital ratio using the ratio of total regulatory capital to risk-weighted assets. We estimate all models with a full set of control variables and robust standard errors.

the Lerner index.[24] Higher values of the Lerner index imply a less competitive environment. The literature generally finds that market power (less competition) increases loan portfolio risk (Akins et al. 2016; Berger, Klapper, and Turk-Ariss 2017), but the estimates are not conclusive (Zigraiova and Havranek 2016). Thus, the crisis mitigation and prevention channel could be stronger in countries with less competition.

Figure 8 shows that tightening of capital- and liquidity-based measures in less competitive countries reduces income inequality more than in more competitive countries, with the effect being about 50 percent stronger. When considering borrower-based measures, we

[24]The results are qualitatively comparable if we switch to the concentration ratio. While market power can be correlated with market concentration, they refer to different dimensions of market competition due to the role of contestability, particularly in the banking sector (Claessens and Laeven 2004).

Figure 8. Banking-Sector Concentration, Macroprudential Policy, and Income Inequality



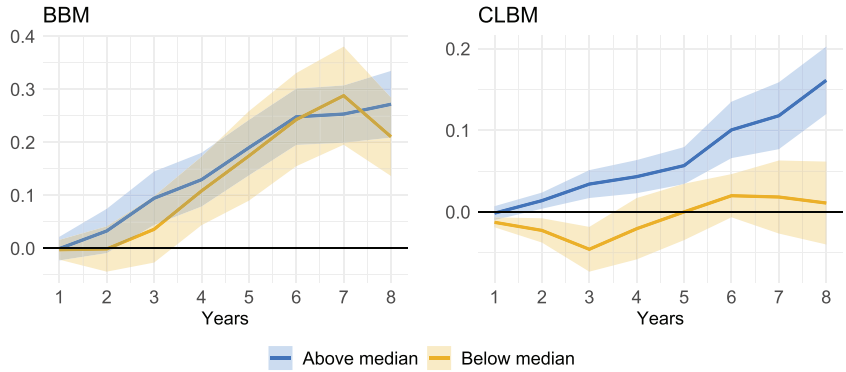
Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (4). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. We measure bank concentration using the Lerner index. The results are qualitatively comparable if we switch to the concentration ratio. We estimate all models with a full set of control variables and robust standard errors.

document a generally positive effect on income inequality, but the effect is about 40 percent weaker in countries with an above-median level of concentration (i.e., below-median level of competition). Overall, we find evidence consistent with the competition–stability view that less banking-sector competition increases the risk of financial instability (Berger, Klapper, and Turk-Ariss 2017), which translates into higher strength of the crisis mitigation and prevention channel.[25]

Financial Development. A growing body of research suggests that the beneficiary effects of greater access to finance on financial stability depends on how that access is managed within the

[25]Using information from the Global Financial Crisis of 2008, Akins et al. (2016) show that states with less competition had higher rates of mortgage approval, experienced greater inflation in housing prices before the crisis, and experienced a steeper decline in housing prices during the crisis.

Figure 9. Financial Development, Macroprudential Policy, and Income Inequality



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (4). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. We proxy for the level of financial development using the IMF's Financial Development Index. We estimate all models with a full set of control variables and robust standard errors.

regulatory and supervisory framework (Cull, Demirgüç-Kunt, and Lyman 2012; Morgan and Pontines 2014). Prasad (2010) shows that financial inclusion can lead to greater efficiency of financial intermediation. We thus estimate the effect of macroprudential policy on income inequality conditional on the country's level of financial development index taken from the IMF.

Figure 9 shows that the level of financial development affects the direction of the relationship between capital- and liquidity-based measures and income inequality. For less financially developed countries, the effect is negative, i.e., tightening the policy reduces income inequality, while it is weakly positive for more financially developed countries. Underdeveloped financial sectors thus seem to benefit from stricter regulation, with the crisis mitigation and prevention channel playing a larger role. When looking at the impact of borrower-based measures, we do not find significant differences for country group splits according to their level of financial development.

5.3 Null Results

During the empirical analysis, we tried several other tests and interactions that ultimately proved to be unnecessary/not statistically relevant. First of all, most of our hypotheses and related tests from the previous chapters were tested for different geographic regions. However, these geographic regions tend to reflect differences in country development (AE versus EMDE) rather than any fundamental geographic differences in our results. For this reason, we do not report the results in the paper, but they are available upon request.

While macroeconomic and socioeconomic variables are important as control variables in explaining inequality, many of them have no effect when used in interaction with macroprudential policy indices. Placing a country in a positive or negative output gap has been shown to not affect the transmission of borrower-based measures or capital- and liquidity-based measures to inequality. Similarly, in interaction with macroprudential instruments, differences in population growth do not affect the transmission (although it is an important determinant of inequality). Differences in other variables mentioned by the literature as major determinants of inequality also do not affect the transmission of macroprudential policy to inequality. This is the case, for example, for education (inconsistent results for primary, secondary, and tertiary education) and globalization (measured as financial or economic globalization or de jure and de facto globalization).

Surprisingly, supply-side factors in the property market, such as construction (volume index of production in construction) and permits (dwellings and residential buildings permits), also had no impact on the effect of borrower-based measures on inequality. These variables are only available for advanced economies, but the reduced-sample results did not show statistically significant differences in their interaction with borrower-based measures.

Finally, we also considered the question of the interaction between borrower-based measures and capital- and liquidity-based measures together. We looked at the effect of borrower-based measures on inequality accompanied by, first, capital- and liquidity-based measures tightening and then capital- and liquidity-based measures loosening. None of this yielded any new insights.

6. Conclusion

Using data from 105 countries, we trace the impact of a wide range of macroprudential policy measures on income inequality over the period 1990–2019. We show that income inequality, measured by the Gini index, changes relative to its trend in several years following a macroprudential policy action. We find the effect on income inequality to be both upward- and downward-sloping, depending on the timing and type of macroprudential policy measure used as well as on a broader set of macrofinancial conditions.

We establish and empirically verify two channels that explain both the upward and downward effects of macroprudential policy on income inequality. First, we find that macroprudential tightening can reduce income inequality by building capacity in the financial sector to mitigate the adverse effects of a crisis (crisis mitigation) and preventing materialization of financial risks (crisis prevention). The crisis prevention and mitigation channel dominate during periods preceding crises and in less stable and less financially developed economies. Second, we show that a more stringent macroprudential policy can lead to higher inequality by depressing credit and house price growth. This channel operates primarily through the tightening of borrower-based measures.

What are the policy implications of these findings? Recent studies, ours notwithstanding, show that macroprudential policy has real economic effects (Richter, Schularick, and Shim 2019; Fidrmuc and Lind 2020). A key concern is whether these real effects might undermine the intended stabilizing effects (Rajan 2011; Kumhof, Rancière, and Winant 2015). Our estimates suggest that this should not be the case, at least in terms of income distribution. Since different macroprudential policy instruments are found to have opposite effects on income inequality, the overall impact is neither clearly negative nor positive. In fact, our analysis suggests that the net effect of macroprudential policy on income inequality could be neutral or even positive, particularly when such policies are applied preemptively. Notably, we document a reduction in income inequality following the tightening of macroprudential policies implemented before the onset of a crisis or a credit boom. The preemptive use of macroprudential measures is crucial for maintaining access to credit for the broader economy, while simultaneously reducing banks'

risk-taking and enhancing their resilience. Timely actions like these are key for mitigating the negative impacts of financial and economic crises, which tend to disproportionately affect lower-income populations.

Based on our estimates, we have two key recommendations. First, our evidence supports the need for macroprudential policy to act preemptively and tighten measures during credit booms. While there are apparent financial stability implications of a preemptive macroprudential policy (Claessens, Ghosh, and Mihet 2013; Galati and Moessner 2013; Cerutti, Claessens, and Laeven 2017), we emphasize that there are also significant real economy effects. This is all the more important as countries have a relatively short history of using macroprudential policy preemptively which may underestimate the estimates of its stabilizing effects. Furthermore, macroprudential policy tightening during good times can be unpopular and political pressures can limit regulators' ability to "lean against the wind" (Sever and Yücel 2022; Müller 2023). Second, economies below a certain level of economic and financial development are most likely to benefit from the stabilizing effects of macroprudential policy with only a limited impact on income inequality.

However, it is important to note that while our analysis focuses on income inequality, it may not fully capture how macroprudential policies affect wealth inequality. For example, borrower-based measures that limit mortgage access might prevent certain groups from buying real estate, potentially increasing wealth inequality. This is particularly relevant for households forced to rent rather than buy, affecting their wealth accumulation differently from their income. Although we assume that wealth inequality often translates into income inequality, and thus is reflected in our analysis, the dynamics can be more complex. Park and Kim (2023) illustrate this with household-level data from South Korea, indicating that the effect of macroprudential policies on wealth accumulation can be substantial. Therefore, while our results show that macroprudential policies generally have a neutral to positive effect on income inequality, their impact on wealth inequality is more complex and deserves further study.

Appendix A. Additional Information on Data

In this appendix, we discuss the data used in our study. We describe the data in detail and list the sources in Table A.1. We also include a list of countries analyzed, distinguishing between advanced and emerging market economies, as shown in Table A.2. Additionally, we provide a detailed list of the macroprudential policy measures we examined, which can be found in Table A.3. We also show the variation of the Gini index across countries and over time in Figures A.1 and A.2. We analyze macroprudential policy actions by type and year, detailed in Figures A.3 and A.4. Lastly, Table A.4 provides the summary statistics for the control variables used in different models.

Table A.1. Data Description and Sources

Variable	Definition	Data Sources
Market Gini Index	Gini index from market income	SWIID
Top and Bottom 20% (50%) Income Share	Pre-tax income shares of households in different income groups	WID
Macroprudential Policy Index	Dummy coded macroprudential policy indices (borrower-based measures, BBM; capital- and liquidity-based measures, CLBM)	iMaPP (IMF), Alam et al. (2019)
Output Gap	Calculated from real GDP per capita using the Hamilton (2018) filter	WDI
Inflation	Annual change to Consumer Price Index	WDI
Trade Openness	The sum of exports and imports as a share of GDP	PWT
Government Expenditures	Ratio of central government expenditures as a share of GDP	PWT
Human Capital Index	Human capital index, based on years of schooling and returns to education	PWT
Population	Population (in millions)	PWT
Financial Crisis	Binary indicator (dummy variable) for the occurrence of financial crises	Laeven and Valencia (2020)
Credit-to-GDP Ratio	Domestic credit to the private sector by banks as a share of GDP	WDI
Short-Term Nominal Interest Rate	Real interest rates plus inflation	WDI
Long-Term Nominal Interest Rate	Long-term interest rates (10-year government bond yields)	FRED
Regulatory Capital Ratio	Regulatory capital to risk-weighted assets	FRED
Lerner Index	A measure of market power in the banking market, defined as the difference between output prices and marginal costs (relative to prices)	FRED
Financial Development	Financial development index	IMF

Note: SWIID = Standardized World Income Inequality Database; WID = World Inequality Database; iMaPP = Integrated Macroprudential Policy database; WDI = World Bank's World Development Indicators; PWT = Penn World Table; BIS = Bank for International Settlements; FRED = Federal Reserve Economic Data.

Table A.2. Countries in the Analysis

Group	No.	Countries
		IMF Classification
Advanced Economies (AE)	35	Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, Taiwan, United Kingdom, United States
Emerging Market and Developing Economies (EMDE)	70	Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bahamas, Bangladesh, Belarus, Benin, Bhutan, Botswana, Brazil, Bulgaria, Cambodia, Colombia, Costa Rica, Croatia, Dominican Republic, Ecuador, El Salvador, Fiji, Georgia, Ghana, Haiti, Honduras, Hungary, Chile, China, India, Indonesia, Jamaica, Kazakhstan, Kenya, Kosovo, Laos, Lebanon, Lesotho, Malaysia, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Nepal, Niger, Nigeria, Oman, Pakistan, Peru, Philippines, Poland, Romania, Russia, Saudi Arabia, Senegal, Serbia, South Africa, Tajikistan, Thailand, Tonga, Tunisia, Turkey, Ukraine, United Arab Emirates, Uruguay, Vietnam, Zambia
Low-Income Developing Countries (LIDC)	*18*	*Bangladesh, Benin, Bhutan, Cambodia, Ghana, Haiti, Honduras, Kenya, Laos, Lesotho, Mauritania, Moldova, Nepal, Niger, Senegal, Tajikistan, Tonga, Zambia*
Switching LIDC	*12*	*Albania, Angola, Armenia, Azerbaijan, Georgia, China, India, Indonesia, Mongolia, Nigeria, Pakistan, Vietnam*

(*continued*)

Table A.2. (Continued)

Group	No.	Countries
Regional Classification		
Africa	12	Angola, Benin, Botswana, Ghana, Kenya, Lesotho, Mauritius, Niger, Nigeria, Senegal, South Africa, Zambia
Asia and Pacific	21	Australia, Bangladesh, Bhutan, Cambodia, Fiji, China, India, Indonesia, Japan, Korea, Laos, Malaysia, Mongolia, Nepal, New Zealand, Philippines, Singapore, Taiwan, Thailand, Tonga, Vietnam
Europe	41	Albania, Austria, Belarus, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom
Middle and South America	15	Argentina, Bahamas, Brazil, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Haiti, Honduras, Chile, Jamaica, Mexico, Peru, Uruguay
Middle East and Central Asia	14	Algeria, Armenia, Azerbaijan, Georgia, Kazakhstan, Lebanon, Mauritania, Morocco, Oman, Pakistan, Saudi Arabia, Tajikistan, Tunisia, United Arab Emirates
North America	2	Canada, United States

Note: We divided countries based on the IMF classification provided in their Fiscal Monitor which divides the world into three major groups: advanced economies, emerging market and middle-income economies, and low-income developing countries (LIDC). EMDE consists of the two latter groups. Switching LIDC are countries that moved from low income to middle income during the analyzed period.

Table A.3. Categorization of Macroprudential Policy Instruments in iMaPP

Capital- and Liquidity-Based Measures	Leverage ratio, countercyclical capital buffer, capital conservation buffer, capital requirements, liquidity requirements, limits of foreign exchange positions, limits on credit growth, loan loss provisions, limits on loan-to-deposit ratio, limits on foreign currency loans
Borrower-Based Measures	Limits on loan-to-value ratio, limits on debt service-to-income, limits on loan-to-income ratio
Source: Alam et al. (2019), own elaboration.	

Table A.4. Summary Statistics of Control Variables

	Obs.	Mean	Median	SD	Min.	Max.
All Countries						
Detrended Gini Index (% of Global Trend)	2,372	0.020	0.380	14.616	–51.771	60.119
Country-Specific Trend (% of Gini Index)	2,322	45.729	45.975	6.702	21.734	72.884
Top 50% Income Share	831	77.053	76.970	3.928	65.600	92.580
Bottom 50% Income Share	831	22.953	23.010	3.931	7.430	34.410
Top 20% Income Share	831	44.664	43.970	5.480	31.900	73.630
Bottom 20% Income Share	831	5.242	5.295	1.339	1.160	9.070
Output Gap (% of Trend)	2,256	0.140	0.473	3.646	–7.941	6.837
Inflation (%)	2,281	6.152	3.501	7.816	0.070	38.918
Trade (% of GDP)	2,317	83.612	76.002	38.212	28.805	166.745
Government Expenditures (% of GDP)	2,336	18.351	17.804	6.007	9.303	31.219
Human Capital Index (% Growth)	2,146	0.801	0.715	0.656	–2.487	4.960
Population (% Growth)	2,270	0.922	0.891	1.213	–21.922	8.923
Financial Crisis (Binary Indicator)	2,372	0.088	0	0.284	0	1
Credit-to-GDP Ratio (%)	2,144	55.295	45.960	39.870	7.063	141.585
Short-Term Nominal Interest Rate (%)	1,421	13.012	10.689	9.718	–6.227	59.976
Long-Term Nominal Interest Rate (%)	769	4.603	4.307	4.206	–0.362	87.376
Regulatory Capital Ratio (%)	1,667	15.890	15.200	4.727	1.755	48.600
Lerner Index	1,563	0.242	0.236	0.148	–1.609	1.076
Financial Development Index	2,318	0.394	0.342	0.243	0	1

(*continued*)

Table A.4. (Continued)

	Obs.	Mean	Median	SD	Min.	Max.
Advanced Economies						
Detrended Gini Index (% of Global Trend)	863	–0.006	1.941	10.303	–35.401	20.996
Country-Specific Trend (% of Gini Index)	860	46.416	47.432	4.851	30.680	56.633
Top 50% Income Share	690	76.252	76.760	3.274	65.600	83.490
Bottom 50% Income Share	690	23.755	23.250	3.276	16.510	34.410
Top 20% Income Share	690	43.472	43.655	3.917	31.900	51.710
Bottom 20% Income Share	690	5.499	5.428	1.148	2.570	9.070
Output Gap (% of Trend)	812	0.217	0.611	3.255	–7.941	6.837
Inflation (%)	838	2.477	1.973	2.935	0.070	38.918
Trade (% of GDP)	838	93.878	82.727	42.477	28.805	166.475
Government Expenditures (% of GDP)	863	18.359	17.826	5.207	9.303	31.219
Human Capital Index (% Growth)	854	0.632	0.559	0.570	–0.522	4.960
Population (% Growth)	854	0.566	0.489	0.811	–1.528	4.479
Financial Crisis (Binary Indicator)	863	0.126	0	0.332	0	1
Credit-to-GDP Ratio (%)	680	94.920	95.300	32.807	7.063	141.585
Short-Term Nominal Interest Rate (%)	319	5.880	5.224	3.528	–1.759	20.750
Long-Term Nominal Interest Rate (%)	658	3.937	4.119	2.312	–0.362	22.497
Regulatory Capital Ratio (%)	706	14.784	13.942	3.919	6.600	35.653
Lerner Index	606	0.213	0.195	0.157	–1.609	1.076
Financial Development Index	838	0.627	0.667	0.199	0.100	1

(*continued*)

Table A.4. (Continued)

	Obs.	Mean	Median	SD	Min.	Max.
Emerging Market and Developing Economies						
Detrended Gini Index (% of Global Trend)	1,509	0.034	–1.014	16.589	–51.771	60.119
Country-Specific Trend (% of Gini Index)	1,462	45.325	44.799	7.555	21.734	72.884
Top 50% Income Share	141	80.971	80.240	4.481	74.210	92.580
Bottom 50% Income Share	141	19.027	19.760	4.482	7.430	25.810
Top 20% Income Share	141	50.499	47.190	7.825	41.430	73.630
Bottom 20% Income Share	141	3.989	4.030	1.500	1.160	6.580
Output Gap (% of trend)	1,444	0.096	0.393	3.848	–7.941	6.837
Inflation (%)	1,443	8.287	5.679	8.898	0.070	38.918
Trade (% of GDP)	1,479	77.795	72.501	34.244	28.805	166.745
Government Expenditures (% of GDP)	1,473	18.346	17.735	6.431	9.303	31.219
Human Capital Index (% Growth)	1,292	0.913	0.898	0.684	–2.487	3.604
Population (% Growth)	1,416	1.136	1.190	1.357	–21.922	8.923
Financial Crisis (Binary Indicator)	1,509	0.066	0	0.249	0	1
Credit-to-GDP Ratio (%)	1,464	36.890	29.579	27.570	7.063	141.585
Short-Term Nominal Interest Rate (%)	1,102	15.076	13.324	9.961	–6.227	59.976
Long-Term Nominal Interest Rate (%)	111	8.551	7.523	8.554	2.348	87.376
Regulatory Capital Ratio (%)	961	16.702	16.090	5.093	1.755	48.600
Lerner Index	957	0.261	0.259	0.139	–1.137	0.677
Financial Development Index	1,480	0.262	0.224	0.148	0	0.739

Note: Output gap is estimated using Hamilton filter. Selected variables are winsorized globally at 5 percent from each side.

Figure A.1. Cross-Country Heterogeneity of the Gini Index

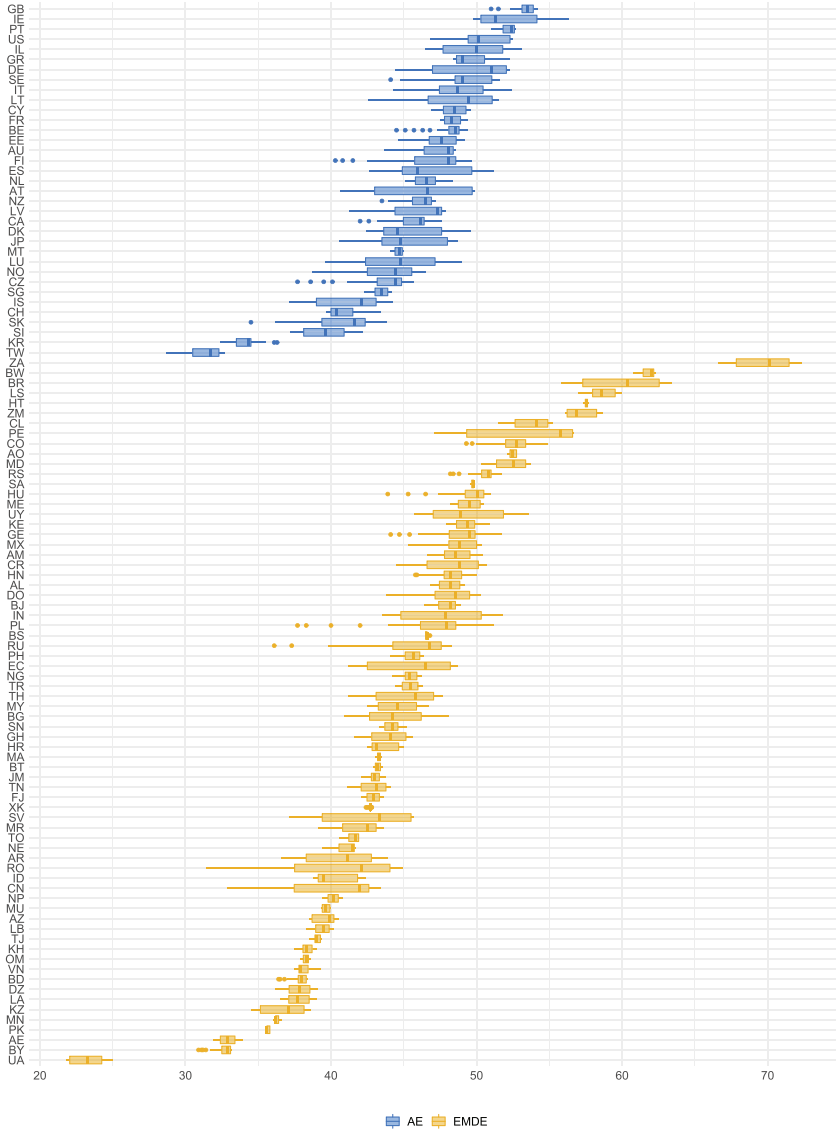


Figure A.2. Heterogeneity of the Gini Index by Year

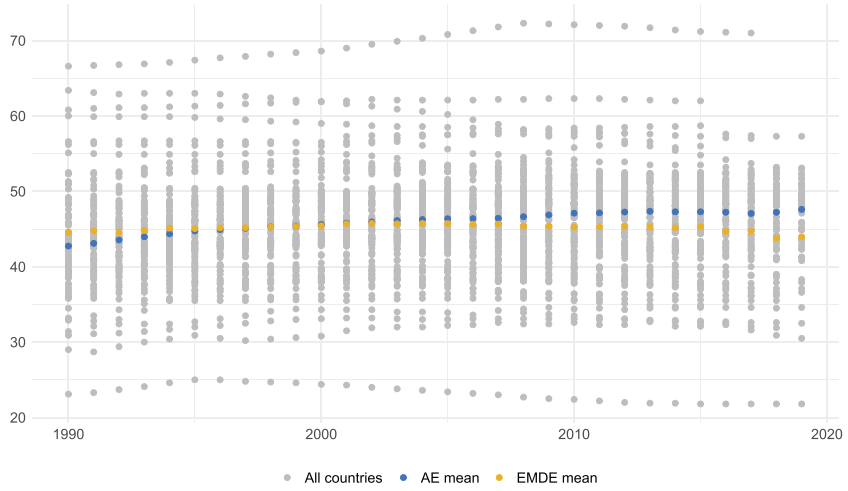
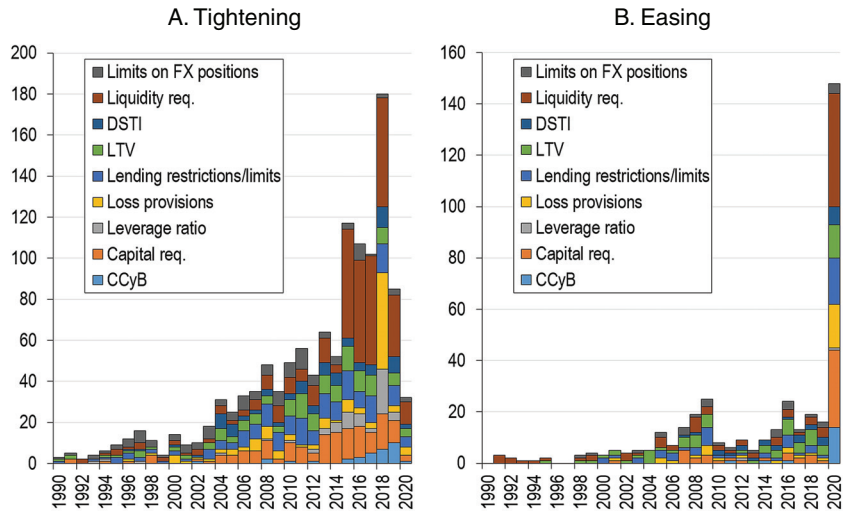
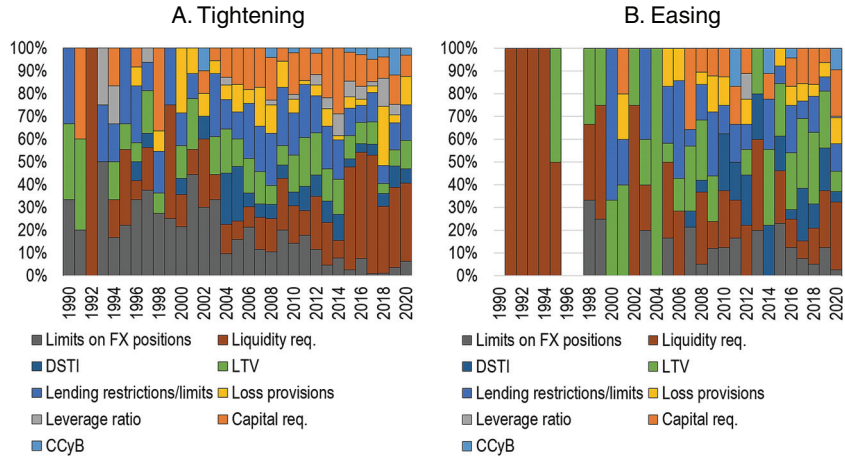


Figure A.3. Breakdown of Macroprudential Policy Actions by Year and Instrument



Note: Graphs show the total number of individual macroprudential policy actions for our sample in a given year.
Source: Alam et al. (2019), own elaboration.

Figure A.4. Breakdown of Macroprudential Policy Actions: Share on All Actions by Instrument



Note: Graphs show the total number of individual macroprudential policy actions for our sample in a given year.
Source: Alam et al. (2019), own elaboration.

Appendix B. Testing for Exogeneity of MaPP Measures

In this appendix, we check whether our macroprudential policy variable is exogenous, as this is important for the accuracy of our econometric model, following the approach of Stock and Watson (2018). Exogeneity means that the policy variable does not influence the model's error term, which is essential for reliable and consistent estimates of causal effects. We investigate the correlation between the macroprudential policy variable and the model's residuals, considering up to three leads and lags. This helps us determine if changes in the policy variable are related to unobserved factors represented by the error term.

We present our findings in Tables B.1 and B.2, showing correlation coefficients and their statistical significance (p-values, reported in parentheses) for each model (BBM versus CLBM) and for all countries, advanced economies, and emerging market and developing economies, across forecasting horizons of up to eight years. Our results indicate that the correlations are generally weak and not

significant, suggesting that the macroprudential policy variable is exogenous. This lack of significant correlation with the residuals supports the reliability of our causal conclusions.

Table B.1. Correlation Between BBM Variable and Lags/Leads of Residuals at Each Forecasting Horizon

Lags/Leads of Residuals	–3	–2	–1	+1	+2	+3
All Countries						
t+1	0.01	0.01	0.01	–0.01	0	–0.01
	(0.508)	(0.416)	(0.466)	(0.276)	(0.496)	(0.15)
t+2	0.01	0.01	0.02	–0.01	–0.01	–0.02
	(0.545)	(0.421)	(0.242)	(0.372)	(0.246)	(0.108)
t+3	0.01	0.02	0.03	–0.02	–0.03	–0.03
	(0.67)	(0.329)	(0.274)	(0.233)	(0.124)	(0.064)
t+4	0.02	0.03	0.04	–0.02	–0.03	–0.04
	(0.514)	(0.325)	(0.197)	(0.384)	(0.206)	(0.112)
t+5	0.02	0.03	0.04	–0.03	–0.03	–0.04
	(0.606)	(0.3)	(0.231)	(0.358)	(0.22)	(0.123)
t+6	0.02	0.03	0.03	–0.03	–0.04	–0.04
	(0.564)	(0.383)	(0.467)	(0.373)	(0.205)	(0.229)
t+7	0.02	0.01	0	–0.02	–0.03	–0.03
	(0.698)	(0.73)	(0.977)	(0.57)	(0.369)	(0.492)
t+8	0.01	–0.01	–0.01	–0.02	–0.02	–0.02
	(0.897)	(0.859)	(0.892)	(0.637)	(0.655)	(0.689)

(*continued*)

Table B.1. (Continued)

Lags/Leads of Residuals	–3	–2	–1	+1	+2	+3
Advanced Economies						
t+1	0	0.01	0.01	0	–0.01	–0.01
	(0.719)	(0.292)	(0.513)	(0.602)	(0.479)	(0.174)
t+2	0.01	0.02	0.02	–0.01	–0.02	–0.02
	(0.504)	(0.3)	(0.254)	(0.488)	(0.172)	(0.158)
t+3	0.01	0.03	0.04	–0.03	–0.04	–0.05
	(0.597)	(0.226)	(0.156)	(0.257)	(0.105)	(0.049)
t+4	0.02	0.05	0.06	–0.02	–0.05	–0.05
	(0.508)	(0.201)	(0.113)	(0.411)	(0.083)	(0.07)
t+5	0.02	0.05	0.06	–0.03	–0.05	–0.06
	(0.559)	(0.224)	(0.203)	(0.385)	(0.148)	(0.106)
t+6	0.02	0.04	0.05	–0.02	–0.04	–0.05
	(0.624)	(0.472)	(0.413)	(0.552)	(0.329)	(0.252)
t+7	0	0.02	0.01	–0.01	–0.03	–0.03
	(0.937)	(0.684)	(0.842)	(0.896)	(0.497)	(0.494)
t+8	0.01	0.02	0.03	–0.01	–0.01	–0.03
	(0.806)	(0.702)	(0.641)	(0.919)	(0.83)	(0.518)

(*continued*)

Table B.1. (Continued)

Lags/Leads of Residuals	**–3**	**–2**	**–1**	**+1**	**+2**	**+3**
Emerging Market and Developing Economies						
t+1	0	0	0	0	0	0
	(0.698)	(0.839)	(0.889)	(0.751)	(0.548)	(0.774)
t+2	0	0	0	–0.01	–0.01	–0.01
	(0.782)	(0.939)	(0.879)	(0.593)	(0.444)	(0.499)
t+3	0	0	0	–0.01	–0.02	–0.01
	(0.836)	(0.978)	(0.9)	(0.645)	(0.486)	(0.505)
t+4	0.01	0	0.01	0	–0.01	–0.02
	(0.777)	(0.889)	(0.807)	(0.882)	(0.694)	(0.574)
t+5	0.01	0.01	0.02	–0.01	–0.02	–0.01
	(0.755)	(0.734)	(0.694)	(0.686)	(0.613)	(0.733)
t+6	0.02	0.02	0.01	–0.01	–0.01	0
	(0.625)	(0.64)	(0.794)	(0.747)	(0.838)	(0.926)
t+7	0.02	0.01	–0.02	0	0.01	0.03
	(0.627)	(0.858)	(0.793)	(0.99)	(0.9)	(0.532)
t+8	0.01	–0.02	–0.05	0	0.02	0.05
	(0.776)	(0.785)	(0.465)	(0.962)	(0.749)	(0.343)

Table B.2. Correlation Between CLBM Variable and Lags/Leads of Residuals at Each Forecasting Horizon

Lags/Leads of Residuals	–3	–2	–1	+1	+2	+3
All Countries						
t+1	0	0	0	0	0	0
	(0.901)	(0.816)	(0.46)	(0.724)	(0.371)	(0.279)
t+2	0	0.01	0.01	0	–0.01	–0.01
	(0.818)	(0.445)	(0.104)	(0.336)	(0.13)	(0.036)
t+3	0	0.01	0.02	–0.01	–0.01	–0.02
	(0.651)	(0.276)	(0.067)	(0.321)	(0.05)	(0.003)
t+4	0.01	0.02	0.03	–0.01	–0.03	–0.04
	(0.513)	(0.163)	(0.052)	(0.208)	(0.005)	(0)
t+5	0.01	0.03	0.04	–0.03	–0.05	–0.06
	(0.378)	(0.109)	(0.038)	(0.056)	(0)	(0)
t+6	0.02	0.03	0.05	–0.04	–0.06	–0.07
	(0.328)	(0.109)	(0.049)	(0.03)	(0)	(0)
t+7	0.02	0.03	0.06	–0.03	–0.06	–0.06
	(0.396)	(0.162)	(0.036)	(0.082)	(0.001)	(0.001)
t+8	0.02	0.04	0.06	–0.04	–0.05	–0.06
	(0.47)	(0.111)	(0.026)	(0.101)	(0.013)	(0.006)

(*continued*)

Table B.2. (Continued)

Lags/Leads of Residuals	–3	–2	–1	+1	+2	+3
Advanced Economies						
t+1	0	0	0	0	0	0
	(0.932)	(0.822)	(0.888)	(0.837)	(0.939)	(0.632)
t+2	0	0	0.01	0	0	0
	(0.894)	(0.983)	(0.52)	(0.742)	(0.8)	(0.691)
t+3	0	0.01	0.02	0	0	–0.01
	(0.962)	(0.68)	(0.38)	(0.929)	(0.812)	(0.482)
t+4	0.01	0.02	0.02	0	–0.01	–0.01
	(0.71)	(0.495)	(0.516)	(0.855)	(0.506)	(0.595)
t+5	0.02	0.02	0.02	–0.02	–0.02	–0.01
	(0.631)	(0.595)	(0.584)	(0.535)	(0.422)	(0.678)
t+6	0.01	0.01	0.01	–0.02	–0.02	–0.02
	(0.79)	(0.771)	(0.804)	(0.619)	(0.585)	(0.66)
t+7	0.01	0.01	0.01	–0.02	–0.03	–0.05
	(0.875)	(0.872)	(0.816)	(0.694)	(0.392)	(0.209)
t+8	0	0.01	0.02	–0.03	–0.05	–0.07
	(0.927)	(0.818)	(0.734)	(0.534)	(0.241)	(0.138)

(*continued*)

Table B.2. (Continued)

Lags/Leads of Residuals	–3	–2	–1	+1	+2	+3
Emerging Market and Developing Economies						
t+1	0	0	0	0	0	0
	(0.979)	(0.833)	(0.951)	(0.675)	(0.68)	(0.748)
t+2	0	0	0	0	0	0
	(0.953)	(0.874)	(0.891)	(0.777)	(0.842)	(0.703)
t+3	0	0	0	0	0	–0.01
	(0.959)	(0.897)	(0.92)	(0.859)	(0.554)	(0.207)
t+4	0	0	0	0	–0.01	–0.02
	(0.989)	(0.967)	(0.908)	(0.757)	(0.328)	(0.051)
t+5	0	0.01	0.01	–0.01	–0.02	–0.03
	(0.858)	(0.743)	(0.696)	(0.515)	(0.091)	(0.011)
t+6	0.01	0.01	0.01	–0.01	–0.03	–0.04
	(0.649)	(0.601)	(0.553)	(0.372)	(0.082)	(0.011)
t+7	0.01	0.01	0.03	–0.02	–0.03	–0.04
	(0.677)	(0.587)	(0.331)	(0.358)	(0.113)	(0.043)
t+8	0.01	0.02	0.03	–0.01	–0.02	–0.03
	(0.735)	(0.451)	(0.377)	(0.519)	(0.302)	(0.146)

Appendix C. Additional Empirical Results

In this appendix, we offer additional results that support the findings presented in the main text. This includes a table version of Figure 3 and more estimates that help confirm the roles of crisis prevention and mitigation channels.

Table C.1. Response of Gini Index to a Change in Borrower-Based Measures

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
All Countries								
BBM	–0.001	0.018	0.069	0.120***	0.200***	0.265***	0.281***	0.289***
	(0.015)	(0.032)	(0.042)	(0.044)	(0.044)	(0.042)	(0.051)	(0.059)
Observations	1,582	1,489	1,396	1,303	1,210	1,118	1,028	940
Countries	93	93	93	93	92	90	88	84
R^2	0.953	0.877	0.779	0.649	0.53	0.438	0.368	0.333
Adj. R^2	0.948	0.864	0.755	0.606	0.47	0.361	0.275	0.23
Advanced Economies								
BBM	0.019	0.065*	0.153***	0.273***	0.452***	0.577***	0.589***	0.528***
	(0.016)	(0.034)	(0.047)	(0.07)	(0.096)	(0.108)	(0.129)	(0.136)
Observations	560	526	492	458	424	390	356	323
Countries	34	34	34	34	34	34	33	31
R^2	0.958	0.871	0.751	0.609	0.497	0.411	0.343	0.28
Adj. R^2	0.95	0.847	0.701	0.526	0.382	0.263	0.164	0.069
Emerging Market and Developing Economies								
BBM	0.009	0.048	0.078	0.136**	0.202***	0.248***	0.267***	0.265***
	(0.017)	(0.039)	(0.051)	(0.06)	(0.06)	(0.041)	(0.036)	(0.055)
Observations	1,022	963	904	845	786	728	672	617
Countries	59	59	59	59	58	56	55	53
R^2	0.977	0.928	0.866	0.781	0.704	0.648	0.577	0.516
Adj. R^2	0.974	0.919	0.849	0.75	0.66	0.592	0.505	0.428

Note: The table shows baseline regression results of Equation (1). For the sake of brevity, we report only responses to the detrended Gini index over the eight years following a unit change in the index of borrower-based measures. The regression models, however, include all control variables and fixed effects. We estimate robust standard errors. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level, respectively.

Table C.2. Response of Gini Index to a Change in Capital- and Liquidity-Based Measures

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
All Countries								
CLBM	–0.006	0.000	0.012	0.032*	0.055**	0.098***	0.109***	0.127***
	(0.006)	(0.01)	(0.015)	(0.02)	(0.022)	(0.03)	(0.037)	(0.044)
Observations	1,582	1,489	1,396	1,303	1,210	1,118	1,028	940
Countries	93	93	93	93	92	90	88	84
R^2	0.953	0.877	0.779	0.647	0.526	0.431	0.36	0.327
Adj. R^2	0.948	0.864	0.754	0.605	0.465	0.354	0.267	0.223
Advanced Economies								
CLBM	0.020**	0.069***	0.139***	0.194***	0.278***	0.341***	0.288***	0.190*
	(0.009)	(0.02)	(0.025)	(0.04)	(0.052)	(0.066)	(0.082)	(0.098)
Observations	560	526	492	458	424	390	356	323
Countries	34	34	34	34	34	34	33	31
R^2	0.958	0.873	0.756	0.609	0.482	0.372	0.289	0.231
Adj. R^2	0.951	0.85	0.707	0.527	0.363	0.214	0.095	0.005
Emerging Market and Developing Economies								
CLBM	–0.012**	–0.026*	–0.044*	–0.047	–0.049	–0.029	–0.005	0.012
	(0.006)	(0.014)	(0.023)	(0.031)	(0.03)	(0.023)	(0.019)	(0.034)
Observations	1,022	963	904	845	786	728	672	617
Countries	59	59	59	59	58	56	55	53
R^2	0.977	0.928	0.867	0.781	0.702	0.643	0.571	0.511
Adj. R^2	0.974	0.919	0.849	0.75	0.657	0.586	0.498	0.421

Note: The table shows baseline regression results of Equation (1). For the sake of brevity, we report only responses to the detrended Gini index over the eight years following a unit change in the index of capital- and liquidity-based measures. The regression models, however, include all control variables and fixed effects. We estimate robust standard errors. ****, **, and * denote significance at the 0.01, 0.05, and 0.1 level, respectively.

Table C.3. Crisis Mitigation and Prevention Channel: Number of Observations

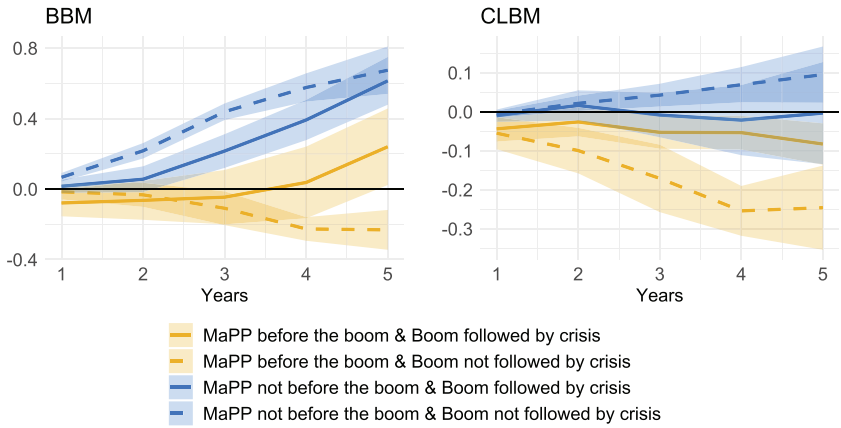
	Baseline	Crisis Mitigation Channel	Crisis Prevention Channel
Observations	1,861	472	964
Countries	93	54	73
AE	34	27	26
EMDE	59	27	47
Crisis	186	186	90
Credit Boom	516	103	516
BBM	567	134	305
CLBM	1,258	250	648
No. of Observations for Different Periods			
BBM Only Before Crisis/Boom		30	35
BBM Only After the Outbreak of Crisis/Boom		97	233
BBM Both Before and After Crisis/Boom		0	10
BBM Not Before the Crisis/Boom		442	919
CLBM Only Before Crisis/Boom		50	92
CLBM Only After the Outbreak of Crisis/Boom		170	444
CLBM Both Before and After Crisis/Boom		3	32
CLBM Not Before the Crisis/Boom		419	840
No. of Countries for Different Periods			
BBM Only Before Crisis/Boom		11	17
BBM Only After the Outbreak of Crisis/Boom		22	40
BBM Both Before and After Crisis/Boom		0	6
BBM Not Before the Crisis/Boom		54	73
CLBM Only Before Crisis/Boom		21	37
CLBM Only After the Outbreak of Crisis/Boom		39	65
CLBM Both Before and After Crisis/Boom		1	16
CLBM Not Before the Crisis/Boom		54	73

Table C.4. Estimated Probability of Crisis

	Dependent Variable: Financial Crisis
Output Gap	–0.200***
	(0.034)
CPI Inflation	0.154***
	(0.031)
Real Credit Growth	–0.049***
	(0.014)
Unemployment	0.109**
	(0.048)
Trade-to-GDP Ratio	–0.0002
	(0.010)
Obs.	1,574
Log-Likelihood	–293.558
Akaike Information Criterion	783.115
Pseudo R^2	0.49

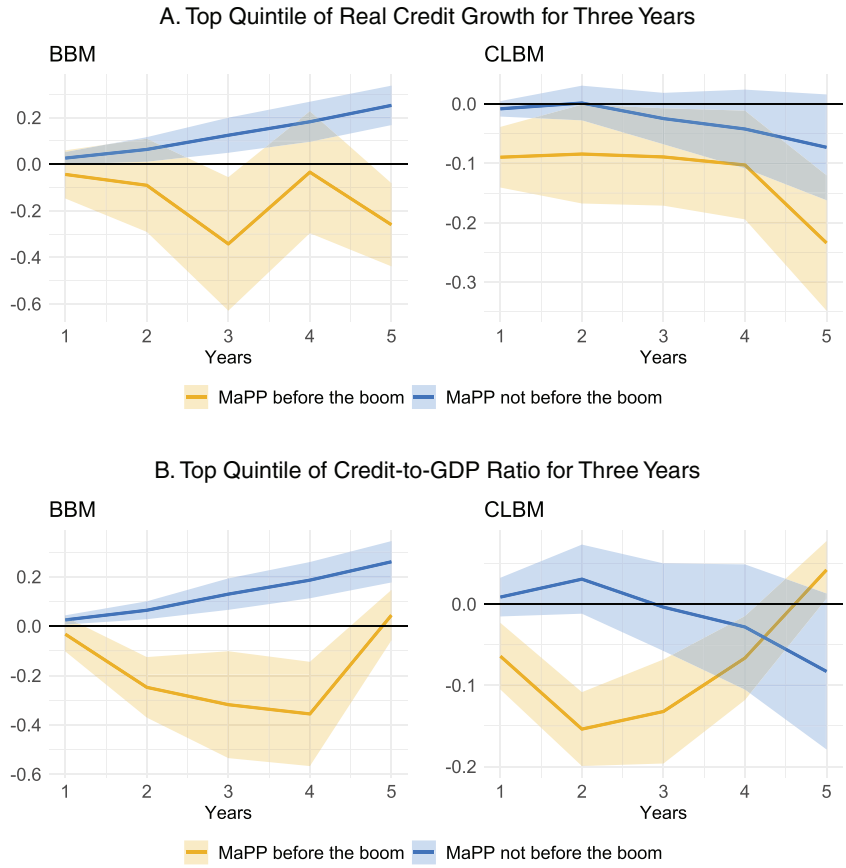
Note: The table shows logit classification models where the dependent variable is a binary indicator equal to one for financial crisis periods and zero otherwise. Country fixed effects are included. Robust standard errors are in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level, respectively.

Figure C.1. Crisis Prevention Channel: With and Without Subsequent Crisis



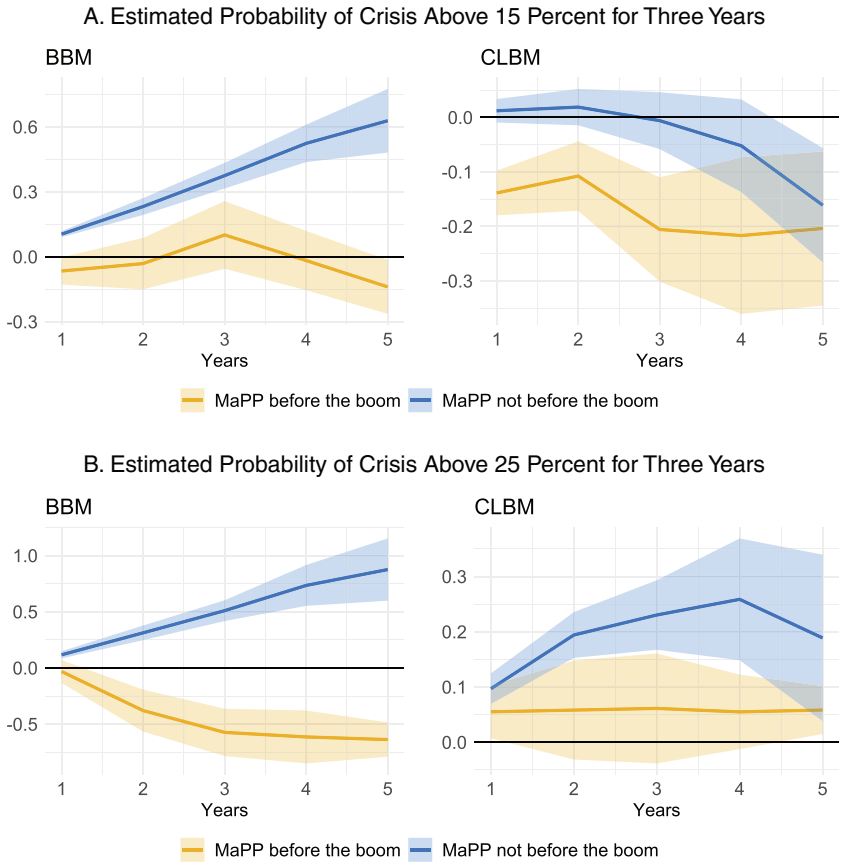
Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the five years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. In the regression, we exclude two control variables: the dummy variable for the financial crisis and the credit-to-GDP ratio. We estimate robust standard errors.

Figure C.2. Alternative Definitions of Boom Periods (1)



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the five years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. In the regression, we exclude two control variables: the dummy variable for the financial crisis and the credit-to-GDP ratio. We estimate robust standard errors.

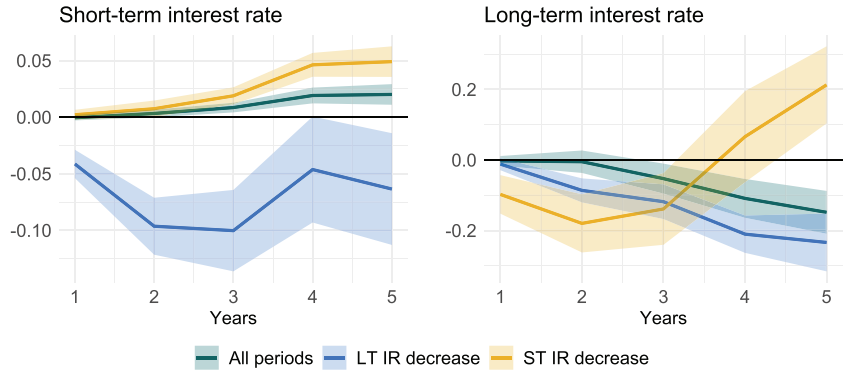
Figure C.3. Alternative Definitions of Boom Periods (2)



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the five years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. In the regression, we exclude two control variables: the dummy variable for the financial crisis and the credit-to-GDP ratio. We estimate robust standard errors.

C.3 Additional Results

Figure C.4. Response of the Gini Index to Change in Short- and Long-Term Interest Rates



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the five years following a 1 pp change in short-term or long-term interest rates. We estimate all models with a full set of control variables and robust standard errors.

Appendix D. Robustness

D.1 Different Specifications

Table D.1. Sensitivity of Gini Index Results to Exclusion of Fixed Effects and Control Variables (response to a change in borrower-based measures)

	Year 1	Year 4	Year 8	Year 1	Year 4	Year 8	Year 1	Year 4	Year 8
All Countries									
BBM	–1.072***	–1.084***	–1.021***	0.328**	0.409***	0.501***	–0.001	0.12***	0.289***
	(0.199)	(0.257)	(0.345)	(0.133)	(0.1)	(0.076)	(0.015)	(0.044)	(0.059)
FE	N	N	N	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	Y	Y	Y
Observations	1,861	1,582	1,210	1,861	1,582	1,210	1,582	1,303	940
Countries	93	93	92	93	93	92	93	93	84
R^2	0.015	0.012	0.006	0.015	0.02	0.029	0.953	0.649	0.333
Adj. R^2	0.015	0.011	0.006	–0.052	–0.056	–0.067	0.948	0.606	0.23
Advanced Economies									
BBM	–1.178***	–1.288***	–1.517***	–0.183***	0.015	0.436***	0.019	0.273***	0.528***
	(0.155)	(0.216)	(0.184)	(0.087)	(0.099)	(0.083)	(0.016)	(0.07)	(0.136)
FE	N	N	N	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	Y	Y	Y
Observations	662	560	424	662	560	424	560	458	323
Countries	34	34	34	34	34	34	34	34	31
R^2	0.066	0.055	0.043	0.009	0	0.041	0.958	0.609	0.28
Adj. R^2	0.065	0.053	0.041	–0.086	–0.109	–0.091	0.95	0.526	0.069

(*continued*)

Table D.1. (Continued)

	Year 1	**Year 4**	**Year 8**	**Year 1**	**Year 4**	**Year 8**	**Year 1**	**Year 4**	**Year 8**
Emerging Market and Developing Economies									
BBM	–0.963***	–0.894***	–0.635	0.877***	0.805***	0.536***	0.009	0.136***	0.265***
	(0.296)	(0.317)	(0.406)	(0.151)	(0.156)	(0.115)	(0.017)	(0.06)	(0.055)
FE	N	N	N	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	Y	Y	Y
Observations	1,199	1,022	786	1,199	1,022	786	1,022	845	617
Countries	59	59	58	59	59	58	59	59	53
R^2	0.007	0.005	0.002	0.067	0.055	0.024	0.977	0.781	0.516
Adj. R^2	0.006	0.004	0	–0.002	–0.026	–0.079	0.974	0.75	0.428

Note: The table shows baseline regression results of Equation (1). We gradually add control variables and fixed effects in the baseline regression to see the sensitivity of the results. For the sake of brevity, we report only responses to the detrended Gini index on three horizons (1, 4, and 8 years) following a unit change in the index of borrower-based measures. We estimate robust standard errors. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level, respectively.

Table D.2. Sensitivity of Gini Index Results to Exclusion of Fixed Effects and Control Variables (response to a change in capital- and liquidity-based measures)

	Year 1	Year 4	Year 8	Year 1	Year 4	Year 8	Year 1	Year 4	Year 8
All Countries									
CLBM	–0.142	–0.260**	–0.268	0.120	–0.015	–0.047	–0.006	0.032**	0.127***
	(0.119)	(0.157)	(0.216)	(0.074)	(0.073)	(0.042)	(0.006)	(0.02)	(0.044)
FE	N	N	N	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	Y	Y	Y
Observations	1,861	1,582	1,210	1,861	1,582	1,210	1,582	1,303	940
Countries	93	93	92	93	93	92	93	93	84
R^2	0.002	0.003	0.001	0.009	0	0.001	0.953	0.647	0.327
Adj. R^2	0.001	0.002	0.001	–0.058	–0.078	–0.098	0.948	0.605	0.223
Advanced Economies									
CLBM	–0.474**	–1.446***	–2.979***	0.043	0.033	0.133	0.020***	0.194***	0.190**
	(0.266)	(0.409)	(0.316)	(0.074)	(0.078)	(0.135)	(0.009)	(0.04)	(0.098)
FE	N	N	N	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	Y	Y	Y
Observations	662	560	424	662	560	424	560	458	323
Countries	34	34	34	34	34	34	34	34	31
R^2	0.057	0.163	0.277	0.001	0	0.003	0.958	0.609	0.231
Adj. R^2	0.055	0.162	0.275	–0.095	–0.109	–0.134	0.951	0.527	0.005

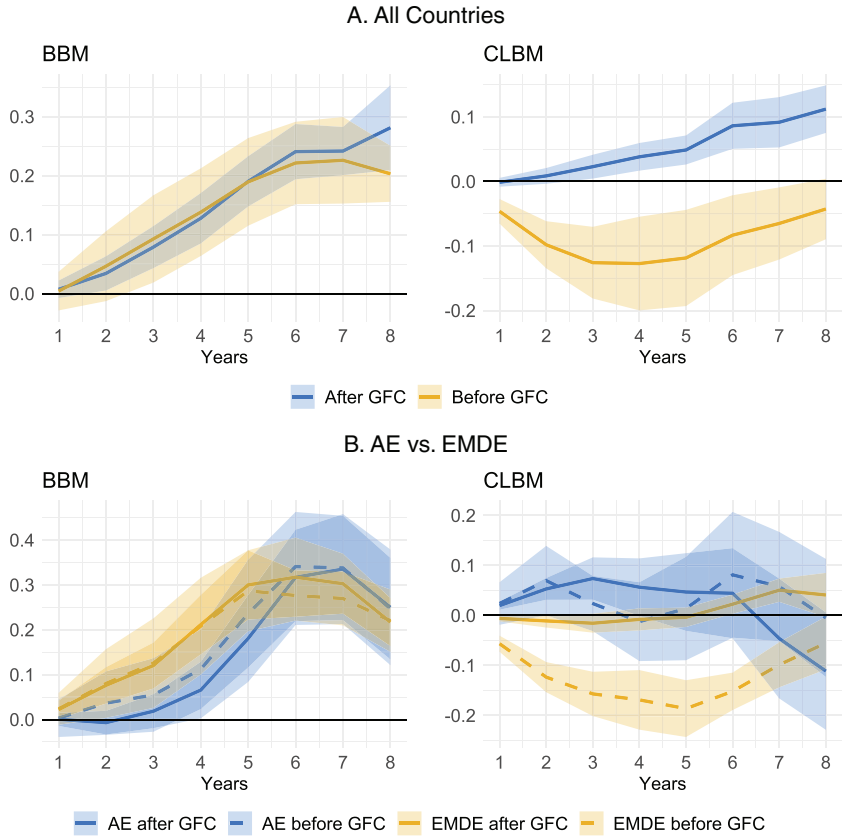
(*continued*)

Table D.2. (Continued)

	Year 1	**Year 4**	**Year 8**	**Year 1**	**Year 4**	**Year 8**	**Year 1**	**Year 4**	**Year 8**
Emerging Market and Developing Economies									
CLBM	0.048	0.175	0.606**	0.170***	0.014	–0.078	–0.012***	–0.047	0.012
	(0.108)	(0.203)	(0.354)	(0.081)	(0.083)	(0.057)	(0.006)	(0.031)	(0.034)
FE	N	N	N	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N	Y	Y	Y
Observations	1,199	1,022	786	1,199	1,022	786	1,022	845	617
Countries	59	59	58	59	59	58	59	59	53
R^2	0	0.001	0.006	0.016	0	0.002	0.977	0.781	0.511
Adj. R^2	–0.001	0	0.005	–0.057	–0.085	–0.104	0.974	0.75	0.421

Note: The table shows baseline regression results of Equation (1). We gradually add control variables and fixed effects in the baseline regression to see the sensitivity of the results. For the sake of brevity, we report only responses to the detrended Gini index on three horizons (1, 4, and 8 years) following a unit change in the index of capital- and liquidity-based measures. We estimate robust standard errors. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level, respectively.

Figure D.1. Specification with Dummy Variable for Period Before and After Global Financial Crisis



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (4). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. Periods before (after) Global Financial Crisis are defined as periods before (after) 2008. We estimate all models with a full set of control variables and robust standard errors.

D.2 Continuous Measure

Table D.3. Response of Gini Index to a Change in the Distance to LTV Limit (continuous measure)

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
All Countries								
Dist. to LTV	0.005***	0.012***	0.024***	0.040***	0.055***	0.069***	0.067***	0.065***
	(0.002)	(0.004)	(0.006)	(0.009)	(0.012)	(0.014)	(0.012)	(0.010)
Observations	1,076	1,015	954	893	832	772	713	655
Countries	61	61	61	61	60	59	58	56
R^2	0.947	0.861	0.755	0.618	0.501	0.424	0.365	0.347
Adj. R^2	0.941	0.844	0.724	0.566	0.429	0.335	0.260	0.232
Advanced Economies								
Dist. to LTV	0.000	0.009	0.029***	0.062***	0.113***	0.160***	0.161***	0.152***
	(0.004)	(0.007)	(0.011)	(0.015)	(0.018)	(0.011)	(0.012)	(0.016)
Observations	558	524	490	456	422	388	354	321
Countries	34	34	34	34	34	34	33	31
R^2	0.958	0.871	0.75	0.614	0.523	0.472	0.414	0.359
Adj. R^2	0.950	0.847	0.701	0.532	0.413	0.339	0.254	0.170

(*continued*)

Table D.3. (Continued)

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**	**Year 6**	**Year 7**	**Year 8**
Emerging Market and Developing Economies								
Dist. to LTV	0.008**	0.022**	0.032**	0.041**	0.042**	0.039**	0.031**	0.023*
	(0.004)	(0.009)	(0.013)	(0.018)	(0.020)	(0.017)	(0.012)	(0.012)
Observations	518	491	464	437	410	384	359	334
Countries	27	27	27	27	26	25	25	25
R^2	0.972	0.914	0.847	0.761	0.693	0.658	0.612	0.584
Adj. R^2	0.967	0.898	0.818	0.713	0.629	0.583	0.521	0.479

Note: The table shows baseline regression results of Equation (1). Instead of macroprudential policy index, we use a continuous measure of distance to the LTV limit, calculated as 100 minus the LTV limit. For the sake of brevity, we report only responses to the detrended Gini index over the eight years following a 1 pp change in the distance to the LTV limit. The regression models, however, include all control variables and fixed effects. We estimate robust standard errors. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level, respectively.

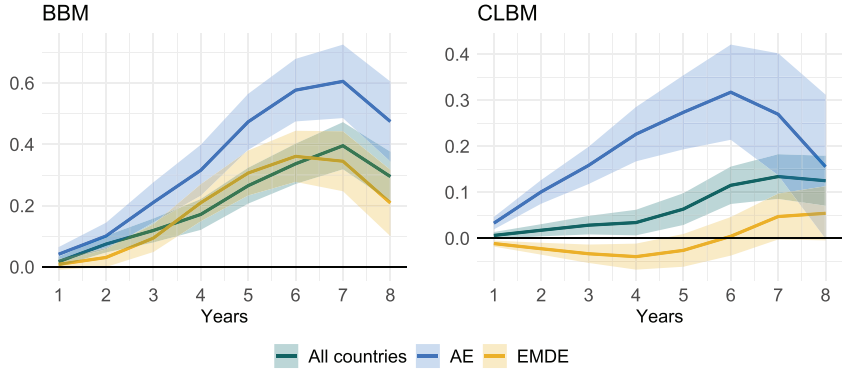
D.3 Inverse-Probability-Weighted Regression Adjustment Estimator

Table D.4. First-Stage Results—Prediction of Macroprudential Tightening Actions

	BBM	**CLBM**
Output Gap	0.124***	0.073***
	(0.032)	(0.017)
CPI Inflation	–0.058*	–0.081***
	(0.029)	(0.016)
Credit-to-GDP Ratio	0.016**	0.023***
	(0.006)	(0.004)
Unemployment	–0.089**	–0.064**
	(0.045)	(0.026)
Pseudo R^2	0.349	0.214
Area Under the Curve	0.879	0.626

Note: The table shows logit classification models where the dependent variable is a binary indicator equal to one if macroprudential policy was tightened and zero otherwise. Robust standard errors are in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level, respectively.

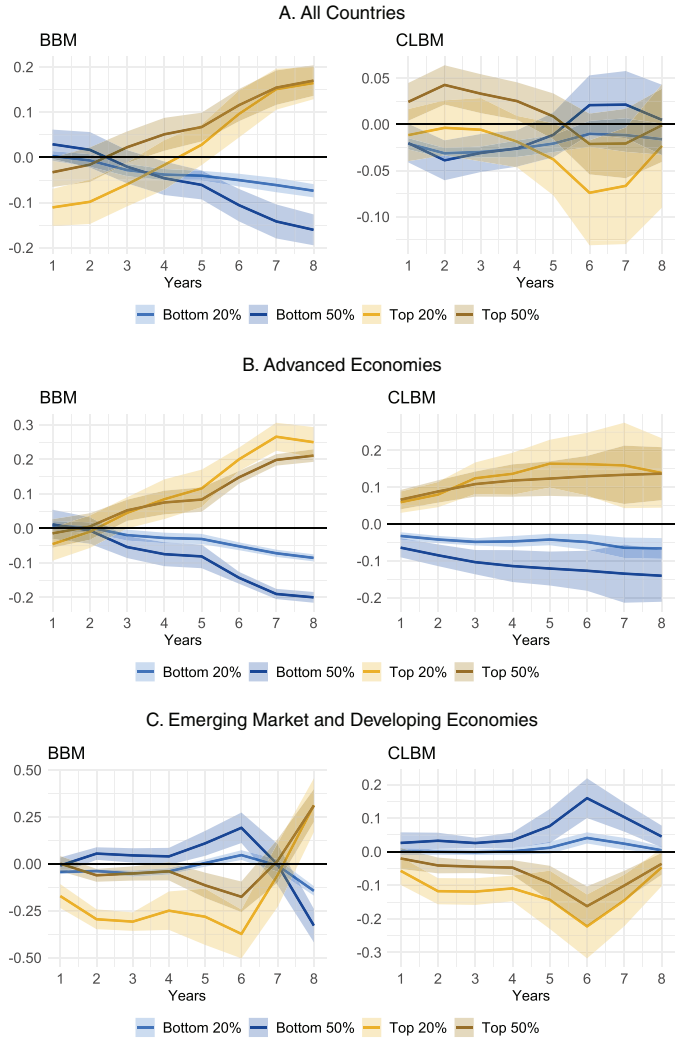
Figure D.2. Second-Stage Results—The Impact on Income Inequality



Note: The charts show impulse response functions constructed from regression results of the inverse-probability-weighted regression adjustment model. Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. We estimate all models with a full set of control variables and robust standard errors.

D.4 Alternative Measures of Inequality

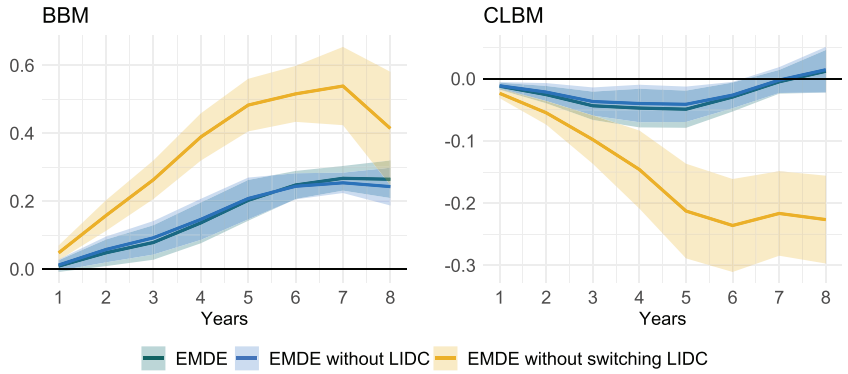
Figure D.3. Impact of Macroprudential Policy on Income Shares



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Instead of the detrended Gini index, we use top and bottom income shares as dependent variables. Solid lines display the coefficients of (noncumulative) responses of income shares over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. We estimate all models with a full set of control variables and robust standard errors.

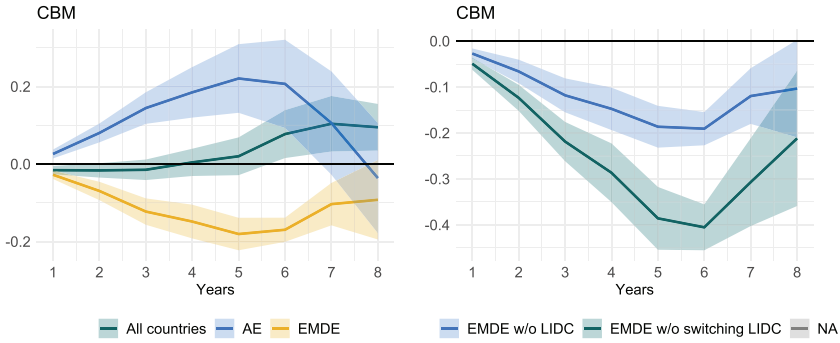
D.5 Excluding Low-Income Countries and Liquidity-Based Measures

Figure D.4. Excluding Low-Income Countries



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. We estimate all models with a full set of control variables and robust standard errors.

Figure D.5. Excluding Liquidity-Based Measures



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (1). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the index of capital-based measures (CBM). Shaded areas refer to one-standard-deviation confidence bounds. We estimate all models with a full set of control variables and robust standard errors.

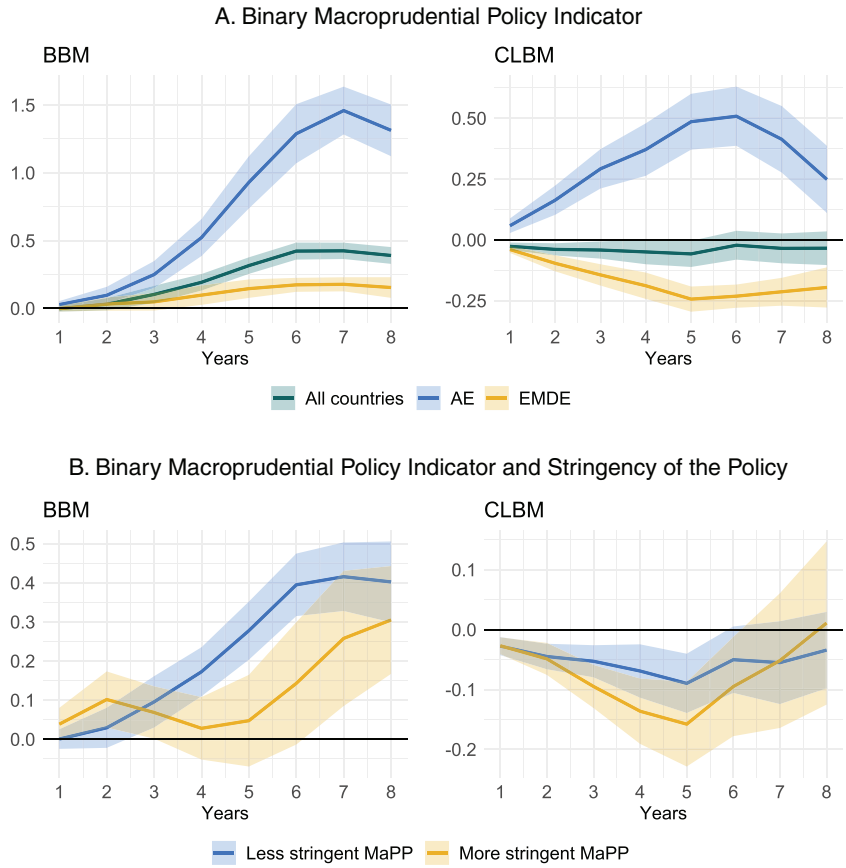
Table D.5. Number of Macroprudential Policy Actions Over 1990–2019

	BBM		CLBM		CBM	
	No. of Events	**No. of Countries**	**No. of Events**	**No. of Countries**	**No. of Events**	**No. of Countries**
All Countries	285	61	1,296	105	557	89
AE	151	29	539	35	252	35
EMDE	134	32	757	70	305	54
EMDE Without LIDC	124	29	683	52	282	45
EMDE Without Switching LIDC	84	23	494	40	213	34

Note: The table shows the total number of macroprudential policy actions in our sample. We differentiate between borrower-based measures (BBM), capital- and liquidity-based measures (CLBM), and capital-based measures (CBM). The total number of observations in our sample is 2,372 (105 countries over 30 years). The number of events is calculated as a sum of the absolute value of the iMaPP indices, which can take both positive (macroprudential policy easing) and negative (macroprudential policy easing) values. For example, a value of 3 means that the policy was tightened three times that year.

D.6 Alternative Specifications of the Macroprudential Policy Index

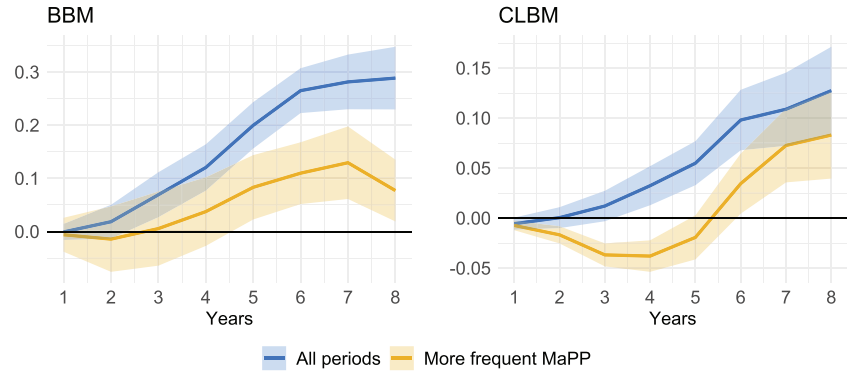
Figure D.6. Alternative Definition of Macroprudential Policy Variable



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (4). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. Periods of more stringent macroprudential policy are defined as a cumulative sum of all macroprudential policy measures being above the fourth quartile. We estimate all models with a full set of control variables and robust standard errors.

D.7 Frequency of Macroprudential Policy and Income Inequality

Figure D.7. Frequency of Macroprudential Policy and Income Inequality



Note: The charts show impulse response functions constructed from regression results of the lag-augmented local projection model in Equation (4). Solid lines display the coefficients of (noncumulative) responses of the detrended Gini index over the eight years following a unit change in the macroprudential policy index. We differentiate between borrower-based measures (BBM) and capital- and liquidity-based measures (CLBM). Shaded areas refer to one-standard-deviation confidence bounds. Periods of more frequent macroprudential actions are defined as a macroprudential policy index above the fourth quartile. We estimate all models with a full set of control variables and robust standard errors.

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Forecasting Core Inflation and Its Goods, Housing, and Supercore Components*

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This paper examines the forecasting efficacy and implications of the recently popular breakdown of core inflation into three components: goods excluding food and energy, services excluding energy and housing, and housing. A comprehensive historical evaluation of the accuracy of point and density forecasts from a range of models and approaches shows that a BVAR with stochastic volatility in aggregate core inflation, its three components, and wage growth is an effective tool for forecasting inflation's components as well as aggregate core inflation. Looking ahead, the model's baseline projection puts core inflation at 2.7 percent in 2026, well below its 2023 level but still elevated relative to the Federal Reserve's 2 percent objective. The probability that core inflation will return to 2 percent or less is much higher when conditioning on goods or nonhousing services inflation slowing to prepandemic levels than when conditioning on these components remaining above the same thresholds. Scenario analysis indicates that slower wage growth will likely be associated with reduced inflation in all three components, especially goods and nonhousing

*We gratefully acknowledge helpful comments from the editor Òscar Jordà, two anonymous referees, Elena Bobeica, and James Mitchell. We also thank Joshua Chan, Niko Hauzenberger (who also kindly provided guidance on usage), and Elmar Mertens for their publicly available replication code, which we use within our paper. Finally, we acknowledge the use of computing resources provided by the Center for the Advancement of Data and Research in Economics (CADRE) at the Federal Reserve Bank of Kansas City. Code and data for the results in this paper are available on our websites. The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System. Author emails: tclarkresearch@gmail.com (corresponding author), mvgordon@sas.upenn.edu, saeed.zaman@clev.frb.org.

services, helping to return core inflation to near the 2 percent target by 2026.

JEL Codes: C32, C53, E17, E31, E37.

1. Introduction

Since inflation surged following the outbreak of the COVID-19 pandemic and Russia's war against Ukraine, central banks around the world have focused on the challenge of reducing inflation. In these efforts, forecasts of inflation have played an important role in policymakers' assessments. Recently, in commenting on inflation developments, policymakers in the United States have often drawn attention to a three-component breakdown of core inflation into goods excluding food and energy, services excluding energy and housing (also known as supercore inflation), and housing. As summarized in sources such as Powell (2022), a common narrative has maintained that the normalization of pandemic-driven changes in supply and demand would contribute to significant declines in the goods and housing components of core inflation, with some progress already evident. That same narrative has indicated that a slowing of inflation in nonhousing services, which has a weight of more than 50 percent in core inflation, would be crucial to returning inflation to the Federal Reserve's 2 percent target and perhaps more challenging to achieve than reductions in the other components. Because labor is even more important as an input to services than goods, a common suggestion has been that a slowing of aggregate wage growth to prepandemic levels will be needed to achieve a reduction in core services inflation. Federal Reserve Chair Powell has suggested that a decline of inflation to 2 percent will likely be associated with reductions in its core goods, supercore, and housing components.[1]

These policy-driven interests raise a number of questions for research. First, how well can the goods, housing, and services components of core inflation be forecast as compared with aggregate core inflation? Second, is aggregate inflation best forecast directly or by aggregating forecasts of the three components? Third, how

[1]See pages 5–6 of the transcript of the Chair's March 20, 2024 press conference: https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20240320.pdf.

important is wage growth to slower inflation in services excluding housing as well as the other components of core inflation? Finally, based on historical comovement, how are the components likely to evolve as aggregate inflation slows? Is it most likely the case that all three components will need to return to prepandemic levels in order for aggregate core inflation to reach 2 percent?

Of course, to varying degrees, previous research has shed some light on these and related questions, although not necessarily directly in the current context. In particular, the forecasting literature has established the following. First, simple univariate models for forecasting aggregate core inflation are very hard to beat compared with multivariate models that include elements of the Phillips curve or other variables such as wage growth (see, e.g., Faust and Wright 2013 and Stock and Watson 2007). Second, most studies (but not all; some have obtained positive results) have found that it is generally difficult to consistently improve accuracy by combining predictions of components rather than forecasting aggregate core inflation directly (see, e.g., Eo, Uzeda, and Wong 2023; Faust and Wright 2013; Hubrich 2005; Joseph et al. 2022; McGregor and Toscani 2022; Tallman and Zaman 2017; and Verbrugge and Zaman 2024).[2] Third, allowing some time variation in means and other regression parameters of a model can help forecast accuracy (see, e.g., Banbura and van Vlodrop 2018 and D'Agostino, Gambetti, and Giannone 2013), although it is not assured of doing so (e.g., Chan 2023). Finally, allowing time variation in conditional variances can improve the accuracy of both point and density forecasts (see, e.g., Chan and Eisenstat 2018; Clark 2011; Clark and Ravazzolo 2015; and D'Agostino, Gambetti, and Giannone 2013).

Building on existing work, in this paper we examine the efficacy and implications of forecasts of the three-component breakdown of core inflation in the U.S. Of course, the accuracy of inflation forecasts has been widely studied; our examination is novel in its focus on the three-component breakdown of core inflation. We begin by

[2]While most studies noted in the text have focused on point forecasts, some work has examined whether density accuracy can be improved by aggregating component forecasts. For example, Ravazzolo and Vahey (2014) find some benefits to using linear opinion pooling to combine the forecast densities of inflation components.

evaluating the accuracy of inflation and component rate forecasts from a range of models and approaches that include some of the key features noted above, particularly stochastic volatility. While our analysis has considered additional models with larger variable sets and nonlinearities (without finding much payoff), we primarily focus on forecasts from Bayesian vector autoregressions (BVARs) that include as variables aggregate core inflation, its goods-housing-services excluding housing components, and wage growth. Our specifications vary in the features of the model—for example, we consider some models with time-varying parameters—as well as in the formulation of the coefficient priors. We compare the forecast performance of this range of models with the univariate unobserved components-stochastic volatility model that Stock and Watson (2007) established as a good model for forecasting aggregate inflation.

After establishing the historical efficacy of our preferred BVAR model specification, we examine medium-term forecasts for the period ahead, 2024 through 2026, and the likelihood (according to our model) of inflation returning to the Federal Reserve's 2 percent target. We conclude the paper with scenario analysis, that is, forecasts of inflation and its components conditional on selected scenarios or conditions. We implement conditional forecasting with entropic tilting (introduced to macroeconomic forecasting by Robertson, Tallman, and Whiteman 2005), which can be seen as a nonparametric approach to conditional forecasting. One scenario conditions on a gradual decline of wage growth to near its prepandemic level to assess the likelihood that such a development may be key to continued disinflation. The second scenario conditions on a decline of aggregate core inflation to 2 percent to provide a joint assessment of the paths of component inflation rates and wage growth most likely associated with a return of aggregate inflation to target.

Overall, we find that a BVAR with stochastic volatility estimated with an adaptive Minnesota-style prior (as developed in Chan 2021) is an effective tool for forecasting inflation in the core services excluding housing, housing, and core goods components of core inflation, as well as aggregate core inflation. Not surprisingly, compared with the range of models we consider, this BVAR model performs better for some components than others. For some inflation measures, its advantage over univariate benchmarks in forecast accuracy has

increased over the past several years, a period in which the pandemic caused variability in inflation. Regarding the specific questions noted above, our findings indicate that the inflation components can be forecast about as well as aggregate core inflation; in fact, our preferred BVAR tends to perform better, compared with a univariate benchmark, for inflation components than for aggregate inflation. However, aggregate inflation is best forecast directly; no consistent benefit can be achieved by aggregating disaggregate components. In our baseline predictive distributions, a return of core inflation to 2 percent or less over the next few years is much higher when conditioning on goods or supercore inflation slowing to near prepandemic levels than when conditioning on these components remaining above the same thresholds. Our scenario analyses indicate that slower wage growth will likely be associated with reduced inflation in all three components, not just supercore, but housing less so than goods and supercore inflation. In addition, it is most likely the case that a return of core inflation to the Federal Reserve's 2 percent target will be associated with all three components returning to near prepandemic levels.

The paper proceeds as follows. Section 2 describes the data used. Section 3 reviews the models used and details our approaches to estimation and forecasting. Section 4 presents our historical forecast evaluation, and Section 5 provides forecasts and scenario analysis for the next few years. Section 6 concludes.

2. Data

Because the Federal Reserve's inflation target is stated in terms of the price index for personal consumption expenditures (PCE), we focus on forecasting PCE inflation excluding food and energy (core PCE inflation) and its goods, housing, and services excluding housing components.[3] Our primary results use quarterly data on PCE price indices—aggregate core inflation and its three components—as

[3]The PCE time series feature a methodologically consistent treatment of housing over time, based on owner-equivalent rent. In contrast, in published data on the consumer price index (CPI), methodological improvements are applied going forward but not to past data. Consequently, published CPI series suffer a significant break in the treatment of housing in 1983, when measurement changed to use the current approach based on owner-equivalent rent.

well as the employment cost index (ECI).[4] We obtained all of these raw data series from Haver Analytics.[5] (Some additional results in the online appendix mentioned in footnote 5 add to the models 19 other macroeconomic variables taken from the FRED-MD database maintained by the Federal Reserve Bank of St. Louis and from Haver Analytics.) We abstract from real-time data considerations and focus on currently available time series due to binding (from a forecast evaluation perspective) constraints on the availability of vintages of the components of PCE inflation.[6]

Inflation and wage growth rates are measured as 400 times log changes in index levels. The raw data sample (before transformations) for our forecast evaluation exercise is 1959:Q1 through 2023:Q4; Section 5's forecasts for 2024–26 use data through 2024:Q1. In the case of the ECI, the raw data do not begin until 1980. We extend the series back to 1959 by backcasting the growth rate of the ECI with fitted values from a regression of ECI growth on the growth rate of the series on compensation per hour (nonfarm business sector) from the Bureau of Labor Statistics. For our forecast evaluations we use data available as of March 28, 2024 while for our conditional forecasts we use data available as of April 30, 2024.

3. Models, Estimation, and Forecasting

This section details the models used for inflation forecasting, their estimation, and our approach to forecasting. For convenience, Table 1 lists the ensemble of models that we consider in our forecasting exercises.

[4]The ECI abstracts from cyclical changes in the sectoral composition of employment, avoiding some of the composition bias that affects other wage measures.

[5]An online appendix (available at https://github.com/zamansaeed/ijcb_cgz_inflation/blob/main/CGZinflation_onlineappendix.pdf) provides the Haver mnemonics. Our results in Section 4 (Section 5) use data downloaded from Haver on March 28, 2024 (April 30, 2024).

[6]For example, in the Federal Reserve Bank of St. Louis' ALFRED database, a primary source of real-time data, vintages of PCE price index components only begin in 2013, and these vintages do not appear to have enough detail to permit us to construct real-time data on inflation in core goods, housing, and services excluding housing.

Table 1. List of Models

Identifier	Model Type	Prior	Time-Varying Parameters	Outlier Adjustment
UC-SV	UC-SV	N/A	N/A	None
NM-BVAR-SV	BVAR-SV	Minnesota	None	None
NM-BVAR-SVO	BVAR-SV	Minnesota	None	CCMM2024
NM-BVAR-SV-TVM	BVAR-SV	Minnesota	Intercept	None
NM-BVAR-SVO-TVM	BVAR-SV	Minnesota	Intercept	CCMM2024
AM-BVAR-SV	BVAR-SV	Adaptive Minnesota	None	None
AM-BVAR-SVO	BVAR-SV	Adaptive Minnesota	None	CCMM2024
AM-BVAR-SV-TVM	BVAR-SV	Adaptive Minnesota	Intercept	None
AM-BVAR-SVO-TVM	BVAR-SV	Adaptive Minnesota	Intercept	CCMM2024
NGM-BVAR-SV	BVAR-SV	Minnesota Normal-Gamma	None	None
NGM-BVAR-SVO	BVAR-SV	Minnesota Normal-Gamma	None	CCMM2024
NGM-BVAR-SV-TVM	BVAR-SV	Minnesota Normal-Gamma	Intercept	None
NGM-BVAR-SVO-TVM	BVAR-SV	Minnesota Normal-Gamma	Intercept	CCMM2024
SVD-GP-NC	SVD-WN	g-prior, No Clustering	Coefficients	None

Note: All models feature stochastic volatility in their innovations. Models with time variation in their intercepts assume a random walk state evolution. SVD models with time variation in their coefficients assume a white-noise state evolution.

3.1 Models

We consider three families of models. The first is multivariate and the other two are univariate.

Our first family consists of BVARs with stochastic volatility, referred to as the BVAR-SV specification. This specification takes the following form, for the $n \times 1$ data vector y_t, which includes aggregate core inflation, its three components, and wage growth (we exclude aggregate core inflation from y_t when we consider the "bottom-up" approach to forecasting aggregate core inflation):[7]

$$\begin{aligned} y_t &= \Pi_0 + \sum_{i=1}^{p} \Pi_i y_{t-i} + v_t \\ v_t &= A^{-1}\Lambda_t^{0.5}\epsilon_t,\ \epsilon_t \sim N(0, I_n),\ \Lambda_t \equiv \mathrm{diag}(\lambda_{1,t}, \ldots, \lambda_{n,t}) \\ \ln(\lambda_{i,t}) &= \ln(\lambda_{i,t-1}) + \nu_{i,t},\ i = 1, \ldots, n \\ \nu_t &\equiv (\nu_{1,t}, \nu_{2,t}, \ldots, \nu_{n,t})' \sim N(0, \Phi), \end{aligned} \tag{1}$$

where A is a lower triangular matrix with ones on the diagonal and nonzero coefficients below the diagonal, and the diagonal matrix Λ_t contains the time-varying variances of conditionally Gaussian innovations. This model implies that the reduced-form variance-covariance matrix of innovations to the BVAR is $\mathrm{var}(v_t) \equiv \Sigma_t = A^{-1}\Lambda_t A^{-1\prime}$. Note that, as in the implementation of Primiceri (2005), innovations to log volatility are allowed to be correlated across variables; Φ is not restricted to be diagonal. For notational simplicity, let Π denote the collection of the BVAR's coefficients. In implementation, we include four lags in the BVAR.

[7]We order our variables so that wage growth is first, followed by supercore, housing, core goods, and aggregate core inflation. As noted in the seminal work of Primiceri (2005) and some subsequent studies, in BVARs with stochastic volatility specified as in this paper, variable ordering affects estimates. Work such as Bognanni (2018) has discussed the issue from a perspective of structural inference. Recent work by Arias, Rubio-Ramirez, and Shin (2023) has shown that ordering choices in VARs with time-varying parameters and stochastic volatility can affect out-of-sample forecasts. In particular, in their results, ordering has little effect on point forecasts but measurable effects on density-related measures, including the standard deviation of the predictive density and the length of prediction intervals. Empirically speaking, ordering impacts can be smaller in models with constant regression parameters.

Furthermore, we consider versions of the BVAR-SV model extended in two dimensions (separately as well as together). First, we treat the intercepts of the VAR as time-varying. In this case, the intercepts follow random walk processes; this makes the model a restricted version of the time-varying parameter VAR of Primiceri (2005), with time variation of intercepts and conditional volatilities but constant slope parameters in the VAR. The time variation of intercepts allows for time variation of the implied conditional means of the data, i.e., time shifts in trend inflation. Second, to reduce the impacts of the extreme, temporary volatility of macroeconomic data following the COVID-19 outbreak, we extend the model by including in the volatility piece the multiplicative volatility outlier specification of Carriero et al. (2024), originally developed by Stock and Watson (2016) for modeling inflation. Adding a second volatility factor that is independent over time serves to reduce the persistence of changes in volatility that affect forecasts over unusual periods such as the pandemic.

Of course, Bayesian estimation entails priors on the parameters of models. In specifying the prior variance matrix for the BVAR coefficients Π, we consider three options: a standard Minnesota-type Gaussian prior that shrinks all coefficients to zero but allows differing degrees of shrinkage for coefficients on own lagged variables as opposed to lags of other variables; a similarly formed but adaptive Minnesota-type prior developed by Chan (2021), where the shrinkage is estimated from the data; and Chan's new adaptive Minnesota-type normal-gamma prior that combines features of the Minnesota and hierarchical priors. Details are omitted in the interest of brevity, but follow the aforementioned citations. We apply these priors to the baseline BVAR-SV model as well as the versions extended to allow time-varying intercepts and volatility outliers.

Our second considered model family, which we call the SVD-WN specification, uses one of the new, novel approaches to the specification and estimation of large time-varying parameter (TVP) regressions (single regression, not a vector autoregression) developed in Hauzenberger et al. (2022). Hauzenberger et al. (2022) develop a computationally efficient estimation algorithm based on singular value decomposition (SVD) that permits application to large regressions and focuses on models that replace the usual assumption of random walk variation in parameters with a hierarchical

mixture model on the time-varying parameters. In particular, we use their specification that features a white-noise state equation and the g-prior of Zellner (1986), without any clustering of the parameters.[8] This model is applied to one inflation measure at a time rather than a vector of measures as in the VAR specifications. Our SVD-WN model takes the same dynamic regression form as Hauzenberger et al. (2022):

$$\begin{aligned}
\pi_t &= x_t'\beta_t + \sigma_t\eta_t,\ \eta_t \sim N(0,1) \\
\beta_t &= \gamma + \widetilde{\beta}_t \\
\widetilde{\beta}_t &\sim N(0, \sigma_t^2 \cdot \Psi) \\
\log(\sigma_t^2) &= \mu_\sigma + \rho_\sigma(\log(\sigma_{t-1}^2) - \mu_\sigma) + \sigma_\sigma\nu_t,\ \nu_t \sim N(0,1),
\end{aligned} \tag{2}$$

where π_t is our scalar inflation measure, x_t is a vector of regressors consisting of lags of the data, β_t is a set of time-varying regression coefficients composed of a time-invariant component (γ) and a white-noise time-varying component ($\widetilde{\beta}_t$), σ_t^2 is the time-varying error variance where its log volatility follows an AR(1) process, and Ψ is a diagonal matrix of shrinkage parameters. In our application, x_t consists of four lags of ECI, disaggregate inflation, and aggregate inflation.

Finally, we consider the univariate unobserved components-stochastic volatility (UC-SV) model that Stock and Watson (2007) established as a good model for forecasting aggregate inflation. We apply this model to aggregate core inflation as well as core inflation's three components. Letting π_t denote a given measure of inflation, this model treats inflation as the sum of a random walk and a serially uncorrelated noise term, both featuring stochastic volatility:

$$\begin{aligned}
\pi_t &= \pi_t^* + v_t,\ \pi_t^* = \pi_{t-1}^* + n_t \\
v_t &= \lambda_{v,t}^{0.5}\epsilon_{v,t},\ \epsilon_{v,t} \sim N(0,1)
\end{aligned} \tag{3}$$

[8]In unreported results, we also considered a specification grouping the time-varying parameters into a smaller number of regimes/clusters, which Hauzenberger et al. (2022) found to be helpful for forecasting inflation with a large number of predictors. However, we found that the clustering approach produced forecasts that performed essentially as well as forecasts without clustering, and in the interest of brevity we omit these results.

$$
\begin{aligned}
n_t &= \lambda_{n,t}^{0.5}\epsilon_{n,t},\ \epsilon_{n,t} \sim N(0,1) \\
\log(\lambda_{v,t}) &= \log(\lambda_{v,t-1}) + \nu_{v,t},\ \nu_{v,t} \sim N(0,\phi_v) \\
\log(\lambda_{n,t}) &= \log(\lambda_{n,t-1}) + \nu_{n,t},\ \nu_{n,t} \sim N(0,\phi_n).
\end{aligned}
$$

As a note, in our VAR models the combination of inflation variables introduces a near-singularity in the variance-covariance matrix. This is because the inflation aggregate in the model is closely approximated by a time-varying linear combination of the three disaggregates of inflation that are also included in the model, leading to strong collinearity.[9] In empirical work, this collinearity can result in a near-singular variance-covariance matrix that can, in turn, lead to explosive model estimates and numerical issues. We have found that this issue is less pronounced for the constant-coefficient models we use (as well as the versions with time-varying intercepts), but it is increasingly prevalent when a richer degree of time variation in regression parameters is allowed, such as the hybrid TVP specification and estimation approach of Chan (2023) that has TVP in some equations but constant coefficients in others, optimized for model fit. (As a result, we omit the hybrid TVP models of Chan 2023 from our paper.)

3.2 Estimation and Forecasting

We estimate all our models with Bayesian methods. For estimation of the BVAR-SV specification, we employ Gibbs sampling and use replication code from Carriero et al. (2024) to estimate these models following Carriero et al. (2022).[10] For clarity, we estimate stochastic volatility following the methods in Kim, Shephard, and Chib (1998). See sources such as Clark and Ravazzolo (2015) and Karlsson (2013) for further details on estimating this family of models. Furthermore,

[9]Under the chain weighting used to construct the published core PCE price index, the core PCE inflation rate is approximated very well but not perfectly by a weighted average of the components, where the weights for inflation in quarter t are averages of spending shares in $t-1$ and t. Because of that approximation and time variation in the spending shares, the collinearity of the components with aggregate inflation is high but not perfect.

[10]The algorithm of Carriero et al. (2022) corrects a problem with the original algorithm of Carriero, Clark, and Marcellino (2019) pointed out by Bognanni (2022).

we follow Carriero et al. (2024) for the estimation of our outlier adjustment. We follow Chan and Eisenstat (2018) for the estimation of our time-varying intercept but continue to use the method of Carriero et al. (2022) for the rest of the model (particularly for the estimation of time-invariant coefficients). Finally, for the estimation of our different considered Minnesota-like priors we follow the estimation procedure of Chan (2021).

In our implementation of BVAR priors, in the baseline case, we follow the prior specifications of Carriero et al. (2024), which include a standard Minnesota prior on the matrix of coefficients Π_i for $i = 0, \ldots, p$. However, since our application uses a quarterly frequency instead of the monthly frequency considered in Carriero et al. (2024), we make a modification and use an inverse Wishart prior for Φ, the variance matrix of innovations to log volatility, with a scale matrix of $0.05 \times (n + 3) \times I_n$ and $n + 3$ degrees of freedom. Furthermore, for simplicity, we assume prior means of 0 for all variables. The priors on our time-varying intercepts follow Chan and Eisenstat (2018). Finally, our adaptive Minnesota-like priors follow those of the baseline model in Chan (2021) with the exception of the prior means on hyperparameters κ_1 and κ_2, which we set so as to imply prior means of .1 and .005, respectively.

For the estimation of our SVD-WN models we use replication code from Hauzenberger et al. (2022) to implement the SVD algorithm and to estimate a time-varying parameters model with a white-noise state equation, g-prior, but no clustering. Our priors also follow the specification of the original paper, and for the prior hyperparameter κ, which determines the upper bound of our innovation variance for the time-varying coefficients, we choose a value of .005.

At each forecast origin, we obtain forecasts from the posterior predictive distribution as follows (in the case of BVAR-SV models, with some adjustments for other models).[11] Over the forecast horizon, we draw time-series vectors of the VAR's shocks

[11]Particularly, for the SVD-WN models, we follow Hauzenberger et al. (2022) and use the direct forecasting approach of Stock and Watson (2002). Thus, for a given forecasting horizon, h, we estimate the SVD-WN model of the form $\pi_t = x'_{t-h}\beta_t + \sigma_t\eta_t$ and produce forecasts for $\pi_{t+h} = x'_t\beta_{t+h} + \sigma_{t+h}\eta_{t+h}$. Values for β_{t+h} and σ_{t+h} are obtained by simulating paths of these variables following their respective laws of motion.

$\epsilon_{T+h}^{(m)} \sim N(0, I_N)$ and volatility shocks $\nu_{T+h}^{(m)} \sim N(0, \Phi^{(m)})$, feed in the volatility shocks and iterate forward to obtain the draw of the time series of (log-)variances over the forecast horizon, compute the draw of the VAR's reduced-form shocks, and use the autoregressive structure of the VAR to iterate forward to obtain a draw of the time series of forecasts as $y_{T+h}^{(m)} = \Pi_0^{(m)} + \sum_{i=1}^{p} \Pi_i^{(m)} y_{T+h-i}^{(m)} + v_{T+h}^{(m)}$. As noted by Waggoner and Zha (1999), for a given Markov chain Monte Carlo (MCMC) node m, the computational costs of simulating forward a path of stochastic volatilities $\ln \lambda_{T+h}^{(m)}$, innovations $v_{T+h}^{(m)}$, and outcomes $y_{T+h}^{(m)}$ can be substantially lower than generating an additional MCMC draw m'. To better balance computational costs against a high degree of accuracy in the Monte Carlo approximation of the predictive density, it might thus be advantageous to draw multiple trajectories $\ln \lambda_{T+h}^{(m,j)}$, innovations $v_{T+h}^{(m,j)}$, and outcomes $y_{T+h}^{(m,j)}$, indexed by $j = 1, 2, \ldots, J$, for every m.[12] The posterior predictive density is then approximated by the ensemble of draws for all m and j. We follow this approximation for our BVAR-SV models, while directly simulating from the posterior predictive density for our SVD-WN and UC-SV models. Estimates and forecasts from the BVAR-SV models are based on 10,000 retained MCMC draws with a burn-in of 2,000 draws. For each MCMC draw, we approximate the posterior predictive density using 25 trajectories, for a total of 250,000 simulated posterior predictive density draws. Estimates and forecasts from the SVD-WN models are based on 30,000 retained MCMC draws with a burn-in of 10,000 draws. For the estimation of our UC-SV model we use the precision sampler of Chan and Jeliazkov (2009) and follow both the prior specification and estimation routine of Section 7.2 in Chan (2017). Estimates and forecasts from the UC-SV model are based on 50,000 retained MCMC draws with a burn-in of 5,000 draws.

We produce out-of-sample forecasts using a recursive scheme, expanding the model estimation sample as forecasting moves forward

[12] In the context of simulating conditional forecasts with only occasionally binding conditions, Waggoner and Zha (1999) provide a formal discussion of the optimal trade-off in choosing J, which also extends to the case of unconditional forecasts (i.e., density forecasts without binding conditions imposed on the forecasts).

in time. Forecasting begins with an origin, t, of 1985:Q1, estimating models with a data sample of 1959:Q2 through 1985:Q1. Forecasts are then produced for $t + h$, where h is the forecast horizon. We then move forward a quarter to the origin of 1985:Q2, reestimate models with data through 1985:Q2, and continue from there. We examine forecast accuracy for three periods: a full-sample period from 1985:Q1 through 2023:Q4, a prepandemic period of 1985:Q1 through 2017:Q4 (with 2017:Q4 as the last forecast origin, the last forecast outcome date considered is 2019:Q4 for $h = 8$), and a period of 2018:Q1 through 2023:Q4 that includes the unusual volatility of the pandemic period. Over this subsample, core inflation swung from 1.7 percent in 2020:Q1 to –0.8 percent in 2020:Q2 and up to 3.1 percent in 2020:Q3. It then jumped to 5.8 percent in 2021:Q2. We report results for forecast horizons of $h = 1$, 2, 4, and 8 quarters ahead.

We evaluate point and density forecasts (computed from posterior predictive densities of inflation, with point forecasts being the means of these densities) based on root mean squared errors (RMSE) and continuous ranked probability scores (CRPS), respectively, as described in, among others, Clark and Ravazzolo (2015) and Krüger et al. (2021). To roughly gauge the significance of differences with respect to the baseline forecast described below, we use t-tests as in Diebold and Mariano (1995) and West (1996), computed with Newey-West standard errors and $h + 1$ lags.

We consider a multitude of models, forecast evaluation measures, forecast horizons, evaluation windows, and variables of interest. As a result, it can be difficult to interpret broad patterns from our results. We use diffusion indices to help address this problem, inspired by Knotek and Zaman (2019). For each model i, each forecast evaluation measure m, each forecast horizon h, each evaluation window w, and each variable of interest v, let $\mu_{i,m,h,w,v}$ be the ratio of the realization of this evaluation measure (that is, RMSE or CRPS) to some realized evaluation measure produced by a benchmark model, where values under 1 suggest improvement in the measure over the benchmark. For a given evaluation measure m and for each i, h, w, and v, let

$$f_{i,m,h,w,v} = \begin{cases} 1, & \text{if } \mu_{i,m,h,w,v} \geq 1 \\ -1 & \text{if } \mu_{i,m,h,w,v} < 1. \end{cases} \tag{4}$$

Then, analogous to Knotek and Zaman (2019), for a given evaluation measure m, the diffusion index at forecast horizon h, with evaluation window w, and for variable of interest v is

$$(\text{Diffusion Index})_{m,h,w,v} = \sum_{i=1}^{r} f_{i,m,h,w,v}, \tag{5}$$

where r is the number of models we consider.

For scenario analysis, we adopt entropic tilting, which can be seen as a nonparametric approach to conditional forecasting, used in studies such as Cogley, Morozov, and Sargent (2005), Krüger, Clark, and Ravazzolo (2017), Robertson, Tallman, and Whiteman (2005), and Tallman and Zaman (2020).[13] Tilting consists of reweighting the draws from the model's predictive distribution so as to obtain a new distribution that satisfies the conditions of interest but remains as close as possible to the original distribution, where closeness is measured by the Kullback-Leibler divergence. In our applications, the conditions of interest are either the path of wage growth or the path of aggregate core inflation over the forecast horizon (the paths are detailed in Section 5). We tilt the first moments of our predictive distribution toward these paths.

4. Historical Forecast Evaluation

This section reports a historical evaluation of the performance of our models in unconditional forecasting. In these comparisons, we use the BVAR-SV model with the adaptive Minnesota prior (AM-BVAR-SV) as the baseline, for a few reasons. First, we are interested in being able to use multivariate models (BVARs) to capture joint dynamics and predictive distribution questions. Second, as will become clear, this model and prior choice work relatively well, and using it as the baseline facilitates comparisons and punchlines in our presentation. Third, a prior of the Minnesota form has a long, successful track record in macroeconomic forecasting, and the adaptive formulation of Chan (2021) is appealing for making the prior's tightness depend on the data.

[13] See Antolín-Díaz, Petrella, and Rubio-Ramirez (2021) for formal proof of the equivalence of entropic tilting to conditional forecasting under Gaussianity.

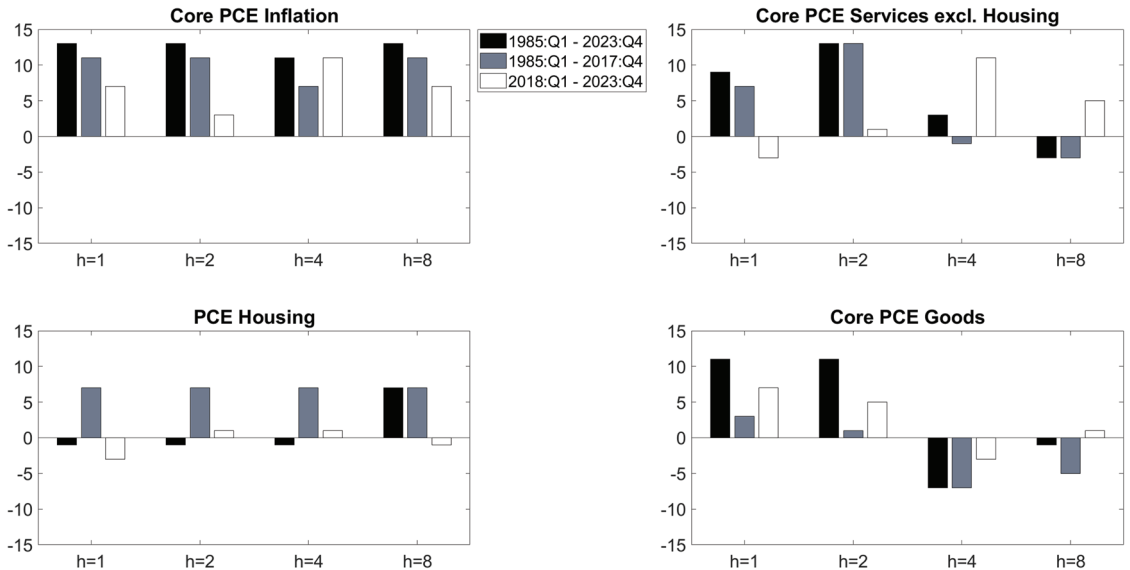
We present our forecasting results for core PCE inflation and its components using ratios of RMSE and CRPS to the corresponding measure for the AM-BVAR-SV baseline forecast. In this case, values below (above) 1 indicate improvement (deterioration) relative to the AM-BVAR-SV model. Forecasts for inflation variables are taken directly from the posterior predictive density implied by our models. That is, since our models include core inflation and its disaggregates, in our main results we directly use the recursive forecasts (of either core inflation or one of its components) from these models for our forecast evaluation. We separately consider the efficacy of obtaining forecasts of aggregate core inflation by aggregating forecasts of the disaggregate components. Throughout, we first consider results for the relatively long subsample of 1985–2017 that ends before the pandemic-induced additional volatility, and then we consider results for the shorter 2018–23 subsample and the full 1985–2023 sample.

This section proceeds to first present the accuracy of forecasts of aggregate inflation and its components obtained directly from our models and then examine aggregate forecasts instead obtained by aggregating forecasts of inflation components.

4.1 Accuracy of Model Forecasts of Aggregate Inflation and Its Components

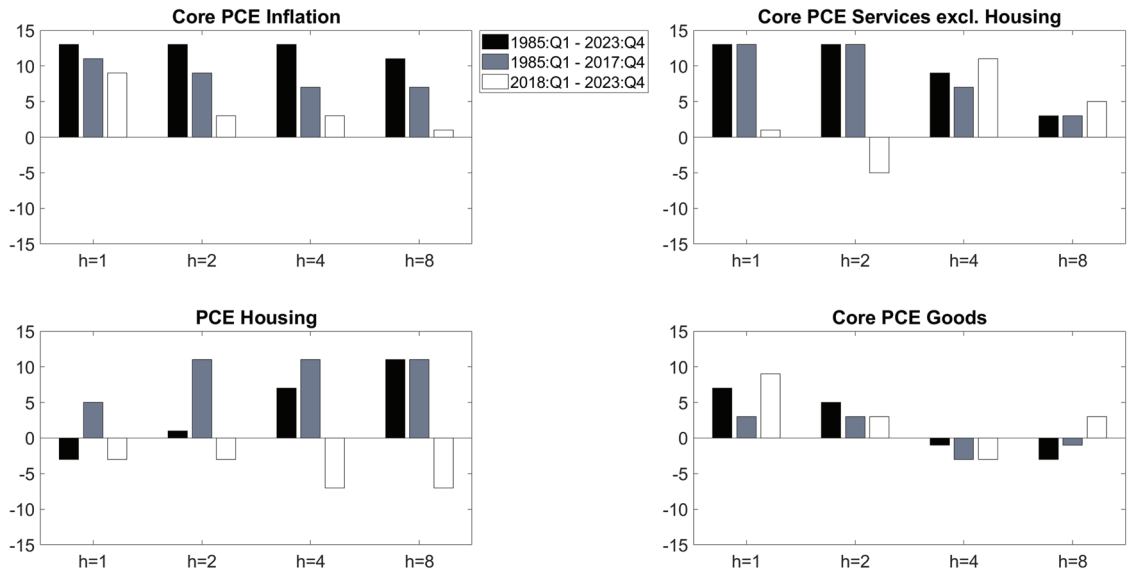
To first provide a broad, visual summary of how alternative forecast models compare with the AM-BVAR-SV baseline, Figure 1 presents diffusion indices for the aggregate and disaggregate point forecasts across evaluation samples and forecasting horizons, and Figure 2 presents analogous findings for density forecasts. These visual summaries abstract from the magnitudes of differences in accuracy and their statistical significance. In these displays, results for CRPS are very similar to those for RMSE. For the 1985–2017 sample, the gray bars indicate that the baseline AM-BVAR-SV model generally performs best (yielding high index readings), although with reduced advantage for supercore and core goods inflation at horizons of $h = 4$ and 8. For the 2018–23 sample, the dominance of the baseline model is reduced, more so for the inflation disaggregates than core PCE inflation. On balance, for most measures, samples, and horizons, the AM-BVAR-SV baseline beats most models, whereas it is not normally beaten by most models.

Figure 1. Diffusion Index of RMSE Ratios for PCE Inflation



Note: Ratios are calculated so that values below 1 indicate improvement over the AM-BVAR-SV model. Diffusion indices are calculated such that we take the count of ratios less than 1 and subtract it from the count of ratios greater than 1, for each horizon, application, and evaluation window.

Figure 2. Diffusion Index of CRPS Ratios for PCE



Note: Ratios are calculated so that values below 1 indicate improvement over the AM-BVAR-SV model. Diffusion indices are calculated such that we take the count of ratios less than 1 and subtract it from the count of ratios greater than 1, for each horizon, application, and evaluation window.

Starting from that broad perspective, we turn to more detailed, quantitative comparisons of accuracy across model specifications. Tables 2–5 present our forecasting results for core PCE inflation and its components, expressed in ratios of RMSE and CRPS to the corresponding measure for the AM-BVAR-SV baseline forecast. Results for the relatively long subsample of 1985–2017 that ends before the pandemic-induced additional volatility appear in the middle panels of Table 2 for core inflation and Tables 3–5 for the three disaggregate components.

Consider first the choice of prior for the BVAR-SV model. Across measures of inflation, the baseline adaptive Minnesota prior (i.e., the AM-BVAR-SV forecast) is consistently at least as good as the simple Minnesota (NM-BVAR-SV) and adaptive Minnesota-type normal-gamma priors (NGM-BVAR-SV). For aggregate inflation, the NM and NGM priors yield forecasts (both point and density) slightly less accurate than the AM baseline. For the three disaggregates, forecasts with the NM and NGM priors are sometimes slightly better than the baseline, but by small margins and without statistical significance. More frequently, these other priors are slightly to modestly less accurate than the baseline.

Now consider the additional model features allowed, which are time-varying means (TVM) and volatility outliers (SVO). Over the 1985–2017 sample, for a given choice of prior, across measures of inflation, neither of these additional model features offers any consistent improvement over the corresponding BVAR-SV specification. But there can be occasional (across the choice of measure and horizon) gains with time-varying means and volatility outliers. More specifically, TVM improves forecast accuracy gains in some cases, more typically at longer horizons (as might be expected, because as the horizon lengthens, the model-implied mean plays a larger role than recent dynamics as the forecast gradually converges to the unconditional mean), but not consistently. Under the baseline AM prior, in forecasting aggregate core inflation, adding TVM slightly reduces forecast accuracy, but not statistically significantly. Among disaggregate components, TVM offers gains for supercore and core goods inflation at long horizons, but harms accuracy for housing. These same patterns with the addition of TVM apply under other BVAR priors. Our finding on the mixed benefits of allowing time variation in means has precedent in studies such as Chan (2023),

Table 2. Forecast Ratios for RMSEs and CRPSs, Core PCE Inflation

	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
Model/Horizon	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
1985:Q1–2023:Q4								
UC-SV	1.059	1.006	1.078	1.012	1.039	1.007	1.037	**0.995**
NM-BVAR-SV	1.008	1.010	1.017	1.020	1.021	1.021	1.025	1.014
NM-BVAR-SVO	1.011	1.024**	1.020	1.047***	1.024	1.084***	1.027	1.118***
NM-BVAR-SV-TVM	1.004	1.012	1.030**	1.033**	1.034*	1.039**	1.038	1.029
NM-BVAR-SVO-TVM	1.009	1.022**	1.027	1.050***	1.034	1.087***	1.031	1.100***
AM-BVAR-SVO	1.001	1.012***	1.000	1.025***	**1.000**	1.058***	1.000	1.093***
AM-BVAR-SV-TVM	1.007	1.009	1.030	1.023	1.025	1.022	1.023	1.012
AM-BVAR-SVO-TVM	1.011	1.018**	1.024	1.038**	1.021	1.064***	1.010	1.071***
NGM-BVAR-SV	1.008*	1.009***	1.003	1.008***	1.002	1.009***	1.004	1.013***
NGM-BVAR-SVO	1.009*	1.020***	1.004	1.035***	1.001	1.071***	1.003	1.112***
NGM-BVAR-SV-TVM	1.011	1.011	1.032	1.018	1.015	1.008	1.017	1.001
NGM-BVAR-SVO-TVM	1.017	1.025*	1.027	1.034*	1.012	1.048**	1.004	1.054**
SVD-GP-NC	1.021*	1.008	1.022*	1.007	1.052	1.021	1.052	1.007
1985:Q1–2017:Q4								
UC-SV	**0.984**	**0.972**	**0.965***	**0.941*****	**0.952***	**0.927*****	1.021	**0.939****
NM-BVAR-SV	1.011	1.012	1.038	1.032*	1.046	1.032	1.011	1.003
NM-BVAR-SVO	1.020	1.031**	1.043	1.067***	1.048	1.119***	1.014	1.167***
NM-BVAR-SV-TVM	1.005	1.015	1.047**	1.042**	1.070**	1.051**	1.071	1.038
NM-BVAR-SVO-TVM	1.015	1.029**	1.044*	1.066***	1.067	1.119***	1.065	1.154***
AM-BVAR-SVO	1.006*	1.017***	1.002	1.035***	0.997	1.082***	1.003	1.147***
AM-BVAR-SV-TVM	1.003	1.008	1.020	1.018	1.024	1.016	1.030	1.009
AM-BVAR-SVO-TVM	1.009	1.020**	1.012	1.041***	1.012	1.078***	1.008	1.107***
NGM-BVAR-SV	1.012**	1.011***	1.007*	1.011***	1.005	1.014***	1.012**	1.021***
NGM-BVAR-SVO	1.018**	1.027***	1.009	1.048***	1.001	1.101***	1.016	1.175***
NGM-BVAR-SV-TVM	1.005	1.010	1.014	1.007	1.007	0.996	1.014	0.988
NGM-BVAR-SVO-TVM	1.018	1.028**	1.008	1.030**	0.999	1.055***	**0.995**	1.078**
SVD-GP-NC	1.026*	1.011	1.028	0.997	1.048	0.982	1.102	0.979

(*continued*)

Table 2. (Continued)

Model/Horizon	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
	RMSE	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
2018:Q1–2023:Q4								
UC-SV	1.150	1.105	1.203	1.215	1.105	1.199	1.047*	1.116**
NM-BVAR-SV	1.004	1.005	0.990	0.988	1.001	**0.997**	1.035**	1.038**
NM-BVAR-SVO	0.998	1.003	**0.990**	**0.987**	1.004	0.999	1.036**	1.012
NM-BVAR-SV-TVM	1.002	1.003	1.010	1.009	1.004	1.011	1.014	1.010
NM-BVAR-SVO-TVM	1.002	1.003	1.006	1.002	1.006	1.008	1.007	0.983*
AM-BVAR-SVO	**0.995**	**0.998**	0.998	0.997	1.002	1.000	0.998	0.976*
AM-BVAR-SV-TVM	1.012	1.011	1.043	1.039	1.026	1.036	1.019	1.019
AM-BVAR-SVO-TVM	1.013	1.010	1.038	1.030	1.029	1.031	1.011	0.990
NGM-BVAR-SV	1.002	1.002	0.998	0.998	**1.000**	0.998	0.997**	0.995***
NGM-BVAR-SVO	0.998	1.001	0.997	0.996	1.001	0.998	**0.995***	**0.972***
NGM-BVAR-SV-TVM	1.018	1.015	1.055	1.048	1.021	1.037	1.020	1.030
NGM-BVAR-SVO-TVM	1.017	1.016	1.051	1.043	1.023	1.032	1.010	1.000
SVD-GP-NC	1.014	1.000	1.015	1.034	1.055	1.117	1.016	1.066

Note: Values below 1 indicate improvement over the AM-BVAR-SV model. Significance assessed by Diebold-Mariano-West test using Newey-West standard errors with $h + 1$ lags. *, **, and *** represent the .10, .05, and 0.1 significance levels, respectively. Entries in bold denote ratios below 1 that are the lowest for a given forecasting horizon and measure. In columns with no bold entries, the benchmark model is best.

Table 3. Forecast Ratios for RMSEs and CRPSs, Core PCE Services Excl. Housing Inflation

	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
Model/Horizon	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
1985:Q1–2023:Q4								
UC-SV	1.050	1.040	1.094**	1.069**	1.084**	1.075**	1.077**	1.072**
NM-BVAR-SV	0.997	1.008	1.003	1.009	1.004	1.004	0.998	0.990
NM-BVAR-SVO	1.002	1.020	1.011	1.027	1.004	1.043*	1.000	1.074**
NM-BVAR-SV-TVM	**0.994**	1.006	1.013	1.014	1.006	1.000	0.997	0.985
NM-BVAR-SVO-TVM	1.004	1.018	1.013	1.024*	1.013	1.040**	0.991	1.046
AM-BVAR-SVO	1.002	1.009***	1.005**	1.017***	0.999	1.037***	1.001	1.074***
AM-BVAR-SV-TVM	1.000	1.004	1.011	1.008	0.996	0.988	0.997	0.981
AM-BVAR-SVO-TVM	1.007	1.014	1.013	1.021	1.001	1.023	**0.982**	1.029
NGM-BVAR-SV	1.010*	1.009**	1.002	1.007**	1.001	1.007***	1.006*	1.013***
NGM-BVAR-SVO	1.011	1.017***	1.007	1.024***	0.999	1.048***	1.007	1.093***
NGM-BVAR-SV-TVM	1.006	1.011	1.009	1.002	**0.994**	**0.986**	0.996	0.980
NGM-BVAR-SVO-TVM	1.015	1.024	1.012	1.015	1.000	1.021	0.983	1.024
SVD-GP-NC	1.002	1.003	1.024*	1.022	1.033	1.019	1.007	**0.971**
1985:Q1–2017:Q4								
UC-SV	1.034	1.034	1.078*	1.053	1.082*	1.063**	1.092*	1.065*
NM-BVAR-SV	**0.995**	1.008	1.007	1.015	1.001	1.004	0.978	0.976
NM-BVAR-SVO	1.004	1.023	1.015	1.035	0.999	1.050*	0.980	1.091**
NM-BVAR-SV-TVM	0.996	1.009	1.017	1.019	1.003	0.997	0.983	0.975
NM-BVAR-SVO-TVM	1.008	1.022	1.019	1.032*	1.011	1.045**	0.977	1.058
AM-BVAR-SVO	1.004	1.011***	1.005*	1.020***	0.996	1.044***	1.002	1.100***
AM-BVAR-SV-TVM	1.003	1.008	1.015	1.013	0.995	0.986	0.983	0.969*
AM-BVAR-SVO-TVM	1.012	1.020	1.020	1.029*	0.999	1.027*	**0.965***	1.035
NGM-BVAR-SV	1.011*	1.010**	1.003	1.009**	1.002	1.009***	1.010**	1.018***
NGM-BVAR-SVO	1.013	1.020***	1.008	1.028***	0.997	1.057***	1.013*	1.124***
NGM-BVAR-SV-TVM	1.014	1.020	1.009	1.004	**0.989**	**0.980**	0.982	**0.964****
NGM-BVAR-SVO-TVM	1.025	1.034**	1.013	1.020	0.994	1.021	0.967	1.025
SVD-GP-NC	0.998	1.001	1.021	1.017	1.040	1.013	1.038	0.974

(*continued*)

Table 3. (Continued)

Model/Horizon	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
	RMSE	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
2018:Q1–2023:Q4								
UC-SV	1.107	1.066	1.150	1.139	1.087	1.119	1.051	1.094
NM-BVAR-SV	1.001	1.010	**0.990**	**0.986**	1.010	1.003	1.032**	1.034*
NM-BVAR-SVO	0.996	1.009	0.996	0.995	1.017	1.017	1.035**	1.019
NM-BVAR-SV-TVM	0.990	0.995	1.000	0.995	1.012	1.011	1.021	1.018
NM-BVAR-SVO-TVM	0.990	0.997	0.992	0.990	1.018	1.022	1.015	1.003
AM-BVAR-SVO	0.996	1.001	1.004	1.007	1.005	1.012	1.000	0.988
AM-BVAR-SV-TVM	0.989	0.985	0.999	0.989	**0.998**	**0.994**	1.020	1.024
AM-BVAR-SVO-TVM	0.988	0.987	0.991	0.986	1.007	1.007	1.013	1.008
NGM-BVAR-SV	1.005	1.004	0.998	0.999	1.001	1.001	0.998	0.996**
NGM-BVAR-SVO	1.003	1.005	1.003	1.007	1.004	1.013	0.997	0.985
NGM-BVAR-SV-TVM	0.976	**0.972**	1.008	0.994	1.005	1.005	1.020	1.033
NGM-BVAR-SVO-TVM	**0.974**	0.977	1.005	0.995	1.015	1.021	1.012	1.017
SVD-GP-NC	1.015	1.008	1.037	1.047	1.017	1.042	**0.948***	**0.958**

Note: Values below 1 indicate improvement over the AM-BVAR-SV model. Significance assessed by Diebold-Mariano-West test using Newey-West standard errors with $h + 1$ lags. *, **, and *** represent the .10, .05, and 0.1 significance levels, respectively. Entries in bold denote ratios below 1 that are the lowest for a given forecasting horizon and measure. In columns with no bold entries, the benchmark model is best.

Table 4. Forecast Ratios for RMSEs and CRPSs, PCE Housing Inflation

	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
Model/Horizon	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
1985:Q1–2023:Q4								
UC-SV	1.001	0.998	1.044	1.047	1.129**	1.119**	1.175**	1.155**
NM-BVAR-SV	1.018	1.018	1.008	1.009	1.015	1.014	1.026*	1.039*
NM-BVAR-SVO	1.016	1.019	1.008	1.011	1.017	1.023	1.027**	1.070**
NM-BVAR-SV-TVM	0.997	0.989	0.980	**0.977**	0.982	**0.989**	1.030	1.035
NM-BVAR-SVO-TVM	0.997	0.993	**0.975**	0.978	**0.979**	0.993	1.027	1.056
AM-BVAR-SVO	0.997**	0.999	1.000	1.001	1.000	1.006	0.998	1.028
AM-BVAR-SV-TVM	0.995	**0.986**	0.986	0.983	0.997	1.003	1.053	1.049
AM-BVAR-SVO-TVM	0.995	0.989	0.982	0.984	0.996	1.007	1.051	1.067
NGM-BVAR-SV	0.997	0.996*	0.998**	0.998	0.999	0.999	0.998	**0.999**
NGM-BVAR-SVO	**0.994***	0.995	0.996**	0.999	0.998	1.006	**0.997**	1.029
NGM-BVAR-SV-TVM	1.236**	1.205***	1.056	1.043	1.023	1.017	1.050	1.047
NGM-BVAR-SVO-TVM	1.239**	1.209***	1.054	1.043	1.022	1.019	1.051	1.060
SVD-GP-NC	1.005	1.002	1.039	1.029	1.072*	1.070**	1.026	1.040
1985:Q1–2017:Q4								
UC-SV	1.013	1.002	1.041	1.036	1.103*	1.097*	1.202**	1.167**
NM-BVAR-SV	1.016	1.019*	1.003	1.010	1.004	1.012	1.040	1.053*
NM-BVAR-SVO	1.015	1.020*	1.003	1.015	1.006	1.031	1.044*	1.108***
NM-BVAR-SV-TVM	1.018	1.003	1.022	1.002	1.033	1.021	1.075	1.065
NM-BVAR-SVO-TVM	1.018	1.006	1.015	1.003	1.027	1.031	1.072	1.105*
AM-BVAR-SVO	0.997**	1.000	0.999	1.004	0.999	1.015	0.999	1.052**
AM-BVAR-SV-TVM	1.018	1.001	1.032	1.010	1.054	1.037	1.096	1.072
AM-BVAR-SVO-TVM	1.017	1.004	1.028	1.013	1.050	1.047	1.097	1.110*
NGM-BVAR-SV	0.997	0.996	0.998	**0.998**	0.998	**0.999**	0.997	**0.999**
NGM-BVAR-SVO	**0.994**	**0.996**	**0.995***	1.001	**0.997**	1.015	**0.996**	1.054**
NGM-BVAR-SV-TVM	1.188**	1.174***	1.066	1.048	1.051	1.033	1.086	1.058
NGM-BVAR-SVO-TVM	1.186**	1.177***	1.063	1.049	1.048	1.040	1.091	1.087
SVD-GP-NC	1.000	0.998	1.023	1.026	1.065	1.068	1.050	1.057

(*continued*)

Table 4. (Continued)

Model/Horizon	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
	RMSE	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
2018:Q1–2023:Q4								
UC-SV	0.952	0.983	1.052	1.087	1.169**	1.187**	1.143	1.123
NM-BVAR-SV	1.023	1.015	1.019	1.005	1.032	1.021	1.009*	1.002
NM-BVAR-SVO	1.021	1.012	1.020	0.998	1.034	0.999	1.008**	0.964**
NM-BVAR-SV-TVM	0.907	0.925	0.877	0.889	**0.894**	0.890	0.978	0.950
NM-BVAR-SVO-TVM	0.912	0.930	0.878	0.886	0.899	**0.875**	**0.972**	**0.917**
AM-BVAR-SVO	0.999	0.997	1.001	0.991	1.000	0.979	0.998	0.962**
AM-BVAR-SV-TVM	**0.900**	**0.915**	0.872	0.883	0.900	0.900	1.001	0.982
AM-BVAR-SVO-TVM	0.903	0.917	**0.870**	**0.878**	0.903	0.883	0.997	0.947
NGM-BVAR-SV	0.996*	0.996	0.998*	0.997*	1.001	1.000	1.000	0.998**
NGM-BVAR-SVO	0.993	0.992	0.997	0.988	1.000	0.979	0.997	0.961**
NGM-BVAR-SV-TVM	1.409	1.349	1.030	1.024	0.977	0.968	1.007	1.015
NGM-BVAR-SVO-TVM	1.426	1.358	1.033	1.020	0.980	0.955	1.003	0.985
SVD-GP-NC	1.024	1.018	1.075	1.042	1.083	1.078	0.999	0.991

Note: Values below 1 indicate improvement over the AM-BVAR-SV model. Significance assessed by Diebold-Mariano-West test using Newey-West standard errors with $h + 1$ lags. *, **, and *** represent the .10, .05, and 0.1 significance levels, respectively. Entries in bold denote ratios below 1 that are the lowest for a given forecasting horizon and measure. In columns with no bold entries, the benchmark model is best.

Table 5. Forecast Ratios for RMSEs and CRPSs, Core PCE Goods Inflation

	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
Model/Horizon	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
1985:Q1–2023:Q4								
UC-SV	1.057	1.015	1.075	1.023	1.081	1.050	1.035	0.992
NM-BVAR-SV	1.023*	1.021**	1.023	1.020	0.994	0.992	1.009	0.993
NM-BVAR-SVO	1.019	1.022**	1.018	1.023	0.992	1.013	1.007	1.037
NM-BVAR-SV-TVM	1.026	1.014	1.037	1.014	0.993	0.982	1.004	0.974
NM-BVAR-SVO-TVM	1.026	1.013	1.039	1.021	0.988	0.992	0.998	0.998
AM-BVAR-SVO	**0.997***	1.000	**0.996*****	1.003	0.998	1.017**	0.998	1.033**
AM-BVAR-SV-TVM	1.013	0.999	1.024	0.995	0.989	0.970	0.982	0.949
AM-BVAR-SVO-TVM	1.011	**0.996**	1.020	0.997	0.982	0.976	0.974	0.967
NGM-BVAR-SV	1.004*	1.006***	1.004*	1.006**	1.001	1.005**	1.003*	1.009***
NGM-BVAR-SVO	1.002	1.007***	1.000	1.010***	0.998	1.023***	1.000	1.044**
NGM-BVAR-SV-TVM	1.021	1.001	1.024	**0.988**	0.981	**0.960**	0.977	**0.942**
NGM-BVAR-SVO-TVM	1.016	0.997	1.019	0.990	**0.973**	0.965	**0.967**	0.958
SVD-GP-NC	1.021**	1.020	1.028	1.030	1.032*	1.047	1.058***	1.052*
1985:Q1–2017:Q4								
UC-SV	**0.967**	**0.967**	**0.949**	**0.949**	0.995	0.964	0.949	0.937
NM-BVAR-SV	1.042**	1.030**	1.044	1.032	0.998	0.993	0.978	0.974
NM-BVAR-SVO	1.039**	1.032**	1.037	1.038*	0.993	1.025	0.974	1.045
NM-BVAR-SV-TVM	1.037	1.016	1.034	1.012	1.003	0.981	1.003	0.960
NM-BVAR-SVO-TVM	1.035	1.014	1.038	1.022	0.988	0.996	0.996	1.001
AM-BVAR-SVO	0.998	1.002	0.993**	1.005	0.955	1.026***	1.000	1.055***
AM-BVAR-SV-TVM	1.005	0.993	0.990	0.977	0.971	0.955	0.956	0.924*
AM-BVAR-SVO-TVM	0.998	0.987	0.985	0.982	0.954	0.966	0.944	0.957
NGM-BVAR-SV	1.008***	1.008***	1.009**	1.008***	1.005	1.008***	1.011***	1.015***
NGM-BVAR-SVO	1.006*	1.009***	1.001	1.015***	0.999	1.036***	1.009**	1.072***
NGM-BVAR-SV-TVM	0.999	0.988	0.976	0.966	0.952	**0.939***	0.936	**0.909****
NGM-BVAR-SVO-TVM	0.990	0.981	0.967	0.969	**0.935***	0.948	**0.920**	0.938
SVD-GP-NC	1.029*	1.020	1.044	1.033	1.044	1.032	1.091**	1.051

(*continued*)

Table 5. (Continued)

Model/Horizon	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
	RMSE	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
2018:Q1–2023:Q4								
UC-SV	1.141	1.134	1.189*	1.205	1.139*	1.243*	1.093*	1.116***
NM-BVAR-SV	1.004	1.001	1.000	0.990	0.991	0.989	1.032*	1.036*
NM-BVAR-SVO	0.998	0.998	0.999	**0.988**	0.991	0.986	1.030*	1.018
NM-BVAR-SV-TVM	1.015	1.008	1.040	1.019	**0.986**	0.984	1.004	1.007
NM-BVAR-SVO-TVM	1.017	1.011	1.041	1.017	0.989	**0.984**	0.999	0.991
AM-BVAR-SVO	**0.996***	**0.997**	**0.998**	0.997	0.999	0.996	0.996**	0.984
AM-BVAR-SV-TVM	1.022	1.014	1.057	1.038	1.002	1.004	1.000	1.005
AM-BVAR-SVO-TVM	1.024	1.017	1.055	1.034	1.002	0.999	0.995	0.988
NGM-BVAR-SV	1.001	1.002	0.999	0.999	0.999	0.997	0.998***	0.997***
NGM-BVAR-SVO	0.998	1.001	0.999	0.997	0.998	0.993	**0.993****	**0.981**
NGM-BVAR-SV-TVM	1.042	1.034	1.070	1.045	1.001	1.008	1.006	1.017
NGM-BVAR-SVO-TVM	1.042	1.037	1.069	1.043	0.999	1.002	1.000	1.001
SVD-GP-NC	1.014	1.019	1.011	1.023	1.023	1.079	1.033***	1.054**

Note: Values below 1 indicate improvement over the AM-BVAR-SV model. Significance assessed by Diebold-Mariano-West test using Newey-West standard errors with $h + 1$ lags. *, **, and *** represent the .10, .05, and 0.1 significance levels, respectively. Entries in bold denote ratios below 1 that are the lowest for a given forecasting horizon and measure. In columns with no bold entries, the benchmark model is best.

in which inclusion of time variation does not necessarily improve forecasting performance.

The addition of volatility outliers to the baseline BVAR-SV specification has essentially no benefit in the 1985–2017 sample of forecasts. For aggregate inflation, under the baseline AM prior, SVO typically harms accuracy a little, more sharply for density forecasts than point (as might be expected, as volatility outlier modeling will affect the spreads of densities more than the means or medians of predictive distributions), at longer horizons more than shorter. For example, at the horizon $h = 8$, the AM-BVAR-SVO forecast is less accurate than baseline by 15 percent for CRPS and less than 1 percent for RMSE. The same broad pattern also applies with inflation disaggregates. It also applies under the NM and NGM priors with SVO as compared with the SV specification.

The performance of the AM-BVAR-SV baseline as compared with univariate models is more mixed. While adding time-varying means to the BVAR models at least occasionally yields some gains in the accuracy of 1985–2017 forecasts, adding richer time variation in parameters in the form of the SVD-GP-NC specification is generally less successful, although with variation across inflation measures and horizons. Forecasts from this model are often—although not always—less accurate than the AM-BVAR-SV baseline and its AM-BVAR-SV-TVM extension that allows time-varying means.

On the other hand, stripping the model down to the UC-SV specification in which inflation is the sum of a time-varying trend and noise can help forecast accuracy for some inflation measures. Consistent with the literature, for forecasting aggregate core inflation, the UC-SV model consistently and modestly (statistically significantly in a majority of cases) improves on the accuracy of the AM-BVAR-SV baseline, by roughly 2 to 5 percent in RMSE and 3 to 7 percent in CRPS. The same applies to forecasts of core goods inflation, with comparable UC-SV gains but without any statistical significance. However, for both point and density forecasts of core services excluding housing and housing inflation, the UC-SV model is less accurate than the AM-BVAR-SV baseline. For these measures, the BVAR's advantage tends to increase with the horizon, peaking at about 10 percent for supercore and 20 percent for housing.

In the shorter subsample of 2018–23 that includes the volatility of the pandemic period, the patterns in forecast accuracy—reported

in the bottom panel of each table—broadly resemble those for the longer subsample, but with some differences. Considering the choice of prior for the BVAR-SV model, it continues to be the case that the AM prior is as good as or better than the NM and NGM priors, although not without some exceptions. In this shorter sample, for both point and density forecast accuracy, the NM and NGM priors perform very similarly to the AM baseline for aggregate inflation, and sometimes slightly better but other times slightly worse for the disaggregate inflation measures (rarely with statistical significance, except at the horizon $h = 8$ for which the sample includes very few independent observations).

As to the additional model features of time-varying means and outlier volatility, in this shorter subsample these features have modestly more benefit than in the longer subsample, but not on a consistent basis. In the shorter subsample, the addition of time-varying means to the baseline AM-BVAR-SV specification slightly reduces the accuracy of forecasts of aggregate and core goods inflation, whereas, at horizons of $h = 1$ through 4 quarters ahead, adding TVM very slightly improves accuracy for supercore inflation and notably improves accuracy (by up to 13 percent) for housing. These same patterns obtained with the baseline AM prior also apply under the NM and NGM priors.

In the case of volatility outliers (SVO), the addition of this feature to the baseline AM-BVAR-SV model has little impact on the accuracy of point forecasts but offers small improvements to the accuracy of density forecasts at longer horizons. At the horizon $h = 8$, the SVO specification improves on the baseline CRPS accuracy by roughly 2 to 4 percent. The finding that the outlier modeling improves forecasts in samples including the pandemic but not generally before is consistent with the macroeconomic forecast results of Carriero et al. (2024).

As to the accuracy of BVAR models compared with univariate specifications, the SVD-GP-NC model that allows rich time variation in parameters has less success in improving forecast accuracy in the shorter subsample than in the longer subsample. Except in the case of supercore forecasts at the horizon $h = 8$, this model is dominated by the AM-BVAR-SV baseline in the recent subsample.

Perhaps more notably, our baseline AM-BVAR-SV model performs better compared with the UC-SV model in the shorter

subsample than the longer subsample. For most inflation measures and horizons, point and density forecasts from the UC-SV model are less accurate than forecasts from the AM-BVAR-SV baseline, by notable degrees (e.g., by roughly 20 percent in both RMSE and CRPS of core PCE forecasts at $h = 2$). In this subsample, the UC-SV model only offers gains for shorter horizon forecasts of housing inflation and otherwise falls short of the baseline forecasts. As we will show below, the better performance of the BVAR baseline in the more recent sample reflects some tendency for its forecasts to more quickly pick up the surge of inflation that began in 2021.

As might be expected, forecast accuracy results for the full sample of 1985–2023 (provided in the top panel of the tables) contain elements of the patterns in the subsample results. In the full-sample results on point and density forecast accuracy, as in the subsamples, among the priors for the BVAR-SV model, the AM prior is in most cases slightly better than the NM and NGM priors, but occasionally slightly worse (with very few instances of statistical significance). Given the AM prior, extending the BVAR-SV model to include time-varying means (TVM) most commonly makes forecasts slightly less accurate but occasionally makes them more accurate (e.g., housing inflation for some horizons, and with gains peaking at 5 percent for core goods at $h = 8$), not by enough to be statistically significant. Similarly, extending the BVAR-SV model to include volatility outliers (SVO) has no consistent benefit; in a few cases the inclusion of volatility outliers very slightly improves accuracy but in most cases reduces it.

As to univariate models compared with the AM-BVAR-SV specification, over the full sample the accuracy of forecasts from the SVD-GP-NC model are nearly always worse than baseline, for all inflation measures and horizons and both point and density forecasts (with one exception, for the CRPS of supercore inflation at $h = 8$). In the case of the UC-SV specification, for both point and density forecasts of core PCE inflation, this univariate trend plus noise model is (except in the CRPS result at $h = 8$) a little less accurate than the AM-BVAR-SV baseline, without any differences that are statistically significant. The baseline AM-BVAR-SV has a larger advantage over the UC-SV model in accuracy of inflation components (supercore and housing inflation modestly more so than goods inflation) than in accuracy of core PCE inflation.

In order to shed some light on time-varying forecast performance, Figure 3 presents time series of aggregate core PCE inflation forecasts from the UC-SV, AM-BVAR-SV, and SVD-GP-NC models.[14] Dates in this figure represent the date of each forecast origin, t. As the figure shows, in broad terms these forecasts generally track together for much of the sample. Near the end of the sample, the AM-BVAR-SV forecast appears to react more quickly to increases in past inflation, rising more quickly than the UC-SV forecast, and subsequently declining more quickly than the UC-SV forecast. That reaction likely helps account for the better performance—for aggregate inflation—of the BVAR-SV model compared with UC-SV in the 2018–23 subsample relative to the 1985–2017 subsample. Future research will be needed to determine whether postpandemic forecast accuracy for these models returns to prepandemic patterns.

Figure 4 focuses on the period of 2020–23, and presents time series of aggregate core PCE inflation forecasts from the UC-SV, AM-BVAR-SV, and the SVD-GP-NC models along with median forecasts from the Survey of Professional Forecasters (SPF). SPF forecasts are aligned with model forecasts so that, for a given SPF release, the last available quarterly inflation date is equivalent to the date of our forecast origin, t. The figure shows that our model forecasts, particularly the AM-BVAR-SV model, have tended to be more accurate than the SPF forecasts. Both our model forecasts and the SPF forecasts have tended to lag behind inflation's rise and subsequent fall.

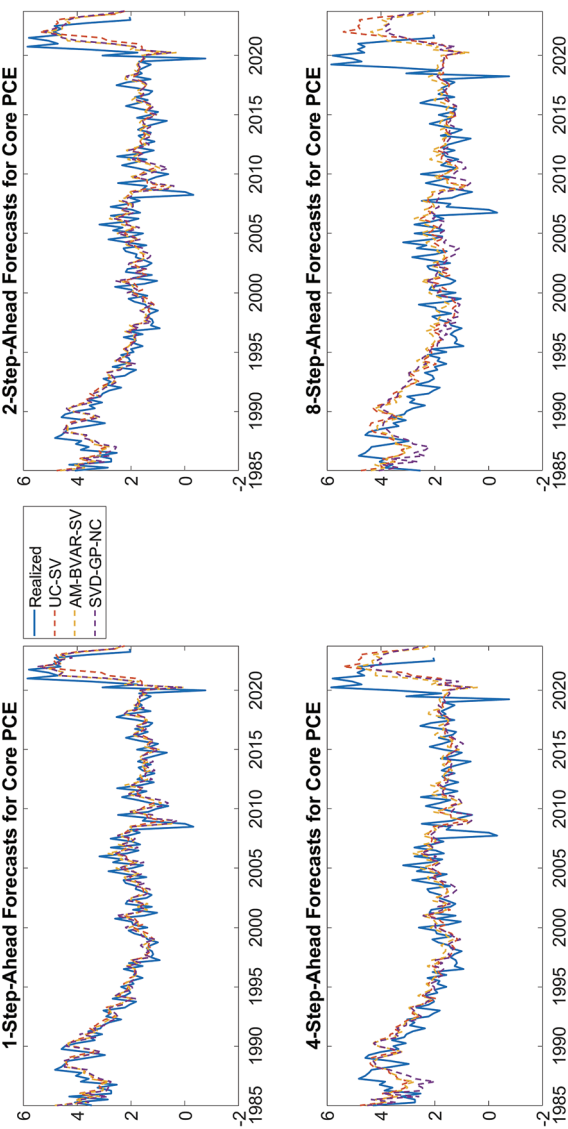
Overall, we view these results as indicating the BVAR-SV model with an adaptive Minnesota-style prior to be an effective tool for forecasting inflation in the core services excluding housing, housing, and core goods components of core PCE inflation.

4.2 "Bottom-Up" Approach to Aggregate Inflation Forecasting

A natural question for research is whether aggregate inflation is best forecast directly or by aggregating forecasts of the three components that we consider. In the results above, the aggregate inflation

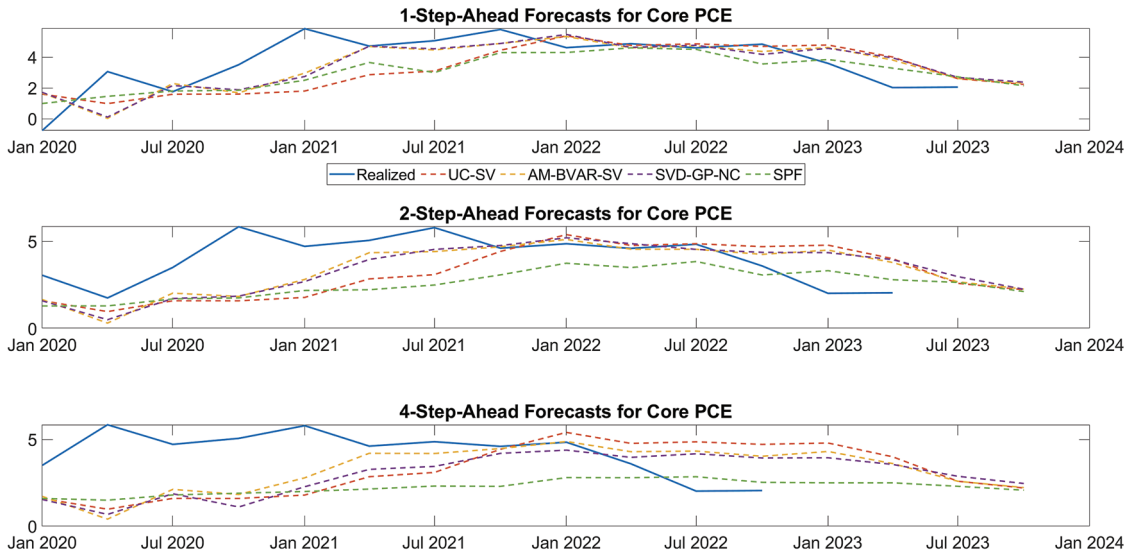
[14] In the interest of readability we only present forecasts for this specific BVAR-SV model. However, other BVAR-SV models exhibit largely the same dynamics and patterns as this particular BVAR-SV model.

Figure 3. Time Series of Forecasts of (aggregate) Core PCE Inflation



Note: Dates on the x-axis represent the date of each forecast origin, t. Realized and forecasted values represent the n-step-ahead value from that given forecast origin.

Figure 4. Time Series of Forecasts of (aggregate) Core PCE Inflation, Focusing on 2020 Onward



Note: Dates on the x-axis represent the date of each forecast origin, t. Realized and forecasted values represent the n-step-ahead value from that given forecast origin. Realized inflation is represented as a quarter-on-quarter annualized rate through the transformation of $400 \cdot \log(\frac{x_t}{x_{t-1}})$, as are forecasts from the UC-SV, AM-BVAR-SV, and SVD-GP-NC models. SPF forecasts represent medians and are represented as the annualized quarterly percent change. SPF forecasts are aligned with model forecasts so that, for a given SPF release, the last available quarterly inflation date is equivalent to the date of our forecast origin, t.

forecast is directly taken from the models that include aggregate inflation. But it is possible that near-singularity arising from collinearity of inflation components with aggregate inflation could adversely affect forecast accuracy due to issues with numerical precision and with distortion in stochastic volatility computations. In our experience, we have found that some models (but less so with the baseline BVAR-SV specifications) that feature this collinearity tend to be vulnerable to explosive forecasts, especially as the model size grows and complexity is added. As a result, an alternative method to forecasting aggregate inflation is to instead drop aggregate inflation from the estimated model, forecast the disaggregate components, and then create an aggregate forecast by using the inflation weights of each component. This approach is commonly known as the "bottom-up" approach and has been widely applied to inflation forecasting (e.g., Hubrich 2005), although not widely with success (e.g., Faust and Wright 2013).

Accordingly, we consider forecasts of aggregate inflation in which we drop core inflation from each model and instead forecast the disaggregates and aggregate inflation as a weighted average of the component forecasts. We approximate the chain-weighted inflation weights by taking, for each pseudo-real-time period, the latest expenditure shares of each component. We then use forecasts of the disaggregates and the approximated weights to produce aggregate forecasts for core inflation. In our application we take just the latest expenditure shares and use them for all forecasting horizons, but alternatively one could forecast expenditure shares.[15] However, this would come at the cost of introducing extra parameters with their associated estimation uncertainty. So we abstain from this procedure, since we find that expenditure shares tend to move little over our forecast horizons. In practice, we produce aggregate UC-SV forecasts by producing univariate UC-SV forecasts for each component of inflation and then aggregating those forecasts. For the BVAR-SV aggregate forecast, we can simply take the component forecasts from the vector y_{t+h}. Finally, for the SVD-WN model we estimate three

[15]An alternative approach to approximating chain weights is to follow the approach used in the replication files of Stock and Watson (2016), which calculates an average expenditure share weight for component i at time t as $w_t^i = \frac{e_t^i + e_{t-1}^i}{\sum_i e_t^i + \sum_i e_{t-1}^i}$, where e_t^i represents the total expenditure on component i at time t.

separate models, one for each component of inflation, and aggregate their respective component forecasts to create an aggregate forecast.

Table 6 compares the bottom-up approach to the direct approach to forecasting aggregate inflation used in earlier tables of results and summarized above. For each model and prior specification, we report the ratio of the RMSE or CRPS from the bottom-up approach to the RMSE or CRPS from the direct approach; entries below (above) 1 mean that the bottom-up approach beats (falls short of) the direct approach. These results fairly consistently show little advantage to a bottom-up approach to forecasting aggregate inflation. For the UC-SV and baseline AM-BVAR-SV specifications, the bottom-up forecasts are less accurate than the direct forecasts, most noticeably for UC-SV density forecasts (less so for UC-SV point forecasts). For other Bayesian prior and model feature choices, the bottom-up approach is sometimes slightly better than the direct, and sometimes slightly worse. For these models, there are no consistent gains to a bottom-up approach. However, at some horizons, the bottom-up approach does slightly improve forecasts from the SVD-GP-NC model. In the 2018–23 subsample, as in the longer subsample, there is no consistent benefit to the bottom-up approach. For example, as regards forecast accuracy from the UC-SV and baseline models, the bottom-up approach is relatively not as poor in the short subsample as in the long subsample, but it is not clearly better, either. On balance, there seems to be little reason to use a bottom-up approach, although in some settings, doing so has small positive impacts on forecast accuracy.

5. Looking Ahead: 2024:Q2–2026:Q4

The last section's results on historical forecast accuracy establish that the BVAR-SV model with an adaptive Minnesota-style prior is an effective tool for forecasting inflation in the core services excluding housing, housing, and core goods components of core PCE inflation, as well as aggregate core inflation. Accordingly, we use the AM-BVAR-SV model to assess the inflation outlook going forward.[16] This BVAR specification is useful for capturing

[16]The BVAR-SV model with time-varying means (i.e., AM-BVAR-SV-TVM) generates similar forecasts for the period ahead; therefore, for the sake of brevity, we do not report them.

Table 6. Forecast Ratios for RMSEs and CRPSs When Using Bottom-Up Approach, Core PCE Inflation

	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
Model/Horizon	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
1985:Q1–2023:Q4								
UC-SV	1.018	1.070***	1.024	1.075***	1.025	1.092***	1.022	1.112***
NM-BVAR-SV	1.003	1.004	1.002	1.002	1.004	1.003	0.998	0.997
NM-BVAR-SVO	1.000	0.998	1.000	**0.998**	1.002	**0.997**	**0.992**	0.989
NM-BVAR-SV-TVM	1.015	1.013*	1.008	1.005	1.012	1.007	1.008	1.001
NM-BVAR-SVO-TVM	1.009	1.009	1.013	1.005	1.013	1.001	1.011	0.988
AM-BVAR-SV	1.004	1.008	1.010	1.017	1.017	1.020	1.010	1.005
AM-BVAR-SVO	1.003	1.003	1.010	1.012	1.015	1.015	1.005	1.001
AM-BVAR-SV-TVM	1.011	1.013	1.009	1.012	1.020	1.017	1.013	1.006
AM-BVAR-SVO-TVM	1.008	1.012	1.016	1.013	1.024	1.015	1.023	1.001
NGM-BVAR-SV	1.000	1.002	1.009	1.010	1.016	1.012	1.010	0.994
NGM-BVAR-SVO	0.998	0.998	1.006	1.003	1.015	1.003	1.005	0.984
NGM-BVAR-SV-TVM	1.020	1.015	1.018	1.014	1.025	1.013	1.016	0.996
NGM-BVAR-SVO-TVM	1.014	1.009	1.023	1.008	1.027	0.999	1.027	**0.980**
SVD-GP-NC	**0.990**	**0.994**	**0.996**	1.001	1.014	1.033	0.998	1.012
1985:Q1–2017:Q4								
UC-SV	1.012	1.088***	1.023*	1.108***	1.013	1.139***	1.008	1.175***
NM-BVAR-SV	1.008	1.006	1.011	1.007	1.015	1.005	1.015	1.000
NM-BVAR-SVO	0.999	0.997	1.007	1.000	1.014	0.999	1.008	0.991
NM-BVAR-SV-TVM	1.011	1.011	**0.997**	0.999	**0.994**	0.995	**0.988**	0.989
NM-BVAR-SVO-TVM	1.000	1.005	1.000	**0.997**	0.994	0.986	0.989	0.969*
AM-BVAR-SV	1.008	1.009	1.031	1.028*	1.041	1.029	1.018	1.005
AM-BVAR-SVO	1.003	1.003	1.028	1.020	1.042	1.023	1.012	1.001
AM-BVAR-SV-TVM	1.008	1.012	1.010	1.011	1.013	1.010	0.998	0.996
AM-BVAR-SVO-TVM	1.003	1.009	1.015	1.011	1.022	1.007	1.015	0.985
NGM-BVAR-SV	0.999	1.001	1.024	1.016	1.038	1.016	1.015	0.987
NGM-BVAR-SVO	0.994	0.996	1.019	1.007	1.040	1.004	1.006	0.976*
NGM-BVAR-SV-TVM	1.002	1.003	1.013	1.008	1.007	0.997	0.991	0.978
NGM-BVAR-SVO-TVM	0.990	0.995	1.018	1.000	1.013	**0.980**	1.008	**0.952****
SVD-GP-NC	**0.981***	**0.986**	1.001	1.001	1.061*	1.056*	1.036	1.031

(*continued*)

Table 6. (Continued)

Model/Horizon	$h = 1$		$h = 2$		$h = 4$		$h = 8$	
	RMSE	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**	**RMSE**	**CRPS**
2018:Q1–2023:Q4								
UC-SV	1.024	1.024	1.024	1.002	1.032	1.003	1.031*	0.996
NM-BVAR-SV	**0.997**	**0.998**	0.990	0.990	0.995	0.999	0.986	0.988
NM-BVAR-SVO	1.002	1.000	0.990	0.992	0.991	0.993	0.981*	0.984*
NM-BVAR-SV-TVM	1.020	1.018	1.023	1.022	1.029	1.038	1.022	1.029
NM-BVAR-SVO-TVM	1.020	1.018	1.029	1.030	1.031	1.038	1.028**	1.037*
AM-BVAR-SV	1.000	1.002	**0.984***	**0.986**	0.996	0.999	1.004	1.006**
AM-BVAR-SVO	1.004	1.004	0.986	0.990	0.993	0.994	1.001	1.002
AM-BVAR-SV-TVM	1.015	1.015	1.009	1.013	1.026	1.035	1.022***	1.029**
AM-BVAR-SVO-TVM	1.016	1.019	1.016	1.020	1.026	1.035	1.029***	1.040***
NGM-BVAR-SV	1.002	1.005	0.989	0.991	0.998	1.004	1.006	1.011***
NGM-BVAR-SVO	1.005	1.006	0.990	0.994	0.995	0.998	1.004	1.005
NGM-BVAR-SV-TVM	1.044	1.050	1.024	1.030	1.038	1.049	1.032**	1.036***
NGM-BVAR-SVO-TVM	1.045	1.049	1.028	1.033	1.038	1.047	1.038***	1.046***
SVD-GP-NC	1.003	1.018	0.990	0.998	**0.974**	**0.984**	**0.967***	**0.974**

Note: Values below 1 indicate improvement over the corresponding core PCE inflation forecast that is taken directly from the model that includes aggregate inflation. The UC-SV model in the table represents the aggregate forecast from three separate disaggregate UC-SV models. *, **, and *** represent the .10, .05, and 0.1 significance levels, respectively. Entries in bold denote ratios below 1 that are the lowest for a given forecasting horizon and measure. In columns with no bold entries, no bottom-up approach beats its direct counterpart.

the historical comovement of inflation, its components, and wage growth and the resulting implications for the inflation outlook over the next few years. We estimate the model using the latest available data, i.e., 1959:Q2 through 2024:Q1, and use the estimated model to forecast inflation, its components, and ECI growth from 2024:Q2 through 2026:Q4.

This section begins by presenting baseline unconditional forecasts and then examines the inflation outlook under some alternative scenarios, one conditioning on a path of wage growth returning to 3 percent and the other conditioning on a path of aggregate core inflation returning to 2 percent.

5.1 Baseline Forecasts

Following standard practice in the literature to incorporate high-frequency intraquarterly information, we entropically tilt (condition) the current quarter, i.e., 2024:Q2, unconditional forecast of core PCE inflation toward the Q2 nowcast estimate (of core PCE inflation, not the other variables in the model) taken from the Federal Reserve Bank of Cleveland's (Cleveland Fed's) website.[17] We refer to the resulting conditional forecasts as the baseline forecasts and characterize them as unconditional forecasts because the only condition is one that simply accounts for the most recent information on aggregate core PCE inflation. Table 7 reports these forecasts (point forecasts computed as posterior means) under the column heading labeled "Base." The top panel in the table reports quarterly annualized growth rates, and the bottom panel reports the corresponding forecasts expressed in four-quarter growth rates (i.e., averages of annualized quarterly log growth rates over four quarters, which in the fourth quarter of each year represent Q4/Q4 inflation rates for the year).

The table shows that the baseline forecast has core PCE inflation slowly decelerating to a quarterly annualized rate of 2.6 percent by

[17]As of May 1, 2024, the Q2 nowcast of core PCE inflation is estimated to be 3.07 percent (quarterly annualized rate), which is nearly identical to the unconditional forecast of 3.11 percent. Cleveland Fed inflation nowcasts are based on the model developed in Knotek and Zaman (2017). Knotek and Zaman (2023) document the competitive accuracy of Cleveland Fed nowcasts compared with nowcasts from professional forecasters and other competing approaches.

Table 7. Looking Ahead, 2024:Q2–2026:Q4: AM-BVAR-SV

Date	Nominal Wage			Supercore			Housing			Goods			Core PCE		
	Base	Wage Sc.	Core Sc.	Base	Wage Sc.	Core Sc.	Base	Wage Sc.	Core Sc.	Base	Wage Sc.	Core Sc.	Base	Wage Sc.	Core Sc.
Quarterly Annualized (QoQ) Forecasts															
2024:Q2	4.0	3.9	3.9	3.8	3.8	3.9	5.2	5.2	5.2	–0.3	–0.3	–0.3	3.1	3.1	3.1
2024:Q3	3.8	3.8	3.8	3.6	3.5	3.5	5.0	5.0	5.0	–0.1	–0.4	–0.3	2.9	2.8	2.9
2024:Q4	3.8	3.7	3.8	3.6	3.3	3.4	4.9	4.9	4.9	0.0	–0.4	–0.2	2.9	2.7	2.8
2025:Q1	3.8	3.6	3.8	3.5	3.1	3.3	4.7	4.7	4.7	0.2	–0.4	–0.2	2.9	2.5	2.7
2025:Q2	3.7	3.5	3.6	3.4	3.0	3.1	4.6	4.5	4.5	0.2	–0.5	–0.3	2.8	2.4	2.5
2025:Q3	3.7	3.4	3.5	3.4	2.8	3.0	4.5	4.4	4.4	0.3	–0.6	–0.4	2.8	2.2	2.4
2025:Q4	3.6	3.2	3.4	3.3	2.7	2.8	4.4	4.2	4.2	0.3	–0.6	–0.5	2.8	2.1	2.2
2026:Q1	3.6	**3.0**	3.3	3.3	2.6	2.6	4.3	4.1	4.1	0.3	–0.5	–0.8	2.7	2.1	**2.0**
2026:Q2	3.6	**3.0**	3.2	3.3	2.6	2.6	4.2	4.0	4.0	0.4	–0.4	–0.7	2.7	2.1	**2.0**
2026:Q3	3.5	**3.0**	3.2	3.2	2.7	2.6	4.1	3.9	3.9	0.4	–0.3	–0.6	2.7	2.1	**2.0**
2026:Q4	3.5	**3.0**	3.1	3.2	2.7	2.6	4.1	3.8	3.8	0.4	–0.2	–0.5	2.6	2.2	**2.0**
Corresponding Four-Quarter Trailing Rate (4Q) Forecasts															
2024:Q2	4.0	4.0	4.0	3.6	3.6	3.6	5.5	5.5	5.5	–1.1	–1.1	–1.1	2.7	2.7	2.7
2024:Q3	4.0	4.0	4.0	3.7	3.7	3.7	5.3	5.3	5.3	–0.6	–0.7	–0.7	2.9	2.9	2.9
2024:Q4	4.0	4.0	4.0	4.0	3.9	3.9	5.2	5.2	5.2	–0.2	–0.4	–0.3	3.1	3.0	3.1
2025:Q1	3.8	3.8	3.8	3.6	3.4	3.5	5.0	5.0	5.0	–0.1	–0.4	–0.3	3.0	2.8	2.8
2025:Q2	3.8	3.6	3.7	3.5	3.2	3.3	4.8	4.8	4.8	0.1	–0.4	–0.3	2.9	2.6	2.7
2025:Q3	3.7	3.5	3.7	3.5	3.1	3.2	4.7	4.6	4.6	0.2	–0.5	–0.3	2.9	2.5	2.6
2025:Q4	3.7	3.4	3.6	3.4	2.9	3.1	4.5	4.5	4.5	0.3	–0.5	–0.4	2.8	2.3	2.5
2026:Q1	3.6	3.3	3.5	3.3	2.8	2.9	4.4	4.3	4.3	0.3	–0.5	–0.5	2.8	2.2	2.3
2026:Q2	3.6	3.2	3.4	3.3	2.7	2.8	4.3	4.2	4.2	0.3	–0.5	–0.6	2.7	2.1	2.2
2026:Q3	3.6	3.1	3.3	3.3	2.6	2.7	4.2	4.0	4.0	0.3	–0.5	–0.6	2.7	2.1	2.1
2026:Q4	3.5	3.0	3.2	3.2	2.7	2.6	4.2	3.9	3.9	0.4	–0.4	–0.6	2.7	2.1	2.0

Note: Numbers reported in the top (bottom) panel are the quarterly annualized (four-quarter trailing rate) forecasts from the AM-BVAR-SV benchmark model for the forecast period spanning 2024:Q2 through 2026:Q4. The columns denoted "Base" refer to baseline forecasts, "Wage Sc." refers to forecasts generated under the wage scenario, and "Core Sc." refers to forecasts generated under the core PCE 2 percent scenario. In the top panel, the numbers in bold indicate conditions imposed from outside the model: 2024:Q2 condition (of 3.1 percent) on core PCE; 2026:Q1–2026:Q4 conditions (of 3.0 percent) on nominal wages for wage scenario; 2026:Q1–2026:Q4 conditions (of 2.0 percent) on core PCE for core PCE scenario.

the end of 2026. The slow decline of Q4/Q4 core inflation from 3.1 percent in 2024 to 2.7 percent in 2026 is associated with a projected gradual moderation in the growth rate of nominal wages, from the current annualized quarterly rate of 4.0 percent in 2024:Q2 to 3.6 percent in 2026:Q1 (and, on Q4/Q4 basis, from 4.0 percent in 2024 to 3.5 percent in 2026).

The baseline forecast projects moderation in both supercore and housing components of inflation, but at a differing pace. Supercore inflation is projected to decline from an annualized quarterly rate of 3.8 percent in 2024:Q2 to 3.2 percent in 2026:Q4, and housing inflation slows from 5.2 percent to 4.1 percent. In contrast, core goods inflation is projected to increase from –0.3 percent to an annualized rate of 0.4 percent at the end of 2026. On a four-quarter basis, smoothing through quarterly fluctuations, both housing and supercore components are forecast to decline from 2024:Q2 to 2026:Q4, most sharply in the case of housing inflation (from 5.5 to 4.2 percent) and significantly in the case of supercore inflation (from 3.6 to 3.2 percent), whereas goods inflation is forecast to increase (from –1.1 to 0.4 percent).

The forecasted Q4/Q4 inflation rates in 2026 are somewhat higher than their pre-COVID (2017–19) averages of 3.3 percent (housing), 2.1 percent (supercore), and –0.6 percent (core goods). Hence, not surprisingly, in 2026 aggregate core PCE inflation is 70 basis points above the Federal Reserve's longer-run inflation target of 2 percent and 100 basis points above its 2017–19 average rate. Note that the solidly negative prepandemic rate of goods inflation reflects a pattern that emerged in 1996. In an accounting sense, sustained modest deflation in goods prices contributed to keeping aggregate core inflation low from the mid-1990s up until the COVID-19 pandemic. However, in recent years, some public commentary has raised some concern that increased global fragmentation in trade and deglobalization could contribute to higher goods inflation and in turn slow progress toward returning aggregate inflation to the Federal Reserve's 2 percent goal. Results below will shed some additional light on the possible importance of returning to below-zero goods inflation.

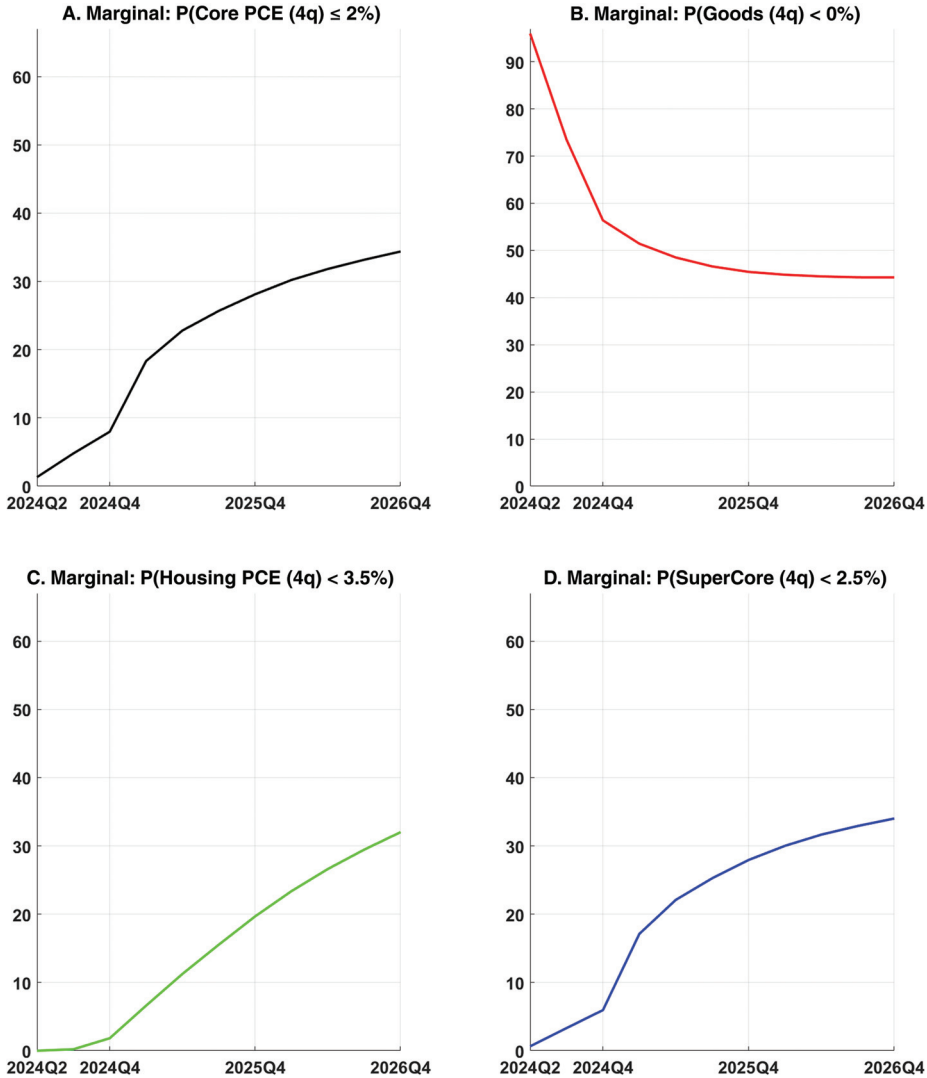
While the baseline forecast just described refers to the means of predictive distributions, there is of course considerable uncertainty around the outlook captured in the model's (posterior) forecast

distributions. We turn now to considering some probabilistic assessments of the outlook using these distributions. Some estimates consider particular cutoff values for inflation, its components, and wage growth. We use cutoffs based on prepandemic (2017–19 average) rates of inflation and wage growth, with some adjustment to reflect the fact that, on average from 2017 through 2019, core PCE inflation was 30 basis points below the Federal Open Market Committee's (FOMC's) longer-run inflation target of 2 percent. For cutoffs used in probabilistic assessments, we take a simple approach of using conditions or scenarios that mark up each component and wage growth by a bit more or a bit less than 30 basis points, consistent with the shortfall in average core PCE inflation for 2017–19. The bit more or bit less is chosen to make for nice round numbers in the conditions. (Weighted by spending shares, the component cutoffs correspond to aggregate core inflation of 2 percent.) For simplicity, below we will refer to "prepandemic averages" of inflation, its components, and wage growth even though the values used in these calculations are by design a little higher than the actual 2017–19 average values.

Panel A of Figure 5 plots the marginal probability of core PCE inflation (the four-quarter average rate) being less than or equal to 2 percent over the forecast horizon. Panels B, C, and D provide the marginal probabilities of the components' inflation rates being less than their respective prepandemic averages (adjusted as noted above). Based on the baseline forecast density, the probability that core PCE inflation averages 2 percent or less is below 35 percent through 2026:Q4. So while the baseline forecast has a mean core inflation rate well above 2 percent in 2026, the (35 percent) probability of reaching 2 percent is not small. As can be seen, contributing factors to this moderate probability are comparable probabilities of negative core goods inflation (probability below 50 percent in most quarters), supercore inflation below 2.5 percent (probability less than 35 percent), and housing inflation below 3.5 percent (probability less than 35 percent).

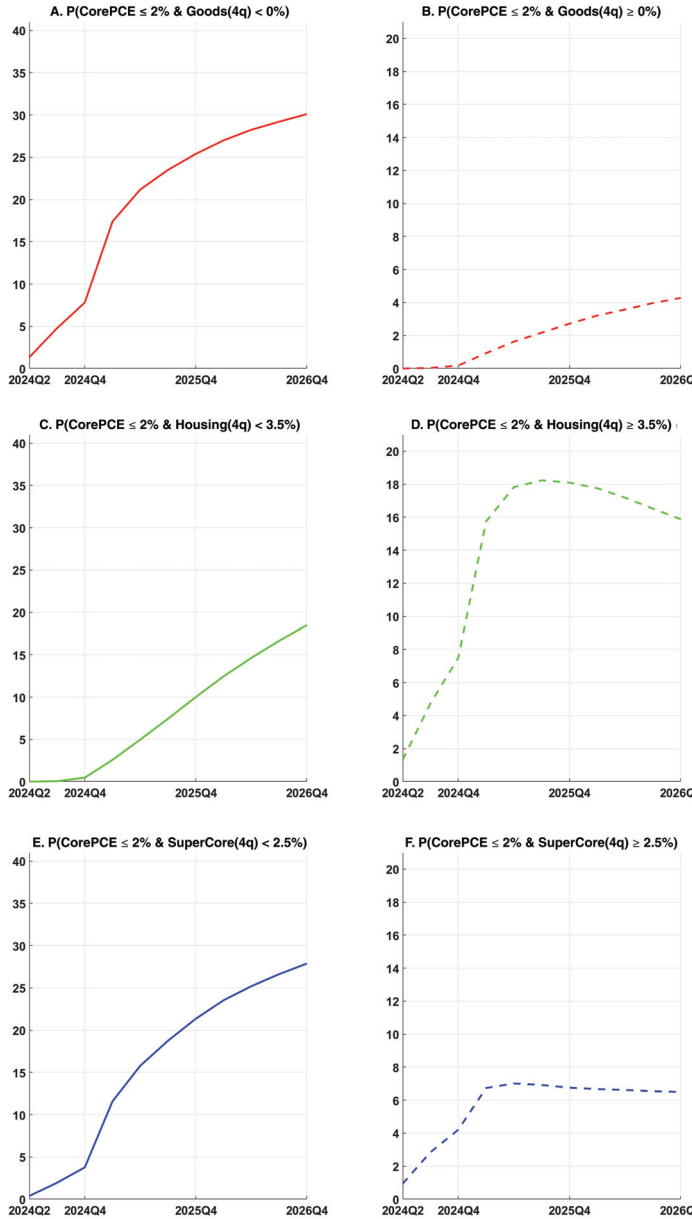
Figure 6 plots *joint* probabilities of observing both core PCE inflation ≤ 2 percent and component inflation rates above or below the cutoff values specified as adjustments of 2017–19 averages. The left panels plot the joint probabilities that are based on the components' inflation rates below the respective thresholds, and the

Figure 5. Marginal Probabilities Based on Baseline Forecasts



Note: The plots are marginal probabilities of core PCE inflation and its components constructed from their baseline density forecasts (four-quarter growth rates). Panel A plots the probability of core PCE inflation at or below 2 percent, panel B probability that goods inflation is negative, panel C probability of housing inflation below 3.5 percent, and panel D probability of supercore inflation less than 2.5 percent.

Figure 6. Joint Probabilities Based on Baseline Forecasts

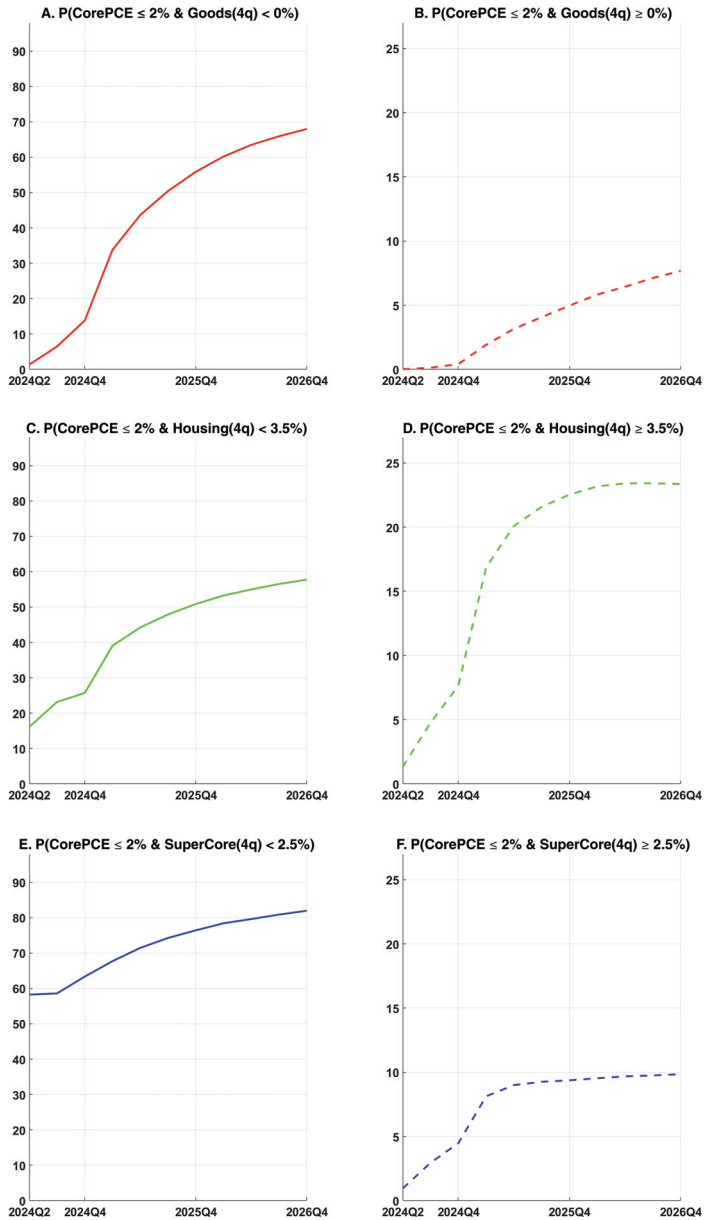


Note: The plots are joint probabilities of core PCE inflation and its components constructed from their baseline density forecasts (four-quarter growth rates).

right panels at or above the thresholds (note that the right panels use an axis scaling different from the left panels). For both the core goods and supercore components, the joint probability of seeing core PCE inflation $\leq$2 percent and the component's inflation rate below the respective threshold is significantly higher (by more than 20 percentage points) than the joint probability of core inflation at or below 2 percent and the component's inflation rate above its respective threshold. In the case of housing, the differences in the joint probabilities of housing above or below the threshold and seeing core inflation at or below 2 percent are relatively modest. For example, in 2026:Q4, the joint probability of PCE inflation at or below 2 percent and housing inflation below 3.5 percent is a little below 20 percent, whereas the corresponding probability with housing inflation at or above 3.5 percent is nearly 16 percent, little different.

Figure 7 reports *conditional* probabilities of core PCE inflation at or below 2 percent, given component inflation rates either below or above the cutoffs representing rough measures of prepandemic levels. The left panels plot the conditional probabilities of core PCE given inflation in the components below the indicated threshold, and the right panels (with axes scaled differently than the left panels) provide results for component inflation rates at or above the threshold. The results in the left panels indicate that, conditional on seeing inflation in the components at levels below their adjusted prepandemic levels, the probabilities of core PCE inflation at or below 2 percent are significantly higher than 50 percent, especially for the goods and supercore components. For example, in 2026:Q4, conditional on core goods inflation below zero, the probability of core PCE inflation at or below 2 percent is 68 percent, and conditional on supercore inflation below 3.5 percent, the probability of core PCE inflation at or below 2 percent is 82 percent. The probability of PCE inflation of 2 percent or less is still high conditioning on housing inflation returning to its prepandemic level, but at 58 percent in 2026:Q4 it is not as high as when conditioning on prepandemic levels of other components. Conversely, conditional probabilities of core PCE inflation at or below 2 percent in 2026 are low if goods inflation is persistently positive, housing inflation stays above 3.5 percent, or supercore inflation is above 2.5 percent, respectively. These probabilities are especially low—between 6 and 10 percent—in the cases of

Figure 7. Conditional Probabilities Based on Baseline Forecasts



Note: The plots are conditional probabilities of core PCE inflation, conditional on the components inflation rates above or below certain thresholds. The probabilities are constructed from their baseline density forecasts (four-quarter growth rates).

goods inflation remaining positive and supercore inflation remaining at or above 2.5 percent, compared with a probability of 23 percent with housing inflation remaining at or above 3.5 percent.

The fact that housing inflation getting back to a prepandemic level is projected to matter for returning inflation to 2 percent but somewhat less sharply than estimated for the other two inflation components is likely tied to the respective weights of the components in aggregate core PCE inflation. Supercore spending is by far the largest component (of these three components) of consumption, with a nominal spending share (in 2024:Q1) of 57 percent. Goods are second in importance, with a spending share of 25 percent, and housing is third, at a spending share of 18 percent.

5.2 Conditional Forecast: Wage Scenario

The baseline forecast has nominal wage growth moderating to an annualized rate of 3.6 percent in 2025 and 3.5 percent on a Q4/Q4 basis in 2026. This pace of wage growth is about 0.5 percentage point higher than 3 percent, the pace we have taken—in view of prepandemic averages—to be roughly consistent with core PCE inflation of 2 percent. There are reasons to believe that the projected slowing in the economy in response to restrictive monetary policy may lead to quicker wage moderation than indicated in the baseline forecast. DeLuca and Van Zandweghe (2023), among others, project nominal wage growth to decline to 3 percent by 2025. If that were to occur, would the slower wage growth be associated with a faster moderation in core inflation than implied in the baseline? To answer this question, we build a scenario using our model, assuming that by the start of 2026 and beyond, nominal wage growth averages 3 percent. The resulting conditional forecasts are shown in Table 7 under the column labeled "Wage Sc."

Conditioning the model with a nominal wage path that calls for wage growth to decline to 3 percent by early 2026 is associated with a quicker decline in core PCE inflation than implied by the baseline. The forecast has core PCE inflation moving down to 2.1 percent in 2026 (slightly higher than the median forecast of 2.0 percent in the Federal Reserve's Summary of Economic Projections released following the March 2024 FOMC meeting). The forecasts of the components reveal that the steeper fall in aggregate core PCE

inflation in the scenario as compared with the baseline projection is associated with declines in the inflation rates of all three components that are also steeper in the scenario than in the baseline. This scenario also reveals that of the three components, supercore and core goods are relatively more sensitive to wage developments than is housing inflation: In 2026, the Q4/Q4 inflation rates for supercore and goods are 50–80 basis points lower in the wage scenario than in the baseline forecast, whereas the inflation rate for housing is just 30 basis points lower in the scenario than in the baseline.

5.3 Conditional Forecast: Core PCE 2 Percent Scenario

The previous scenario illustrated that, according to our benchmark AM-BVAR-SV model, a moderation in nominal wage growth to 3 percent is consistent with returning core inflation closer to 2 percent, but not quite with getting core inflation there. Alternatively, we can assess what paths of inflation components and wage growth will be consistent with core inflation reaching 2 percent in 2026 by explicitly conditioning on such a lower path of core PCE inflation. The resulting conditional forecasts are reported in Table 7 under the column labeled "Core Sc."

Under this scenario, our baseline BVAR projects that moderation of core PCE inflation to 2 percent in 2026 would be associated with more slowing of inflation in the supercore and goods components than is projected under the baseline case and the wage growth scenario, more so when compared with the baseline forecast than the wage growth scenario. On a Q4/Q4 basis, goods (supercore) inflation is projected to slow to –0.6 (2.6) percent in the 2 percent inflation scenario, compared with –0.4 (2.7) percent in the wage scenario and 0.4 (3.2) percent in the baseline. Housing inflation and wage growth show relatively less change in this scenario as compared with the wage scenario and baseline forecast. The Q4/Q4 housing inflation forecast for 2026 is 3.9 percent in the 2 percent inflation scenario, the same as in the wage scenario in which core PCE inflation remains a little above 2 percent, and 30 basis points below the baseline. The Q4/Q4 forecast of wage growth in this scenario is very close to the 3 percent pace considered in the wage scenario.

Together, the results of the slower wage growth and 2 percent core PCE inflation scenarios may be seen as pointing to the

likelihood that, for core PCE inflation to near or reach the FOMC's longer-run target of 2 percent over the next few years, the three components of core inflation and wage growth will need to slow to rates close to, although a little above, their prepandemic averages.

6. Conclusions

Motivated by the recent emphasis that some economic commentators and policymakers have placed on a three-component breakdown of core inflation into goods excluding food and energy, services excluding energy and housing, and housing, this paper examines the efficacy and implications of forecasts of the three-component breakdown of core inflation in the U.S.

We first examine a range of models and establish the historical efficacy of a BVAR with stochastic volatility in five variables, consisting of core PCE inflation, its three components, and wage growth. An examination of the historical accuracy of point and density forecasts indicate that this model estimated with an adaptive Minnesota-style prior is an effective tool for forecasting inflation in the core services excluding housing, housing, and core goods components of core PCE inflation, as well as aggregate core inflation (although less so for aggregate inflation than its components). Adding features such as time-varying parameters or more variables either fails to improve or harms forecast accuracy. Our historical results also indicate that aggregate inflation is best forecast directly; no consistent benefit can be achieved by aggregating disaggregate components.

We also examine medium-term forecasts for the period ahead, 2024 through 2026. In particular, we consider the likelihood of inflation returning to the Federal Reserve's 2 percent target under our model's baseline forecast distribution. Our model's baseline (mean) projection puts core inflation at 2.7 percent in 2026, well below its level in 2023 but still elevated relative to the Federal Reserve's longer-run target of 2 percent. But the model's forecast puts a 35 percent probability on hitting 2 percent core inflation in 2026. In these baseline predictive distributions, a return of core PCE inflation to 2 percent or less over the next few years is much higher when conditioning on goods or supercore inflation slowing to near prepandemic levels than when conditioning on these components remaining above the same thresholds.

We also analyze alternative scenarios. One features a gradual decline of wage growth to near its prepandemic level to assess the likelihood that such a development may be key to continued disinflation. The second scenario conditions on a decline of aggregate core inflation to 2 percent to provide a joint assessment of the paths of component inflation rates and wage growth most likely associated with a return of aggregate inflation to target. These scenario analyses indicate that slower wage growth will likely be associated with reduced inflation in all three components, not just supercore, but housing less so than goods and supercore inflation. In addition, based on the historical dynamics of inflation and its components as captured by the BVAR, it is most likely the case that a return of core inflation to the Federal Reserve's 2 percent target will be associated with all three components returning to near prepandemic levels.

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The Resilience of the U.S. Corporate Bond Market during Financial Crises*

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Corporate bond markets proved remarkably resilient against a sharp contraction caused by the 2020 COVID-19 pandemic. We document three important findings: (i) bond issuance increased immediately when the contraction hit, whereas, in contrast, syndicated loan issuance was low; (ii) Federal Reserve interventions increased bond issuance, while loan issuance also increased, but to a lesser degree; and (iii) bond issuance was concentrated in the investment-grade segment for large and profitable issuers. We compare these results to previous crises and recessions and document similar patterns. We conclude that the U.S. bond market is an important and resilient source of funding for corporations.

JEL Codes: E51, E58, G01, G12, G32.

1. Introduction

While the common wisdom in finance and macroeconomics is that credit markets are highly procyclical, it is unclear how strongly procyclicality is driven by the demand for credit or its supply.[1] Moreover, less is known about the composition of credit and the differential behavior of different segments of credit markets over the

*We thank Nina Boyarchenko, Sergey Chernenko, Nicolas Crouzet, Edie Hotchkiss, Victoria Ivashina, Stephan Luck, João Santos, Sascha Steffen, Adi Sunderam, Stephane Verani, and seminar participants at Carnegie Mellon University (Tepper), Georgia State University, Cambridge University, HEC Montréal, FRIC, New York Federal Reserve, European Winter Finance Conference, IWH Halle, and Nova University Lisbon for very helpful comments. We are grateful to Judy Steenstra from the Investment Company Institute for providing data. We also thank Victoria Ivashina for sharing data.

[1]See Bernanke and Gertler (1989), Holmström and Tirole (1997), Becker and Ivashina (2014), and Benmelech and Bergman (2017).

business cycle. Are bank loan originations more cyclical than corporate bond issuance? If so, why? Is this cyclicality driven by market segmentation in which some borrowers cannot access certain parts of credit markets during financial crises and economic downturns? That is, do banks curtail credit during difficult times whereas flows into bonds are less cyclical? Last, are some policy interventions more effective in stabilizing and stimulating parts of the corporate credit market but not others? With a few exceptions—notably, Becker and Ivashina (2014)—the literature focuses on segments of the U.S. credit market, not on joint behavior. Yet the different components of credit markets are interconnected and work in tandem. To understand the cyclical behavior of credit to corporations and to obtain a panoramic view of credit markets, bonds and loans should be studied jointly.

We provide an empirical overview of the functioning of U.S. long-term corporate credit markets during several financial crises, including the Global Financial Crisis (GFC) of 2008–09 and the crisis triggered in 2020 by the COVID-19 pandemic. The COVID-19 crisis provides an interesting setting for studying corporate credit markets during a financial crisis. In a traditional financial crisis and recession, the decline in credit may stem from shocks to both demand and supply. Obviously, COVID-19 affected both the demand and the supply of credit. Yet empirically, bond issuance increased significantly, whereas loan origination did not. This suggests that the two markets play different roles in meeting corporate demand for financing in a crisis.

The U.S. corporate bond market proved remarkably resilient when the COVID-19 pandemic first shook financial markets. Bond issuance increased substantially in the last week of March 2020 and peaked in the first week of April 2020: 64 bonds totaling $73 billion were issued. Bond issuance in April remained substantially above the average for 2009–19. Issuance increased again in May, reaching the highest level—in numbers issued—in early May before declining and returning to normal levels by late May. By the end of June 2020, the cumulative number of bond issues was 630, compared to an average of 422 during the period 2009–19. In terms of aggregate issuance, between March and June 2020, $502 billion of corporate bonds were issued, compared to $151 billion in 2019, $204 billion in 2018, and $157 billion per year on average in 2009–19. In contrast, during the

same period, the origination of syndicated loans remained below the 2010–19 average in both number and total amount originated. We observe similar patterns during the GFC. By January 2009, the number of bonds issued had reverted to the precrisis average, while total amounts issued had increased significantly and remained high for the remainder of the crisis. In contrast, syndicated loan origination remained below average during the same period.

Why is the U.S. bond market more resilient than the syndicated loan market? We provide three congruent explanations. First, bond issuers are of higher credit quality than firms that tend to rely on bank funding. For example, 87 percent of bond issuers between 2009 and 2019 were rated as investment grade, whereas only 19 percent of syndicated loans were rated as investment grade. If noninvestment-grade firms become even riskier during financial crises while investment-grade firms are less affected, then it is not surprising that bond issuance is less countercyclical than loan origination. In fact, credit market segmentation may become more pronounced during a crisis. Indeed, in 2020 the share of investment-grade issuers in the bond market was 94 percent—an increase of 7 percentage points over 2009–19. Similarly, the share of loans originated to investment-grade firms increased in 2020 to 24 percent, up 5 percentage points from 2009–19.

A second explanation concerns the fundamental difference between commercial banks and bond investors such as insurance companies, mutual funds, and pension funds. During a crisis, a balance-sheet shock stemming from nonperforming loans or other losses sometimes creates a debt overhang problem that prevents banks from originating new loans. In contrast, the bond market does not suffer from such a problem since institutional bond investors such as pension funds and insurance companies are long-term investors that are less sensitive to balance sheet shocks.[2] It is argued that banks can potentially alleviate the balance sheet-induced debt overhang problem by syndicating loans or selling them to securitization conduits. However, during crises the structured finance market tends

[2]Many bond investors have limited or no leverage (pension funds), but insurance companies have implicit leverage from the policies they sell (Koijen and Yogo 2022)—however, much less than banks.

to freeze and collapse. Benmelech and Bergman (2017) provide evidence on the collapse of structured finance markets during the GFC. More recently, issuance of collateralized loan obligations (CLOs)—the main financial structure used to package and securitize corporate loans—declined significantly between February and May 2020 compared to their levels in 2019.[3]

A third possible explanation is that credit and monetary interventions are more effective for bond markets than they are for loan markets. In an ultra-low interest rate environment, the central bank may have difficulty stimulating bank lending through traditional balance sheet channels. Similarly, financially stressed banks may not respond to monetary policy (e.g., Stein 2012, Jiménez et al. 2014). In contrast, nonconventional polices—in particular, the Secondary Market Corporate Credit Facility (SMCCF) and the Primary Market Corporate Credit Facility (PMCCF), announced on March 23, 2020, and extended in size and scope on April 9, 2020—targeted bond markets directly, without going through financial intermediaries, and appear to have stimulated bond issuance significantly.[4]

Our regression results suggest that there is merit in all three explanations for the resilience of the bond market. In time-series regressions we find that the 10-year Treasury yield is negatively correlated with loan origination but is uncorrelated with bond issuance. Moreover, we find that the Aaa–Baa spread—a measure of the price of credit risk—affects loan origination much more than bond issuance. Together, these results suggest that loans are more sensitive to the cost of debt—both the risk-free rate and the credit risk spread—than bonds are and that this differential effect is likely driven by the risk profile of firms that are bank-dependent compared to firms that rely on bond financing.

Next, and consistent with the hypothesis that the fundamental difference between commercial banks and bond investors affects their behavior during crises, we find that flows into bond mutual funds are positively correlated with bond issuance but not with loan origination. Our measure of bond mutual fund flows likely captures

[3]See Kothari et al. (2020) and Boyarchenko, Kovner, and Shachar (2022).

[4]The SMCCF was allowed to invest in exchange-traded funds, which in turn invested in corporate bonds. This is discussed in more detail below (see Table 3). See also Boyarchenko, Kovner, and Shachar (2022).

"flight to safety"—the tendency of investors to sell assets perceived as risky and to purchase safe assets such as bonds—and may partly explain the resilience of bond markets during financial crises. We also find that the elasticity of loan origination to an aggregate measure of nonperforming loans is almost twice that of bonds issuance—suggesting that banks are more likely to suffer from contaminated balance sheets that diminish their ability to originate loans during financial crises and economic downturns.

Last, we find that unconventional monetary policy in the form of credit market interventions affects bond issuance to a greater degree than loan origination—a phenomenon that holds separately in both the GFC and the COVID-19 crisis.

Our paper is related to the literature on corporate finance in the COVID-19 period. Bond issuance during this period is studied by Halling, Yu, and Zechner (2020) and Darmouni and Siani (2020). Equity issuance contributed to funding corporations, according to Hotchkiss, Nini, and Smith (2020), as did reduced payout (Pettenuzzo, Sabbatucci, and Timmermann 2021).[5] Several papers document that firms drew down revolving credit lines in the spring of 2020.[6] This finding appears to diminish our main finding that credit provision in the form of syndicated loans was low in the spring of 2020. However, credit lines are generally not used for long-term funding, and indeed both Acharya and Steffen (2020) and Hotchkiss, Nini, and Smith (2020) provide evidence that bond issuance replaced a large part of credit line drawdowns. In other words, the corporate funding provided by credit lines is different in nature from the long-term financing which is our focus. Darmouni and Siani (2020) document that many credit lines remained untouched, presumably because the short-term funding they provide is of limited use, and Chodorow-Reich et al. (2022) show that small firms did not draw

[5] A related possibility is that bond issuance was used to replace bonds that were maturing or redeemed. This probably took place, but not in levels exceeding earlier years. According to Mergent FISD data, there were 411 bond calls in 2020, representing $244 billion of par value, which is a little below prior years (e.g., 2019 had 433 bonds, $248 billion).

[6] See Acharya and Steffen (2020), Greenwald, Krainer, and Paul (2020), Hotchkiss, Nini, and Smith (2020), Darmouni and Siani (2020), and Li, Strahan, and Zhang (2020). Acharya and Steffen (2020) find that the overhang from credit lines depressed the share price of some banks.

down credit lines as much as large firms. Our results on the role of different types of corporate credit therefore broadly agree with patterns on bond issuance documented elsewhere. Fleckenstein et al. (2020) assign the contraction in loan origination during the spring of 2020 to nonbank funding flows rather than banks.

The resilience of corporate bond markets in the COVID-19 period is also consistent with earlier findings comparing loans and bonds (Kashyap, Stein, and Wilcox 1993; Becker and Ivashina 2014), and the results on the greater resilience of investment-grade issuance are consistent with the finding of Greenwood and Hanson (2013) on the cyclicality of the high-yield share of bond issuance. Our results are also related to an emerging literature on the increasing importance of the U.S. bond market for nonfinancial firms (Benmelech, Kumar, and Rajan 2020; Crouzet 2021). Our results are connected to the question of how firms substitute between various sources of credit financing. Goel and Zemel (2018) point out that only large firms can issue bonds, and this is part of our motivation for looking at syndicated loans (which also are mainly issued by large firms).

The rest of this paper is organized as follows. Section 2 lists the different data sets used in the paper and describes variable construction. Section 3 presents an analysis of bond issuance and loan origination during the COVID-19 crisis. Section 4 analyzes the behavior of credit markets during the GFC. Section 5 analyzes the determinants of bond issuance and loan origination. Section 6 concludes.

2. Data and Empirical Strategy

2.1 Dependent Variables

We use information from SDC and DealScan to construct the bond issuance and loan origination series which we use as our main dependent variables.

2.1.1 SDC Bond Data

We use data from SDC and Mergent on bonds issued between January 2002 and June 2020. We collect characteristics of bond issues

such as issue date, maturity date, coupon yield and type (floating or fixed), principal amount, instrument credit rating from Moody's and S&P, and whether the issuer is publicly listed. We drop withdrawn issues, convertibles, non-U.S. issues, and bonds issued by the federal government, government agencies, and local governments. We also drop bonds issued by financial and utility firms. Financial firms are defined as issuers belonging to industries with SIC codes between 6000 and 6999, as well as any issuer where the SDC industry code contains the word "bank," "credit," "securities," or "finance." We drop duplicates (observations with the same SDC deal number). We classify bonds as investment-grade (IG) if their S&P credit rating is BBB– (Moody's credit rating of Baa3) or higher and high-yield (HY) if their S&P credit rating is BB+ (Moody's credit rating of Ba1) or lower. When we have a split rating—that is, when S&P and Moody's assign different ratings to a bond—we use the lower rating. The remaining bond data set contains 17,379 bonds. Panel A of Table 1 presents summary statistics of the SDC bond data. As the table shows, 57 percent of the bonds are rated as investment-grade, 15 percent are rated as high-yield, and 28 percent are unrated. Almost half of the bonds have a call feature, and 57 percent are issued by publicly listed firms. The median bond has a principal amount of $283 million and a maturity of 10 years at the time of issuance.

Several of our empirical tests focus on bond issuance patterns over time. We produce monthly time series of aggregate bond issuance volume (either number of bonds or total dollar value) for 2002–20. We use these monthly data in our regression specifications. We also produce *weekly* bond issuance series, used in many of the figures in this paper. We use two separate subsamples of the weekly data, for (i) the GFC and (ii) the COVID-19 crisis. For the GFC sample, we use weekly bond issuance during 2002–09. For the COVID-19 sample, we use weekly issuance for the first six months of every year, 2009–20. We add up issuance volumes by week—sometimes after imposing filters based on credit ratings, bond time to maturity, or issuer industry. Summary statistics for the weekly time-series bond issuance data are reported in panel A (COVID-19) and panel C (GFC) of Table 2.

Table 1. Summary Statistics: Individual Bonds and Loans

A. Bonds				
Number of Issues	17,379			
Rated	12,521	(72 percent of issues)		
Investment-Grade	9,906	(79 percent of rated)		
High-Yield	2,615	(21 percent of rated)		
Callable	7,528	(44 percent of issues)		
Publicly Listed Issuer	9,924	(57 percent of issues)		
	10^{th} Percentile	Median	90^{th} Percentile	Standard Deviation
Principal ($m)	30	283	1,000	537
Maturity (Years)	3.5	10.0	30.0	9.3
B. Loans				
Number of Issues	17,940			
Rated	4,500	(25 percent of issues)		
Investment-Grade	1,292	(29 percent of rated)		
High-Yield	3,208	(71 percent of rated)		
PE Borrower	3,504	(20 percent of issues)		
Secured	9,222	(51 percent of issues)		
	10^{th} Percentile	Median	90^{th} Percentile	Standard Deviation
Principal ($m)	30	95	640	497
Maturity (Years)	3.5	5.0	7.0	2.0

Note: This table presents summary statistics for a data set of corporate bond and syndicated loans issued between 2002 and 2020. Bond data are from SDC, and loan data are from DealScan. Amounts are in millions of dollars. Investment-grade (IG) refers to bonds with issue ratings of Baa3/BBB– or better. Panel A summarizes data on individual bonds. Panel B summarizes data on individual loans.

2.1.2 DealScan Loan Data

We collect data on syndicated loan origination from DealScan—the primary source for syndicated loans. We focus on term loans and drop credit lines, since these do not typically provide credit at

Table 2. Summary Statistics: Weekly Data Sets

A. Weekly Bond Issuance during the COVID-19 Crisis						
	2020, March–June			2009–19, March–June		
	10^{th} Perc.	Median	90^{th} Perc.	10^{th} Perc.	Median	90^{th} Perc.
Number of Bonds	8	24	64	6	17	31
Number: IG	8	21.5	63	2	9	22
Number: HY	0	0.5	4	0	1	4
Number: Unrated	0	0	2	0	4	11
Total Amount ($bn)	4.6	22.8	68.2	1.6	7.0	20.0
IG Share of Issues	0.79	0.97	1.00	0.37	0.82	0.98
Principal Value ($m) of Individual Bonds	400	750	1,750	40	400	1,250
IG Bonds	400	750	1,750	188	500	1,500
HY Bonds	300	500	1,750	300	410	1,000
Unrated Bonds	550	900	1,250	14	74	258
B. Weekly Loan Issuance during the COVID-19 Crisis						
	2020			2010–19		
	10^{th}	Median	90^{th}	10^{th}	Median	90^{th}
Number of Term Loans	1	9	20	7	17	32
Total Amount ($bn)	0.6	3.5	11.2	1.7	7.5	18.9
Secured Share of Loans	36%	51%	69%	44%	59%	74%
Number of Lines of Credit	10	15	23	9	17	31

(*continued*)

Table 2. (Continued)

C. Weekly Bond Issuance during the GFC						
	September 2008—September 2009			January 2002—August 2008		
	10^{th} Perc.	Median	90^{th} Perc.	10^{th} Perc.	Median	90^{th} Perc.
Number of Bonds	5	14	22	5	18	32
Number: IG	2	8	16	2	7	16
Number: HY	0	1	7	0	4	11
Number: Unrated	0	2	8	1	5	12
IG Share of Issues	0.42	0.85	0.98	0.17	0.58	0.91
Principal Value ($m) of Individual Bonds	50	395	1,250	22	162	600
IG Bonds	250	500	1,500	15	250	800
HY Bonds	190	375	1,000	100	200	500
Unrated Bonds	17	62	225	19	65	200
D. Weekly Loan Issuance during the GFC						
	September 2008—September 2009			January 2002—August 2008		
	10^{th}	Median	90^{th}	10^{th}	Median	90^{th}
Number of Term Loans	4	10	21	11	21	37
Total Amount ($bn)	0.3	1.2	3.2	0.9	3.3	7.3
Secured Share of Loans	29%	57%	71%	48%	68%	83%
Number of Lines of Credit	11	20	36	23.5	42	68.5

Note: This table presents summary statistics for a time-series data set of weekly corporate loan and bond issuance, based on the individual issues presented in Table 1. The Global Financial Crisis (GFC) subsample covers each week from September 2003 to August 2009, and the COVID-19 crisis subsample covers January to June of each year from 2009 to 2020. Panels A and C summarize data on individual bonds. Panels B and D summarize data on individual loans.

issue.[7] We also exclude term loans made for acquisition or buyout purposes, since these do not provide corporations with funds.[8] We exclude non-U.S. borrowers. We do not count amendments as new loans, but we do include additional amounts added in amendments and assign the amounts to the amendment dates. The loan data contain 17,940 new term loans issued between January 2002 and June 2020. For reference, 27,415 new credit lines were issued in the same period. Also, 9,034 amendments with additional credit are included in the time-series data. As with bonds, we classify loan issues as investment-grade if rated Baa3/BBB– or better. High-yield loans are those with a lower credit rating. Panel B of Table 1 presents summary statistics on loan characteristics.

Unlike the bond market—in which the majority of the bonds are rated (Table 1, panel A)—only 25 percent of the loans are rated (Table 1, panel B). Also, whereas 79 percent of the rated bonds are investment-grade, only 29 percent of the rated loans are classified as IG. About half of the loans are secured, and 20 percent have a sponsor (i.e., are used for a buyout). Syndicated loans are considerably smaller than bonds, with a principal amount of $95 million, and shorter in maturity, with a median of five years.

We also produce monthly time series of aggregate loan origination volume for 2002–20, as well as *weekly* loan origination series. As with the SDC data, we use two separate subsamples of the weekly data, for (i) the GFC and (ii) the COVID-19 crisis. For the GFC sample, we use weekly loan origination during 2002–09. For the COVID-19 sample, we use weekly origination for the first six months in every year from 2010 to 2020. Summary statistics for the weekly

[7]Our results for the number of loans and bonds are qualitatively very similar if we include the granting of new credit lines as loans (when undrawn, revolvers are zero value, so we have not included them in tests with loan values). Drawdowns of credit lines in the COVID-19 period are documented by Greenwald, Krainer, and Paul (2020). Li, Strahan, and Zhang (2020) show that large banks provided most drawdown credit. Acharya, Engle, and Steffen (2021) argue that drawdowns caused bank stock prices to fall, and Greenwald, Krainer, and Paul (2020) posit that drawdowns negatively affected term lending. Hotchkiss, Nini, and Smith (2020) show that many drawdowns were later replaced by capital raising, including from the bond market.

[8]We implement this by requiring the variable Primary Purpose to be one of "General Purpose," "General Purpose/Refinance," "Working Capital," "Capital Expenditure," and "Equipment Upgrade/Construction."

loan origination data are reported in panel B (COVID-19) and panel D (GFC) of Table 2.

2.2 Explanatory Variables

We use several explanatory variables in our time-series regressions. We obtain the yield on 1- and 10-year Treasury bonds from the St. Louis Federal Reserve's data service, FRED. We also use the "ICE BofA BBB US Corporate Index Option-Adjusted Spread, Percent, Weekly, Not Seasonally Adjusted," here termed "Credit Spread," from FRED. These data series are monthly, and the units are percentage points.

We use net inflows into bond mutual funds, as a share of assets, from the Investment Company Institute (ICI).[9] The units are percentage points (i.e., if net inflows in a month are 1 percent of assets, the variable takes the value of 1). We exclude funds focused on government and municipal bonds. We collect quarterly data on "Nonperforming Commercial Loans (past due 90+ days plus nonaccrual) to Commercial Loans, Percent, Quarterly, Not Seasonally Adjusted" from FRED (here "Nonperforming Loans"). The units are percentage points (i.e., if 1 percent of loans are reported as past due, the variable takes the value of 1). The variable is calculated as total nonperforming loans divided by total loans. Nonperforming loans are those loans that bank managers classify as 90 days or more past due or nonaccrual in the call report.

We look at aggregate bond market data from the U.S. Flow of Funds Table F.213, Corporate and Foreign Bonds, downloaded from FRED. Quarterly data are seasonally adjusted (nonadjusted data are not available; given low seasonality, this is likely not quantitatively important).

We also examine the impact of Federal Reserve asset purchase programs. Table 3 provides descriptive information for some of the key programs and their announcement dates.

Last, we match Mergent bond issuance data to Compustat data using CUSIP numbers to obtain firm-level data, such as sales, assets,

[9]For the flows into bond mutual funds, we add the fund categories "Investment-Grade Bond," "High-Yield Bond," and "Multi-Sector Bond" to capture flows into funds that invest in corporate bonds. All categories focusing on municipal bonds and Treasury securities are excluded.

Table 3. Summary of Federal Reserve Programs

Program	First Large-Scale Asset Purchases	Second Large-Scale Asset Purchases	Third Large-Scale Asset Purchases	Various*	Secondary Market Corporate Credit Facility	Primary Market Corporate Credit Facility
Acronym	QE1	QE2	QE3		SMCCF	PMCCF
Announcement Date	Nov. 25, 2008	Nov. 3, 2010	Sept. 13, 2012	Mar. 15–19, 2020	Mar. 23, 2020	Mar. 23, 2020
Adjustment Date	Mar. 18, 2009	-	Dec. 12, 2012	-	Apr. 9, 2020	-
Maximum Amount ($bn)	1,650	600	-	200 (Agency Debt) and 500 (Treasuries)	500 (initial) 850 (adjusted)	750
Target Asset Class	Agency Debt and MBS	Longer-dated Treasuries	MBS	Agency Debt and Treasuries	Corporate Bonds and ETFs	Corporate Bonds and Syndicated Loans
Credit Rating Range	-	-	-	-	BBB– or better at purchase or BB– or better and BBB– or better as of Mar. 22, 2020	BBB– or better at purchase or BB– or better and BBB– or better as of Mar. 22, 2020
Maturity at Purchase	-	-	-	-	Max. Five Years	Max. Four Years
Industry	-	-	-	-	Not Bank	Not Bank
Purchases Commence	Nov. 2008	Nov. 2010	Sept. 2012	-	May 12, 2020	May 12, 2020

Source: Krishnamurthy and Vissing-Jørgensen (2011), Kuttner (2018), and Ma, Xiao, and Zheng (2020).
*Including the Commercial Paper Funding Facility (CPFF), the Primary Dealer Credit Facility (PDCF), and the Money Market Mutual Fund Liquidity Facility (MMLF).
Note: This table presents a summary of notable Federal Reserve programs launched during the Global Financial Crisis and during the COVID-19 pandemic.

employees, EBITDA to sales, and book leverage (defined as debt over book assets).

3. Credit Markets during COVID-19

We begin our analysis by zooming in on weekly data on bond issuance and loan origination before and during the COVID-19 pandemic.

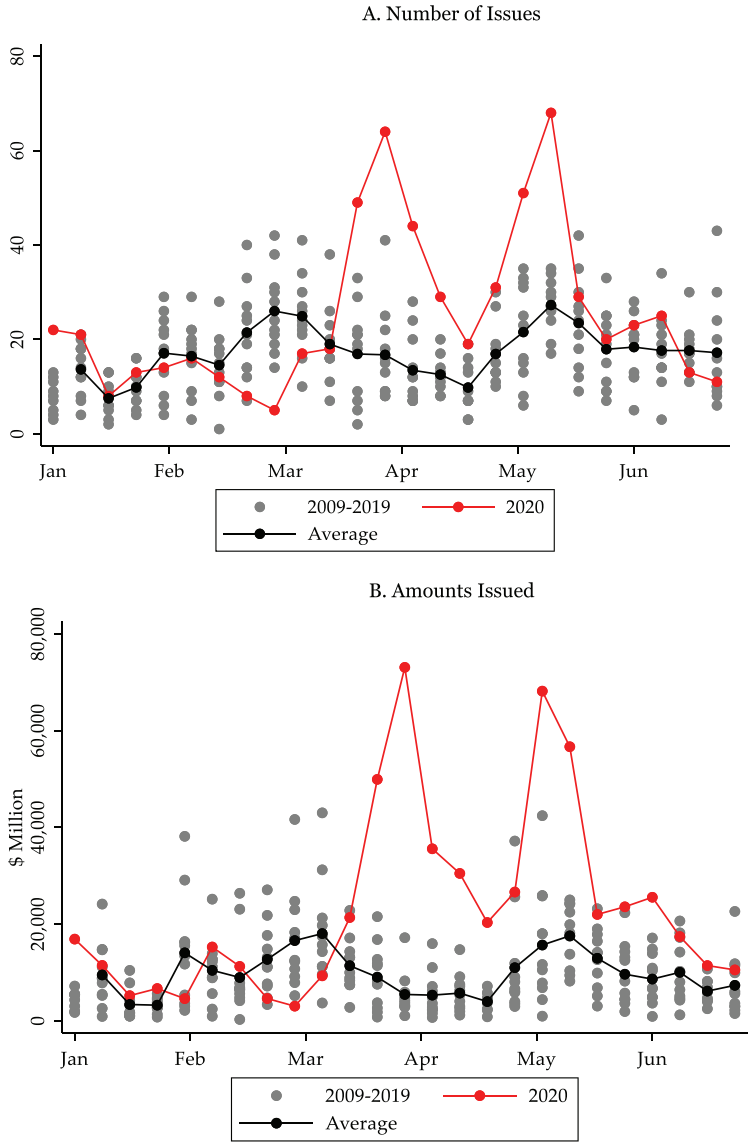
3.1 Bond Issuance during the COVID-19 Months

Figure 1 displays weekly bond issuance between 2009 and 2020. To compare bond issuance during the COVID-19 pandemic to previous years we highlight bond issuance in 2020 (in red) relative to weekly bond issuance in previous years (in gray) and relative to the average weekly issuance during 2009–19 (in black). Panel A of the figure displays issuance patterns based on the number of bond issues, while panel B presents results based on the amount issued. The COVID-19 virus was first discussed in international news media in late 2019. The U.S. stock market did not react until mid-February 2020. The S&P 500 index reached an all-time high on February 6, 2020, before dropping in the following weeks. The index reached its lowest value for 2020 on March 23, a decline of more than 30 percent relative to the February peak. This day also saw the highest value for credit spreads (the BBB High Yield Index spread was 10.87 percent, the highest since 2009).

As Figure 1 illustrates, bond issuance declined slightly in February 2020 relative to the 2009–19 average in both number (panel A) and amount (panel B). This decline is likely driven by the uncertainty that resulted from the initial spread of COVID-19 in Asia. Bond issuance increased substantially in the last week of March and reached a peak in the first week of April 2020, with 64 bonds issued, amounting to $73 billion.[10] Bond issuance declined relative to the peak for the following three weeks of April but remained above the weekly average of the years 2009–19. Issuance increased again in May, reaching the highest level—in terms of the number issued—in early May before declining and returning to normal levels by late May. The pattern of very high issuance of new bonds agrees with

[10]Monday, March 30–Friday, April 3, week 13 of 2020.

Figure 1. Flow of Bond Issues, 2020



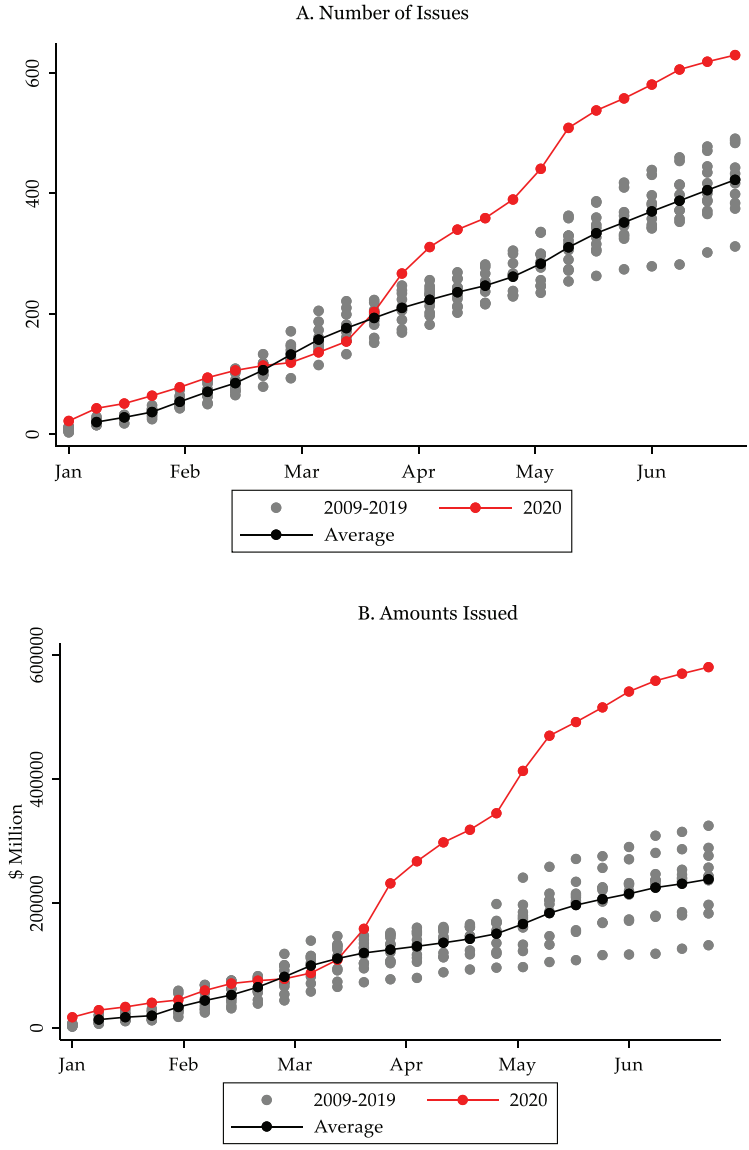
Note: This figure compares weekly bond issuance in 2020 (in red) with earlier years (gray) and the average for 2009–19 (black). The data are described in Table 1.

data on firm balance sheets reported by Hotchkiss, Nini, and Smith (2020), on revolving lines of credit reported by Acharya and Steffen (2020) and by Greenwald, Krainer, and Paul (2020), and for bond issues in the beginning of 2020 reported by Halling, Yu, and Zechner (2020).

Having documented the increase in the weekly issuance of bonds, we next illustrate the increase in cumulative bond issuance during the COVID-19 crisis. Figure 2 plots the cumulative number of issues (panel A) and the cumulative amount issued (panel B). In each panel we plot the cumulative figures for 2020 (in red) along with each year, 2009–19 (in gray), and the 2009–19 average (in black). The cumulative issuance of bonds was comparable to earlier years before the events of March 2020—slightly high in January and then slightly low in February—and then accelerated rapidly to exceed any previous year by a wide margin by late spring. For example, as panel A shows, the cumulative number of bonds issued by mid-March in 2020, 154, is comparable to the average cumulative number of bonds issued, 176.2, at the same time in the years 2009–19. However, by the end of June 2020 the cumulative number of bond issues was 630, compared to an average of 422 during the 2009–19 period. Panel B, which plots the cumulative principal amount of bonds issued, displays an even more striking pattern. The cumulative amount of bonds issued by mid-March 2020 was in line with the cumulative amounts issued by that calendar time in the previous 10 years. By the end of June 2020, however, the cumulative amount of bonds issued was $580 billion, more than double the average of $240 billion in 2009–19. For the period between March and June 2020 (weeks 10 through 25), corporate bonds totaling $502 billion were issued. This can be compared to $151 billion in 2019, $204 billion in 2018, and $157 billion on average for 2009–19.

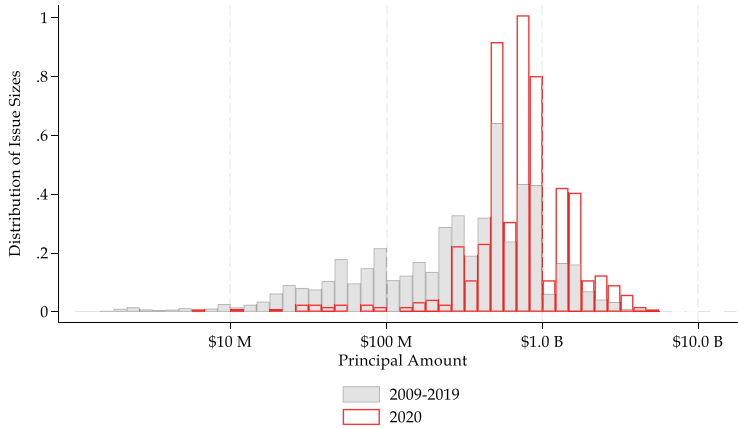
The plots in Figure 2, panels A and B, suggest not only that the number of bonds issued increased substantially during the COVID-19 months but also that the average principal amount of these bonds was significantly larger than in previous years. Panel A of Table 2, which presents summary statistics on weekly bond issuance, confirms this observation. The median principal amount of bonds issued in 2009–19 was $400 million, compared to $750 million in 2020. Some of the bonds issued during the COVID-19 months were very large. For example, the 90th percentile bond principal amount was

Figure 2. Cumulative Bond Issues, 2020



Note: This figure compares cumulative weekly bond issuance in 2020 (in red) with earlier years (gray) and the average for 2009–19 (black). The data are described in Table 1.

Figure 3. The Size of Individual Corporate Bond Issues, 2020



Note: This figure compares the principal amount of individual bond issues in 2020 (in red) with the distribution for 2009–19 (gray). The data are described in Table 1.

$1.75 billion, compared to a 90th percentile of $1.25 billion in 2009–19. Figure 3 illustrates this point: the distribution of principal values during the COVID-19 months is clearly shifted to the right compared to earlier periods.

The boom in issuance during the COVID-19 months was not uniform across issuers of different credit quality. Bond issuance was concentrated in investment-grade bonds.[11] Investment-grade bond issuance was high because of both the number of bonds issued and their size. Median issues of investment-grade bonds increased by 40 percent (from 17 per week for the same period in prior years to 24 per week in 2020), and median size increased by 88 percent (from $400 million to $750 million). This implies that the aggregate mix coming to market shifted considerably: the median share of weekly issuance that was investment-grade (by principal amount) was 97 percent in 2020, compared to 82 percent in 2009–19. High-yield issuance in 2020 was very similar to prior years: a median of half a bond per week

[11]Investment-grade is defined as an S&P credit rating of BBB– (Moody's credit rating of Baa3) or higher.

(see Table 2, panel A), with a median size of $500 million versus $410 million.

Figure 4 plots the cumulative number of investment-grade bonds (panel A) and high-yield bonds (panel B) issued in 2020 compared to 2009–19. As the two panels illustrate, the growth in the number of bonds issued in 2020, documented in Figure 2, is driven by the issuance of highly rated investment-grade bonds. In fact, as panel B illustrates, the issuance of high-yield bonds halted in March 2020 and began increasing only in mid-April—with the cumulative number of high-yield bonds staying below the 2009–20 cumulative number through the end of June 2020.

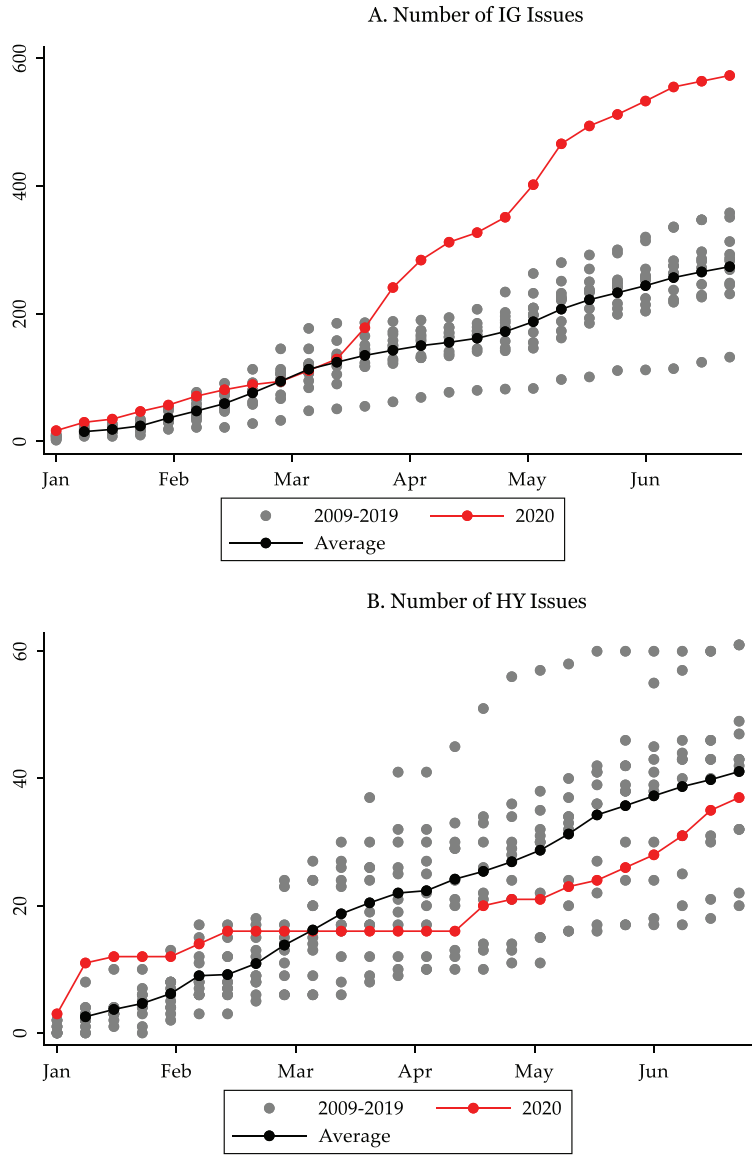
3.2 Syndicated Loan Origination during the COVID-19 Months

As the previous section shows, bond issuance increased significantly between mid-March and June 2020. In contrast, syndicated loan issuance did not. We compared the origination of syndicated loans in the spring of 2020 to the origination of such loans in the same period of the previous 10 years.

Figure 5 displays weekly term loan origination between 2009 and 2020. To compare loan origination during the COVID-19 pandemic to previous years we highlight loan origination in 2020 (in blue) relative to both weekly loan origination in previous years (in gray) and average weekly origination in 2009–19 (in black). Panel A shows issuance patterns based on the number of new term loan originations, and panel B presents results based on the loan amounts. Unlike the patterns we document for bond issuance, there is no significant increase in the number of syndicated loan originations during the COVID-19 pandemic.

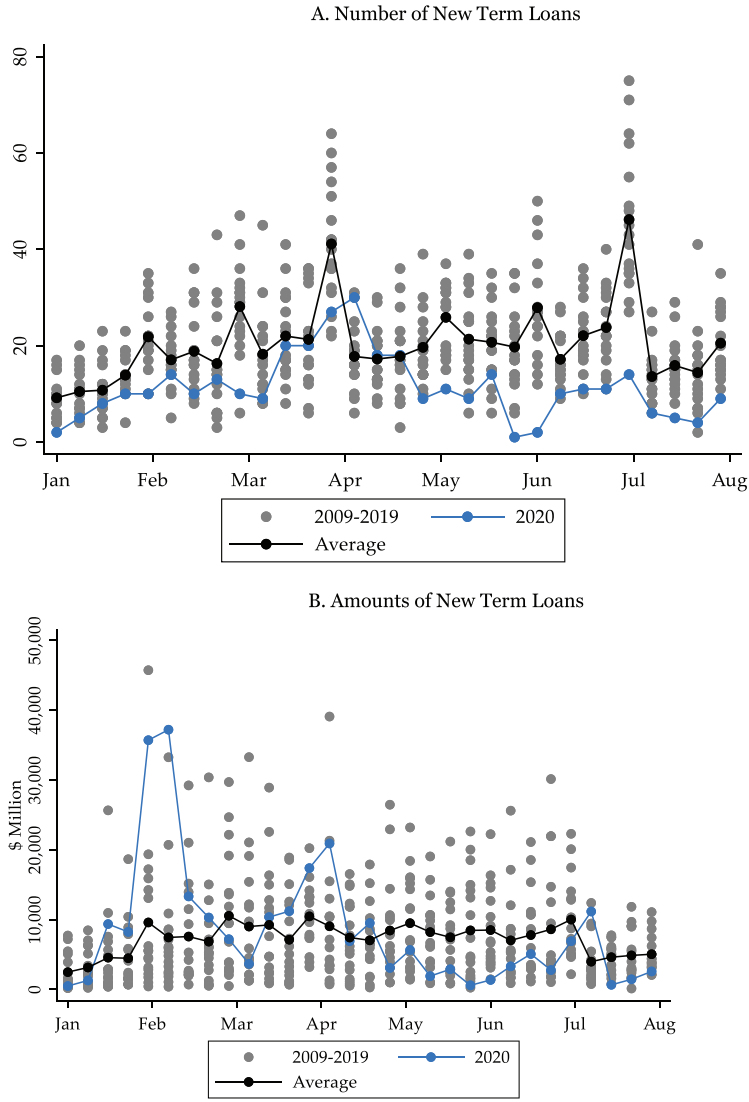
As panel A of Figure 5 illustrates, except for the first week of April 2020, the number of syndicated loans was below the 2009–19 average. Panel B shows that despite the lower number of loans originated in February 2020, the amount originated was larger than the 2009–19 average. From the end of February and through August 2020, the origination of syndicated loans remained below the 2010–19 average in terms of both the number of loans and the total amount originated. New revolving credit facilities issued were also either similar to earlier years or slightly lower in 2020.

Figure 4. Flow of Bond Issues in 2020 by Credit Quality



Note: This figure compares cumulative weekly bond issuance in 2020 (in red) with earlier years (gray) and the average for 2009–19 (black), as in Figure 2, but separately by credit rating. IG refers to bonds rated BBB− or better by S&P, and HY refers to those with lower credit ratings. The data are described in Table 1.

Figure 5. Flow of Loans, 2020: Term Loans



Note: This figure compares weekly issuance in 2020 (in blue) with earlier years (gray) and the average for 2009–19 (black). The data on weekly issuance are described in Table 1.

Panel B of Table 2 reports summary statistics on loan origination and confirms the patterns displayed in Figure 5. The median weekly number of term loan originations was 9 in 2020, less than the median (17) during 2010–19. Total amounts were around half of the prior period median ($3.5 billion in 2020 versus $7.5 billion in 2009–19). New credit lines were also below historical averages (15 versus 17 per week). Existing lines of credit provided at least temporary liquidity during the spring of 2020. However, as Acharya and Steffen (2020) point out, many companies subsequently replaced drawdowns with bond issues.

3.3 The Role of Federal Reserve Interventions during the COVID-19 Crisis

The Federal Reserve responded to disruptions in the credit market by announcing several programs of unconventional monetary policy. For corporate debt, the two most important were the Secondary Market Corporate Credit Facility (SMCCF) and the Primary Market Corporate Credit Facility (PMCCF), announced on March 23, 2020, and extended in size and scope on April 9, 2020. These programs involved Federal Reserve purchases of corporate bonds and exchange-traded funds that invest in corporate bonds. Their announcement had an immediate effect on the bond market (cf. O'Hara and Zhou 2020 and Gilchrist et al. 2020). The announcements coincide with the first peak of corporate bond issuance visible in Figure 1B. Purchases commenced on May 12 (Board of Governors 2021), around the second peak in Figure 1B. The PMCCF and SMCCF programs are summarized in Table 3, together with several earlier Federal Reserve interventions.

A key question concerns the role that Federal Reserve interventions played in bond and loan issuance in the spring of 2020. The coincidence of peaks of issuance with the announcement and start of purchases, respectively, points to a large potential role of the central bank interventions. We test this more carefully in a linear regression of weekly issuance for the whole 2009–20 sample, with an indicator for the three weeks following the Fed announcements (weeks 12, 13, and 14 of 2020), and report the results in Table 4. The identifying assumption is that abnormal issuance volumes in this period reflect

Table 4. Bond and Loan Issuance Volume by Week

A. Bond Issuance				
	(1)	(2)	(3)	(4)
Sample	All Bonds	All Bonds	All Bonds	All Bonds
Dependent Variable	Bond Number	Bond Number	Bond Value	Bond Value
Dependent Variable Mean	2.728	2.728	8.598	8.598
Regression	OLS	GLS	OLS	GLS
Federal Reserve 2020 Interventions	**1.242***** (0.410)	**1.224***** (0.206)	**2.245**** (0.901)	**2.033***** (0.508)
Week Number F.E. Year F.E.	No No	Yes Yes	No No	Yes Yes
Observations Autocorrelation R-squared Clusters	598 - 0.015 Week	598 –0.047 0.484 Week	598 - 0.010 Week	598 –0.085 0.507 Week

(*continued*)

Table 4. (Continued)

B. Term Loan Issuance				
	(1)	(2)	(3)	(4)
Sample	All Bonds	All Bonds	All Bonds	All Bonds
Dependent Variable	Loan Number	Loan Number	Loan Value	Loan Value
Dependent Variable Mean	2.735	2.735	8.566	8.566
Regression	OLS	GLS	OLS	GLS
Federal Reserve 2020 Interventions	**0.537** (0.449)	**0.358*** (0.186)	**1.119*** (0.673)	**0.891***** (0.223)
Week Number F.E. Year F.E.	No No	Yes Yes	Yes Yes	Yes Yes
Observations Autocorrelation R-squared Clusters	598 - 0.002 Week	598 0.671 0.459 Week	598 - 0.005 Week	598 0.236 0.419 Week

Note: This table presents regression results for the number of bonds and loans issued in the United States by week from 2009 to June 2020. The data are described in Table 1. The variable "Federal Reserve 2020 Interventions" is an indicator that takes the value of 1 for weeks 12, 13, and 14 in 2020, based on Federal Reserve announcement dates of the SMCCF and PMCCF programs, and 0 at all other times (see Table 3). Standard errors are robust and, when indicated, allow first-order autocorrelation. * denotes significance at the 10 percent level, ** at 5 percent, and *** at 1 percent.

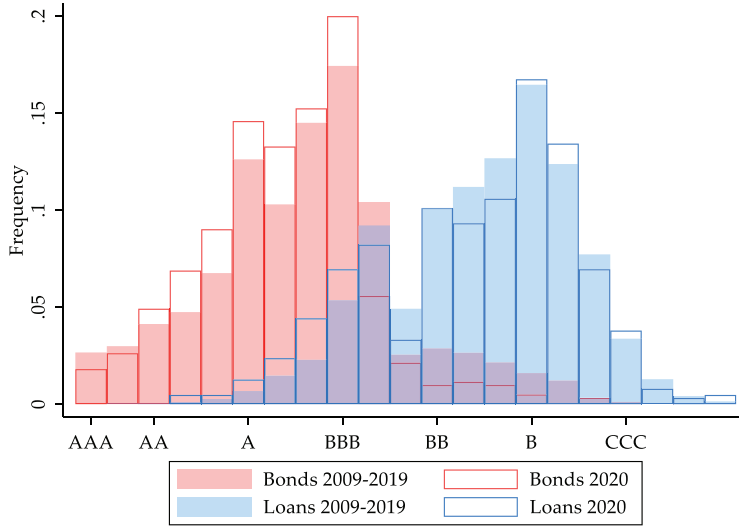
Fed policy. Panel A reports tests for bond issuance for the number of bonds (columns 1–2) and the amount issued (columns 3–4). Column 1 includes no controls. The coefficient on the Fed indicator is 1.19, meaning that weekly issuance was 229 percent higher than expected in this period. To address possible seasonality, we include fixed effects for each week (1, 2, 3, etc.), and to address long-term trends, we include year fixed effects. We also allow for first-order autocorrelation. Results for this specification are in column 2. The point estimate, taken at face value, implies that 100 bonds were issued that would not have been issued absent the Federal Reserve interventions.[12] Columns 3 and 4 show similarly large results for the log of total value of issuance per week. The value of bond issuance was elevated by 442 percent, as shown in column 4. This point estimate implies that aggregate issuance exceeded expected values by about $93 billion in these three weeks (in line with Figure 2). Panel B reports term loan issuance for the same period. The coefficient on the Fed indicator is significantly different from zero when fixed effects are included and autocorrelation is allowed (for loan issuance, unlike bonds, autocorrelation is very high). Magnitudes are about half as large as for bonds, indicating an increase of 50 percent by number and 150 percent by value. The results in Table 4 suggest that Fed announcements were very important for corporate bond issuance and positive but less so for syndicated loan issuance.

One reason bond and loan markets diverge in the COVID-19 crisis period is that the bond market is dominated by investment-grade issuers while the loan market is more focused on high-yield and unrated issuers. Figure 6 shows the distribution of credit ratings for 2009–19 as well as for 2020. The ratings distributions for the two markets show a modest overlap. This dichotomy is true both before and during the crisis. The pattern suggests one possible reason for the strength of the corporate bond market: it serves a segment of corporate entities that are less affected by a crisis (Greenwood and Hanson 2013; Berg, Saunders, and Steffen 2021).[13]

[12] Calculation using three weeks, "normal" issuance of 17 per week from Table 1, and 202 percent increase ($2.02 = e^{1.106} - 1$).

[13] Figure 6 excludes unrated loans and bonds. There are more unrated loans than bonds. See below (Figure 14) for more details on this.

Figure 6. Credit Rating Distribution of Bonds and Loans, 2020



Note: This figure plots the credit rating distribution of bonds (in red) and loans (in blue) for the years 2009–19 and 2020. Unrated loans and bonds are excluded from the sample. Full bars represent the earlier period, and outline bars represent the later period. The data are described in Table 1.

In Table 5, we test the role that credit quality plays in bond issuance and loan origination. We repeat the analysis in Table 4 but organized by credit rating instead of credit type. Panel A shows bonds split by IG and non-IG, by value and number. The table shows that the IG bond segment drives the overall issuance increase associated with interventions. The (smaller) non-IG segment has a negative coefficient for number and insignificant coefficient for value, whereas IG coefficients are slightly higher than for the overall bond market. In panel B, we split loans by credit quality. Again, we find large positive effects for IG issuance, and small or insignificant coefficients for non-IG loans (in order to interpret these, it is important to keep in mind that the IG loan market is much smaller than the non-IG segment). In panel C we aggregate the two markets, and split by credit quality. As might be expected, there are very large and highly significant positive coefficients for IG issuance, and small, insignificant coefficients for non-IG issuance. These results highlight

Table 5. Bond and Loan Issuance Volume by Week, Split by Credit Quality

A. Bond Issuance				
Sample Period	(1) IG	(2) Non-IG	(3) IG	(4) Non-IG
Dependent Variable	Bond Number	Bond Number	Bond Value	Bond Value
Dependent Variable Mean	2.089	1.885	7.942	6.691
Regression	GLS	GLS	GLS	GLS
Federal Reserve 2020 Interventions	**1.508***** (0.206)	**−1.129***** (0.174)	**2.281***** (0.310)	**−1.782** (1.916)
Week Number F.E. Year F.E.	No No	Yes Yes	No No	Yes Yes
Observations Autocorrelation R-squared Clusters	598 0.264 0.012 Week	598 0.153 0.008 Week	598 0.199 0.021 Week	598 0.130 0.000 Week

(*continued*)

Table 5. (Continued)

B. Term Loan Issuance				
Sample Period	(1) IG	(2) Non-IG	(3) IG	(4) Non-IG
Dependent Variable	Loan Number	Loan Number	Loan Value	Loan Value
Dependent Variable Mean	0.685	2.763	4.504	8.161
Regression	GLS	GLS	GLS	GLS
Federal Reserve 2020 Interventions	**1.748***** (0.234)	**0.095** (0.187)	**4.521***** (0.297)	**0.304**** (0.126)
Week Number F.E. Year F.E.	No No	Yes Yes	Yes Yes	Yes Yes
Observations Autocorrelation R-squared Clusters	598 0.037 0.038 Week	598 0.682 0.002 Week	598 0.024 0.010 Week	598 0.016 0.561 Week

(*continued*)

Table 5. (Continued)

C. Bond and Loan Issuance by Credit Quality				
Sample Period	(1) IG	(2) Non-IG	(3) IG	(4) Non-IG
Dependent Variable	Loan and Bond Number	Loan and Bond Number	Loan and Bond Value	Loan and Bond Value
Dependent Variable Mean	2.185	3.111	8.427	8.853
Regression	GLS	GLS	GLS	GLS
Federal Reserve 2020 Interventions	**1.629***** (0.183)	**−0.139** (0.242)	**2.028***** (0.266)	**0.253** (0.165)
Week Number F.E. Year F.E.	No No	Yes Yes	Yes Yes	Yes Yes
Observations Autocorrelation *R*-squared Clusters	587 0.220 0.023 Week	587 0.415 0.000 Week	587 0.210 0.076 Week	587 0.564 0.186 Week

Note: This table presents regression results for the number of bonds and loans issued in the United States by week from 2009 to June 2020, similar to Table 4, but for samples split by credit rating. The data are described in Table 1. The variable "Federal Reserve 2020 Interventions" is an indicator that takes the value of 1 for weeks 12, 13, and 14 in 2020, based on Federal Reserve announcement dates of the SMCCF and PMCCF programs, and 0 at all other times (see Table 3). Standard errors are robust and, when indicated, allow first-order autocorrelation. * denotes significance at the 10 percent level, ** at 5 percent, and *** at 1 percent.

the key role played by credit quality. Credit seems to flow freely to IG issuers, especially in the bond market where these issuers dominate, in the stressed period.

4. Credit Markets during the Global Financial Crisis

Next, we analyze bond issuance and loan origination during the Global Financial Crisis (GFC).

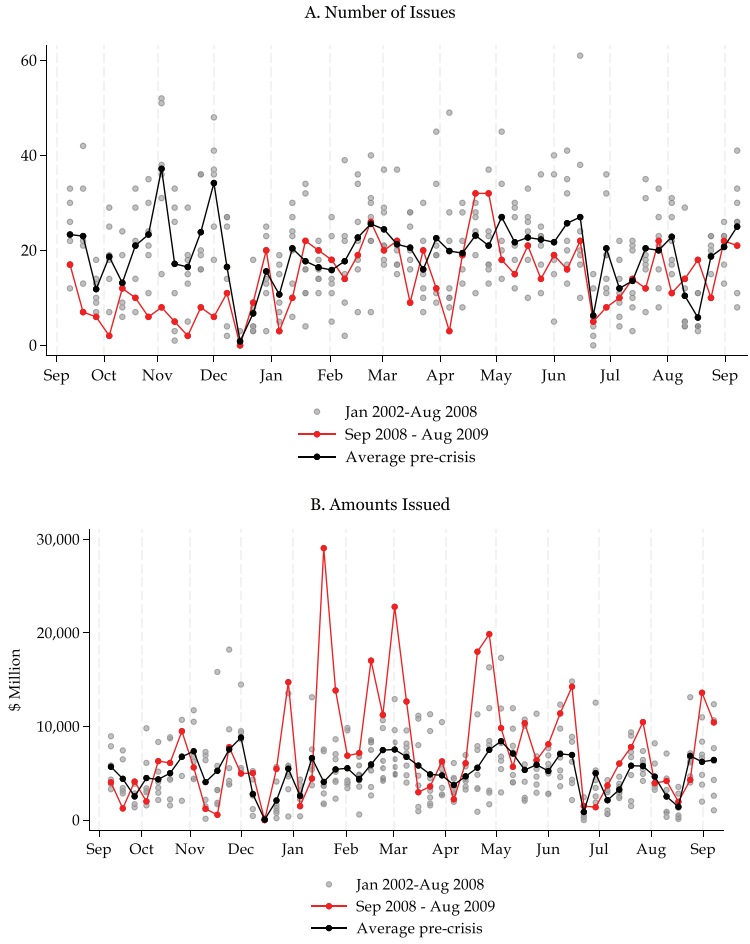
4.1 Bond Issuance during the GFC

Figure 7 displays weekly bond issuance between October 2002 and 2009. To compare bond issuance during the GFC to previous years, we highlight bond issuance in the GFC (in red) relative to weekly bond issuance in previous years (in gray) and relative to the average weekly issuance during 2002–08 (in black).[14] Panel A displays issuance patterns based on the number of bond issues, and panel B presents results that are based on the amount issued. As Figure 7 illustrates, the issuance of bonds declined significantly between October 2008 and January 2009 relative to the 2002–08 average in terms of both the number of bonds (panel A) and the amount issued (panel B).[15] By January 2009 the number of bonds issued had reverted to its precrisis average, whereas the amount issued increased significantly and remained high for the remainder of the crisis period. For example, the median weekly number of bond issues declined from 18 in the precrisis period to 14 in September 2008–September 2009 (Table 2, panel C). However, the median principal of bonds issued between September 2008 and September 2009 was $395 million, compared to a median of $162 million in the precrisis period. The cumulative effects of bond issuance are depicted in Figure 8, which plots the cumulative number of issues (panel A) and the cumulative amount issued (panel B). In each panel, we plot the cumulative figures for September 2008–September 2009 (in red)

[14]Lehman Brothers' bankruptcy filing on September 15, 2008, marks the beginning of the GFC.

[15]Capital markets largely froze around the Lehman bankruptcy (see, e.g., Krishnamurthy 2010, He and Xiong 2012, and Benmelech and Bergman 2017). Bank lending fell rapidly in the United States and abroad (Ivashina and Scharfstein 2010, De Haas and Van Horen 2012).

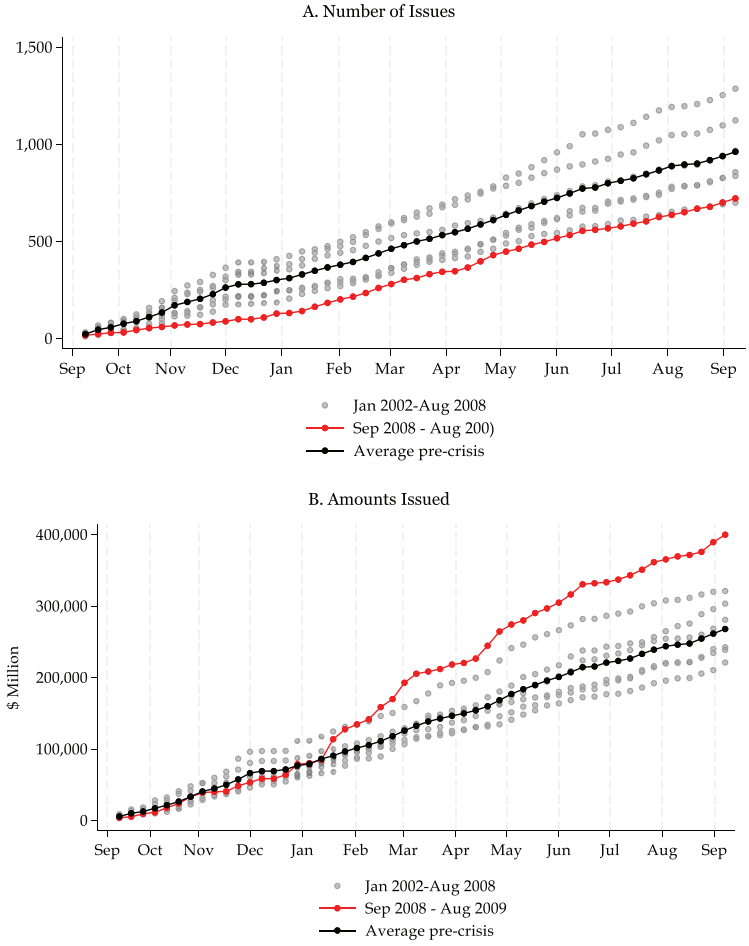
Figure 7. Flow of Bond Issues in the Global Financial Crisis



Note: This figure compares weekly bond issuance for September 2008–September 2009 (in red) with the preceding period of January 2002–August 2008 (gray) and the average for the preceding period (black). The data are described in Table 1.

along with each of the years from 2002 to 2008 (in gray) and the January 2002–September 2008 average (in black). As panels A and B demonstrate, the cumulative number of bonds issued in the crisis period was below the cumulative number of issues in the precrisis period—mostly due to the freezing of the bond market in the last

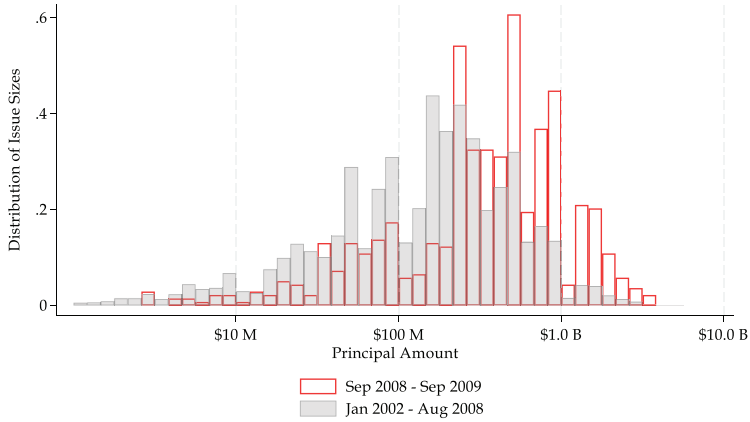
Figure 8. Cumulative Bond Issues in the Global Financial Crisis



Note: This figure compares cumulative weekly bond issuance for September 2008–September 2009 (in red) with earlier years (gray) and with the average for January 2002–August 2008 (black). The data are described in Table 1.

three months of 2008. As panel B shows, the cumulative amount of bonds issued increased dramatically starting in February 2009 and remained above its precrisis average through September 2009. By the end of September 2009, cumulative issuance amounted to $400 billion, compared to an average of $267 billion in 2002–08. The plot

Figure 9. The Size of Corporate Bond Issues in the Global Financial Crisis



Note: This figure compares the principal amount of individual bond issues in September 2008–September 2009 (in red) with the preceding period of January 2002–August 2008 (gray). The data are described in Table 1.

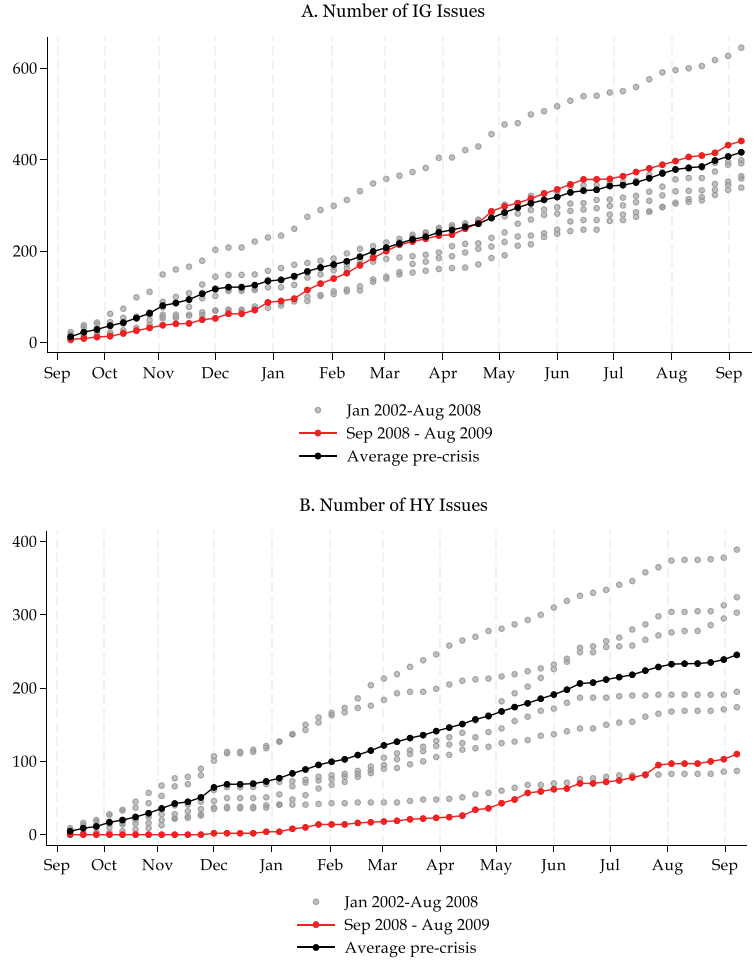
in panel B of Figure 8, as well as Figure 9—which compares the size of corporate bond issues during the GFC to the years before the crisis—suggests that, similar to the COVID-19 months, the average principal amount issued during the GFC was significantly larger compared to the precrisis period.

As in the COVID-19 crisis, bond issuance during the GFC was concentrated in IG bonds. Figure 10 plots the cumulative number of IG bonds (panel A) and HY bonds (panel B) issued in September 2008–August 2009 compared to January 2002–August 2008. IG bond issuance increased in January 2009 and returned to its precrisis average by April 2009. In contrast, issuance of HY bonds came to a halt in September 2008 and remained depressed until May 2009. Issuance began increasing only in the second half of 2009, but the cumulative number of HY bonds remained below the 2002–08 cumulative number through October 2009.

4.2 Syndicated Loan Origination during the GFC

As in our analysis of credit markets during the COVID-19 crisis, we now analyze the origination of syndicated loans before and during

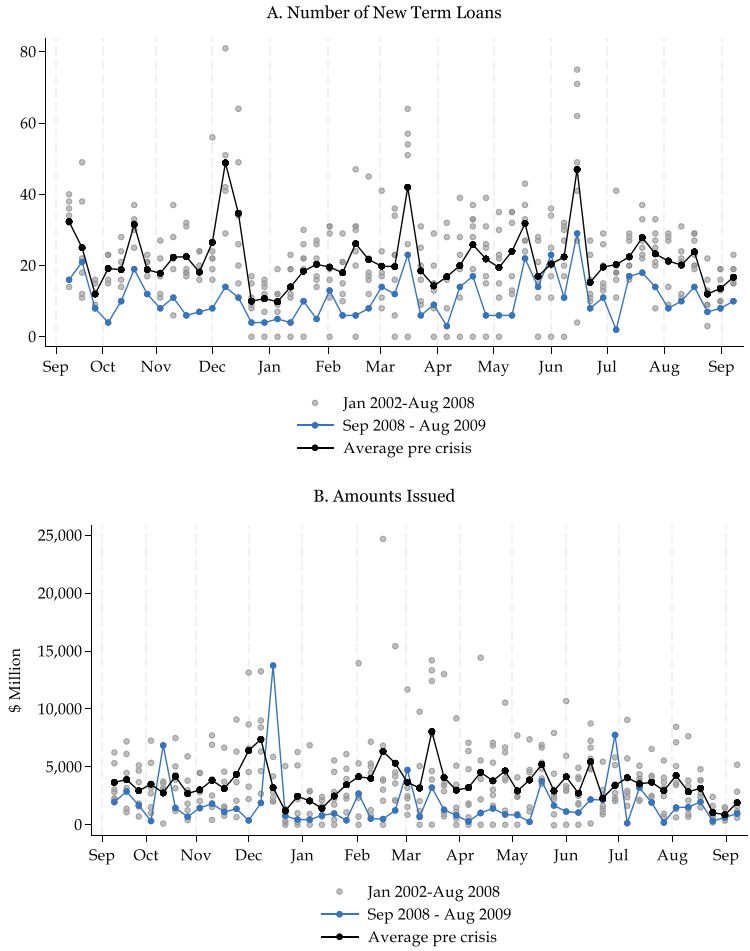
Figure 10. Flow of Bond Issues in the Global Financial Crisis by Credit Quality



Note: This figure compares cumulative weekly bond issuance during the GFC (in red) with January 2002–August 2008 (gray) and the average for January 2002–August 2008 (black), separately by credit rating. IG refers to bonds rated BBB– or better by S&P, and HY refers to those with lower credit ratings. The data are described in Table 1.

the GFC. Figure 11 displays weekly term loan origination between 2002 and 2009. To compare loan origination during the GFC to the precrisis years, we highlight loan origination in the GFC (in blue)

Figure 11. Flow of Loans in the Global Financial Crisis



Note: This figure compares weekly issuance during the GFC (in blue) with January 2002–August 2008 (gray) and the average for January 2002–August 2008 (black). The data on weekly issuance are described in Table 1.

relative to both weekly loan origination in previous years (in gray) and to the average weekly origination in 2002–08. Panel A displays issuance patterns based on the number of new term loan originations, and panel B presents results based on the loan amount. Unlike the patterns we document for bond issuance, and similar to issuance

during the COVID-19 crisis, there is no significant increase in syndicated loan origination during the GFC. In fact, loan origination in terms of both the number and the amount of loans were below their precrisis levels throughout most of 2009.

As panel A of Figure 11 illustrates, from September 2008 to September 2009 syndicated loan origination remained below its 2002–08 average, and regular end-of-quarter spikes were absent or diminished during the crisis year. Panel B shows that the amount of new loans spiked in the last week of December 2008 due to a single large loan to General Motors (part of the federal rescue for that company) but then remained below the average levels for most of 2009. These patterns of low issuance agree with what Ivashina and Scharfstein (2010) document for the crisis period. Figure 11 refers to term loans—the volume of new credit facilities granted was also low in this period (not reported).

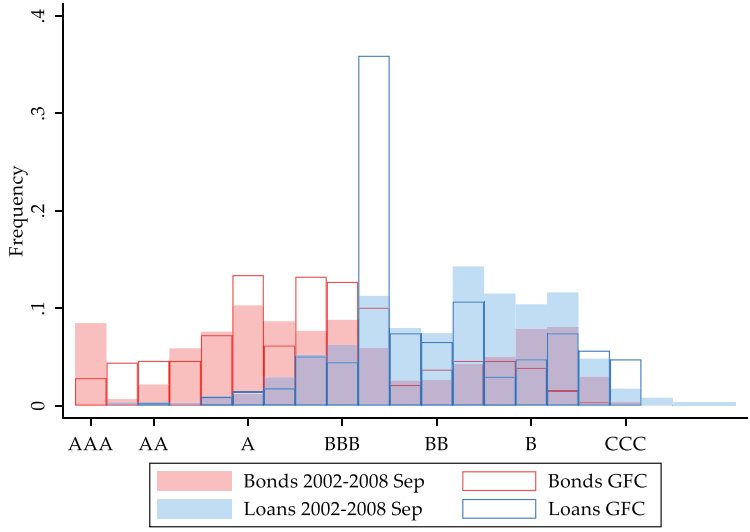
Panel D of Table 2 reports summary statistics on loan origination and confirms the patterns displayed in Figure 11. The median weekly number of term loan originations was 10 during the GFC, less than the median (21) in 2002–08. New credit lines were also below historical medians (20 versus 42 per week). Moreover, the median principal value of loans originated during the GFC was $1.2 billion, compared to $3.3 billion in 2002–08.

4.3 The Role of Federal Reserve Interventions during the GFC

The Federal Reserve responded to the COVID-19 pandemic with several credit programs. The programs were based on the quantitative easing (QE) programs implemented after the GFC, with the difference that they included new asset classes, including corporate bonds. Of course, the QE interventions in 2009–14 were also intended to affect the corporate bond market, but indirectly.[16] Unlike the 2020 experience, the announcement of QE policies at the end of November 2008 was not associated with increased bond or loan issuance.

[16] Analysis of the asset market impact of asset purchase programs is provided by Krishnamurthy and Vissing-Jørgensen (2011) for the QE programs following the GFC and by Gilchrist et al. (2020) and O'Hara and Zhou (2020) for the COVID-period programs.

Figure 12. Credit Rating Distribution of Bonds and Loans in the Global Financial Crisis



Note: This figure plots the credit rating distribution of bonds (in red) and loans (in blue) for the period January 2002–September 2008 and for the period October 2008–September 2009. Full bars represent the earlier period, and outline bars represent the later period. Unrated loans and bonds are excluded from the sample.

How did the credit quality of bond and loan issuers behave during the GFC? Figure 12 shows the distribution for the two groups of issuers both before and during the crisis. As with the COVID-19 period (Figure 6), ratings distributions are relatively stable: the crisis does not move the ratings distribution of issuers much. However, the sharp separation between IG bond issuers and HY loan issuers that is seen both before and during the COVID-19 crisis is less clear in the GFC. Bond issuers are of much higher quality on average before and during the crisis. However, during the crisis, many loan issuers had IG ratings (usually BBB–, barely investment grade). This lower segmentation suggests an explanation for the divergence of different corporate credit markets in the COVID-19 crisis: this time stronger firms largely focused on the bond market for their funding needs. It is also possible that ratings standards have evolved and that some of the 2008 BBB− firms would be high-yield in 2020 (see, e.g., Alp 2013).

5. What Drives Aggregate Bond Issuance and Loan Origination?

In Sections 3 and 4 we demonstrate that the bond market has shown more resiliency than the syndicated loan market during and after financial crises. During the GFC both the bond and loan markets froze during the last quarter of 2008, but issuance of bonds increased in 2009 and exceeded the average amount issued in each of the years leading up to the GFC. Starting in March 2020, issuance of bonds surpassed that of previous years, and even though the number of confirmed cases of COVID-19 in the United States grew rapidly and the economy ground to a halt, the corporate bond market was booming. In contrast, the syndicated loan market did not follow the same pattern. During the GFC, the syndicated loan market froze in September 2008 and remained below its precrisis average through most of 2009. Likewise, in the COVID-19 crisis, the number of new term loan originations remained below its 2009–19 average for most of 2020. Why is the U.S. corporate bond market more resilient to crises than the syndicated loan market? We attempt to answer this question using a multivariate analysis of the determinants of bond issuance and loan origination over time.

5.1 The Determinants of Aggregate Bond Issuance and Loan Origination

Time series results for loan and bond issuance are presented in Table 6. The log of the total weekly issuance amount of bonds in the U.S. market is the dependent variable for the bond regression, and the log of the total weekly value of syndicated loan originations is the dependent variable for the loan regression. We also calculate the share of bonds in new issues as the face value of new bonds divided by the sum of the face value of new bonds and term loan amounts, and use this as a dependent variable. The table spans around 900 weekly observations for the years 2003–20. The mean log weekly bond amount is 8.60, with a standard deviation of 1.05. Loan weekly amounts are similar in size, with a mean log weekly loan of 8.36 and a standard deviation of 1.01 (average weekly bond issuance is $8.2 billion, and loan issuance is $6.7 billion).

Table 6. Time Series of Bond and Loan Issues

Sample	(1) Full	(2) Full	(3) Full	(4) Full	
Dependent Variable	Bond Amount	Loan Amount	Bond Share	Bond Share	Variable Std. Dev.
Mean	8.448	8.361	0.61	0.61	
Treasury Bond Yield, 1yr	**–0.058**	**–0.161****	**0.013**	**-**	**1.50**
	(0.082)	(0.070)	(0.014)		
Treasury Bond Yield, 10yr	**–0.156**	**–0.137**	**0.014**	**-**	**3.06**
	(0.111)	(0.080)	(0.020)		
Credit Spread	**–0.054**	**–0.397*****	**0.077*****	**-**	**2.10**
	(0.089)	(0.081)	(0.016)		
Net Bond Mutual Fund Flow	**0.317*****	**–0.01**	**0.042*****	**-**	**0.40**
	(0.112)	(0.067)	(0.016)		
Nonperforming Loans	**–0.178**	**–0.402*****	**0.043****	**-**	**1.26**
	(0.127)	(0.092)	(0.021)		
Global Financial Crisis	**0.259**	**0.524**	**–0.130***	**0.212*****	**0.06**
	(0.321)	(0.362)	(0.068)	(0.046)	
Federal Reserve 2008–13 Interventions	**0.139**	**0.148**	**0.037**	**0.121***	**0.03**
	(0.351)	(0.349)	(0.063)	(0.066)	
COVID Crisis	**0.279**	**–0.413**	**0.196****	**0.172***	**0.02**
	(0.764)	(0.307)	(0.087)	(0.088)	
Federal Reserve 2020 Interventions	**3.183*****	**1.327****	**0.158**	**0.040**	**0.00**
	(0.802)	(0.564)	(0.118)	(0.094)	
Observations	909	909	909	909	
R-squared	0.039	0.131	0.098	0.039	
Autocorrelation	0.136	0.371	0.249	0.308	

Note: This table presents regression results for features of bonds issued in the U.S. corporate credit market, 2003–20. Each observation is a calendar week. The model is a generalized least squares regression with robust errors and serial correlation. The dependent variables are the log of the total value of either loans or bonds issued in the week or the share of bonds in weekly total volume. There are three period indicators. The Global Financial Crisis variable is an indicator for bonds issued between September 15, 2008, and September 30, 2009; the COVID Crisis refers to February 17, 2020, until the end of the sample (June 2020). The Federal Reserve Intervention variables cover months with announcements of purchases (see Table 3). Treasury rates and credit spreads are weekly averages. Credit Spread refers to BBB spreads. Net Bond Mutual Fund Flow refers to net inflows as a fraction of assets for taxable bond funds (from ICI), times 100. NPLs are from Federal Reserve data on the fraction of loans 90 days or more overdue. Independent variables except indicators and Treasury yields are lagged. * denotes significance at the 10 percent level, ** at 5 percent, and *** at 1 percent. Standard deviations are reported below coefficients.

As explanatory variables we use the yields on the 1- and 10-year Treasury bonds (in percentage points), the Moody's Aaa–Baa credit spread (in percentage points), net bond mutual fund flow, and the share of nonperforming loans as well as indicator variables for the GFC, the dates of the announcements of the Federal Reserve unconventional monetary policy interventions between 2008 and 2013, the COVID-19 crisis, and the announcement dates of the Federal Reserve unconventional monetary interventions in 2020.[17] Sources and variable definitions are described in the appendix. For each independent variable, the appendix reports sample standard deviations.

We report regression results in Table 6, for bonds (column 1), loans (column 2), and bond share (columns 3 and 4). Because the issuance of bonds and especially loans is highly autocorrelated at the weekly frequency, we use a generalized least squares (GLS) specification. The specification allows first-order serial correlation of the error terms and employs the Stata command "prais."[18] We also report a regression for the bond share in aggregate issuance (i.e., bond issuance divided by the sum of bond and loan issuance).

Although we do not find statistically significant effects of the 1-year Treasury yield on either bonds or loans, the 10-year Treasury yield is negatively correlated with loan origination, though uncorrelated with bond issuance. The coefficient on the 10-year Treasury yield is –0.123 (s.e. 0.076) in the bond amount regression, compared to a statistically significant –0.198 (s.e. 0.092) in the loan origination regression. The coefficient estimate in column 2 implies that a percentage point increase in the 10-year Treasury yield is associated with an 18 percent decline in syndicated loan origination.[19] Next, we find that the Aaa–Baa spread affects loans more than bonds. The coefficient on credit spread is −0.042 (s.e. 0.063) in the bond amount regression, compared to a statistically significant –0.381 (s.e. 0.080) in the loan origination regression. The coefficient estimate in the loan

[17]We can also use the 5-year Treasury bond rate, either together with or instead of the 10-year rate (the two are correlated). In general, results are similar (the 5-year rate tends to have slightly better power and slightly more significant coefficient estimates than the 10-year rate).

[18]Regressions without serial correlation adjustments (i.e., OLS) give similar results but with larger t statistics.

[19]The dependent variable is in logs: the effect is $1 - e^{-0.198} = 0.18$.

regression (column 2) implies that a one-standard-deviation increase in the Aaa–Baa spread is associated with a 32 percent decline in syndicated loan origination.

Taken together, the coefficients on the 10-year Treasury yield and the credit spread suggest that loan origination is more sensitive to the cost of debt—both the risk-free rate and the credit risk spread—than bonds are. The differential effect of interest rates and credit spreads on loan volumes may be driven by the fact that loans tend to be issued by risky firms, those that are either nonrated or at the lower end of the credit rating distribution (see Figures 6, 12). Since credit spreads are related to economic conditions, it is possible that weaker firms may be more affected by economic downturns, reducing their demand for financing at such times. Moreover, because the credit spread is also likely to capture overall financial risk in the economy (Gilchrist and Zakrajšek 2012), an increase in that risk is likely to affect credit origination to riskier borrowers (Greenwood and Hanson 2013).

Our next explanatory variable is net bond mutual flow and is designed to capture flight to safety—the tendency of investors to sell assets perceived as risky and to purchase safe assets such as bonds (Baele et al. 2019). We conjecture that one reason for bond market resiliency during financial crises stems from such flights to safety. Table 6 confirms the conjecture that flows into bond investing play an important role: the coefficient on *Net Bond Mutual Fund Flow* is 0.218 (s.e. 0.063) and is significant both economically and statistically in explaining bond issuance. For example, a one-standard-deviation increase in *Net Bond Mutual Fund Flow* is associated with a 9 percent increase in bond issuance. In contrast, the effect of *Net Bond Mutual Fund Flow* on syndicated loan origination is zero (a –0.024 coefficient with a s.e. of 0.069).

As Table 6 demonstrates, both bond issuance and syndicated loan origination are negatively correlated with the percentage of nonperforming loans. However, the elasticity of loan origination to the nonperforming loan variable is almost twice that of bonds. For example, the coefficient on *Nonperforming Loans* is –0.361 and is statistically significant at the 1 percent level (column 2) compared to –0.146 (significant at the 10 percent level) in column 1. The bond share of new issues is increasing nonperforming loans. This pattern is consistent with the hypothesis that one source of strength for

bond markets in crises is that they are less dependent on commercial bank financial health (or, more generally, willingness to bear risk) than loans.

Last, we investigate the effect of the timing of financial crises and unconventional monetary policy interventions on bond issuance and syndicated loan origination. Our regression estimates suggest that bond issuance increased during the GFC (coefficient: 0.373, s.e. 0.185), while the coefficient on loan origination is positive but statistically insignificant. Moreover, the Federal Reserve's announcements of nonconventional monetary policy programs between 2008 and 2014 (QE1, QE2, and QE3) had positive and statistically significant effects on bond issuance, with a coefficient of 0.368 (s.e. 0.186), implying that bond issuance increased by 44 percent during these announcement periods. In contrast, we find no significant effect on syndicated loan origination. Similar to our findings in Figures 1, 2, and 4 and in Tables 4 and 5, column 1 of Table 6 shows that bond issuance increased dramatically during the COVID-19 crisis (the coefficient on *COVID Crisis* is 0.904 (s.e. 0.291) in the bond issuance regression). In contrast, and consistent with Figure 5 and Table 4, column 2 of Table 6 shows a significant decline of syndicated loan origination of 69 percent (i.e., $1 - e^{-1.140} = 0.69$) during the COVID-19 period. Thus, although we find that the Federal Reserve's unconventional monetary policies led to increases in both bond issuance and loan origination, the effect on bonds was twice as high as it was on loans.

Column 3 of Table 6 reports the effect of each explanatory variable on the share of bond financing in total credit, and column 4 shows results for the effect of the crisis and intervention dummies alone (to simplify interpretation of coefficients). As column 3 demonstrates, increases in the 10-year Treasury yield, credit, and credit spreads led to an increase in the bond share. Likewise, increases in flows into bond mutual funds and in nonperforming loans led to an increase in bond share. The coefficient on the COVID-19 indicator is positive and significant in both specifications (columns 3 and 4). The GFC indicator has a (weakly significant) negative coefficient in column 3 and a positive (and significant) coefficient in column 4. The difference is that column 3 controls for spreads, yields, fund flows, and nonperforming loans, whereas column 4 does not. One interpretation is that the bond share was high during the GFC,

but not unexpectedly high given the low yields, high spreads, and strong mutual fund flows. Apparently, these variables do not fully explain the strong bond issuance in the COVID-19 crisis. Perhaps funding demand was unusually high in 2020 (e.g., because the cash flow impact of the pandemic was expected to be very severe, while long-term investment demand was not much affected). This would agree with anecdotal evidence from the period.

Presumably, the empirical patterns reflect both how issuers' demand for funds and investors' demand for securities move over time. We next repeat the tests in Table 6 for firms with maturing debt. The results in Table 6 refer to all issuance of bonds and loans. By isolating issuers with a known strong need for funding (due to maturing debt), we can hope to isolate more of the movement on the investor side (this follows the approach of Almeida et al. 2012). We follow Benmelech, Bergman, and Seru (2021), using a Compustat variable for maturing debt to identify any firm with at least 10 percent of its debt maturing in the current calendar year. Using this variable limits the sample to firms in Compustat and with a match between Mergent (bond issues) and DealScan (loan issues) and Compustat; this reduces the amount of loans especially (more bond issuers than loan issuers are in Compustat). Results are reported in Table 7. Overall, results are similar to full sample results, but with a few differences. First, risk-free rates matter more than credit spreads here, reflecting a strong negative connection between *both* loan and bond issuance. This may be because high spreads reflect low supply of credit in general. Second, mutual fund flows and nonperforming loans are predictive of a high bond share in new issues. This may reflect that these variables impact the relative supply of bonds and loans. Third, financial crisis and COVID period indicators are less predictive of issuance in this smaller sample, perhaps because a driver of issuance was precautionary demand from firms. The 2020 interventions are strongly predictive of both loan and bond issuance, in line with the idea that interventions supported market function.

5.2 Characteristics of Bond Issuers over Time

Table 5 and the associated figures clearly document that bond issuance is robust in crises and that a large share of corporate debt

Table 7. Time Series of Bond and Loan Issues—Firms with Maturing Debt

	(1)	(2)	(3)	(4)	
Sample	Full	Full	Full	Full	
Dependent Variable	Bond Amount	Loan Amount	Bond Share	Bond Share	
Mean	2.841	8.334	0.09	0.09	Variable Std. Dev.
Treasury Bond Yield, 1yr	**−0.241**	**−0.158***	**0.018****	-	**1.50**
	(0.168)	(0.069)	(0.009)		
Treasury Bond Yield, 10yr	**−1.654*****	**−0.145**	**−0.082*****	-	**3.06**
	(0.236)	(0.115)	(0.014)		
Credit Spread	**−0.464*****	**−0.400*****	**−0.012**	-	**2.10**
	(0.173)	(0.080)	(0.012)		
Net Bond Mutual Fund Flow	**0.546*****	**−0.001**	**0.022****	-	**0.40**
	(0.163)	(0.067)	(0.009)		
Nonperforming Loans	**0.186**	**−0.400*****	**0.047*****	-	**1.26**
	(0.259)	(0.092)	(0.014)		
Global Financial Crisis	**0.696**	**0.537**	**0.034**	**0.019**	**0.06**
	(0.824)	(0.359)	(0.058)	(0.044)	
Federal Reserve 2008–13 Interventions	**0.553**	**0.129**	**0.106**	**0.158***	**0.03**
	(0.787)	(0.351)	(0.073)	(0.082)	
COVID Crisis	**−1.093**	**−0.412**	**0.108**	**0.233****	**0.02**
	(1.163)	(0.305)	(0.080)	(0.091)	
Federal Reserve 2020 Interventions	**6.877*****	**1.343****	**0.163**	**0.059**	**0.00**
	(1.369)	(0.570)	(0.266)	(0.150)	
Observations	893	893	893	893	
R-squared	0.255	0.133	0.157	0.040	
Autocorrelation	0.165	0.365	0.142	0.262	
Clusters	Issuer	Issuer	Issuer	Issuer	

Note: This table presents regression results for features of bonds issued in the U.S. corporate credit market, 2003–20. Each observation is a calendar week. The model is a generalized least squares regression with robust errors and serial correlation. The dependent variables are the log of the total value of either loans or bonds issued in the week or the share of bonds in weekly total volume. Only bonds and loans issued by firms with maturing debt exceeding 5 percent of assets in Compustat are included (following the methodology in Benmelech, Kumar, and Rajan 2020). There are three period indicators. The Global Financial Crisis variable is an indicator for bonds issued between September 15, 2008, and September 30, 2009; COVID Crisis refers to February 17, 2020, until the end of the sample (June 2020). The Federal Reserve Intervention variables cover months with announcements of purchases (see Table 3). Treasury rates and credit spreads are weekly averages. The credit spread refers to BBB spreads. Net Bond Mutual Fund Flow refers to net inflows as a fraction of assets for taxable bond funds (from ICI), times 100. NPLs are from Federal Reserve data on the fraction of loans 90 days or more overdue. Independent variables except indicators and Treasury yields are lagged. * denotes significance at the 10 percent level, ** at 5 percent, and *** at 1 percent. Standard deviations are reported below coefficients.

issuance in crises consists of bonds. Specifically, Table 5 shows that bond issuance is less sensitive than loan origination to credit spreads. One potential contributing factor to this strong pattern is the relative strength of typical bond issuers. Notably, bond issuers are generally investment-grade firms, whereas syndicated loan issuers tend to have lower credit ratings. To better understand the role of issuer characteristics, we next study the composition of bond (Table 8) and loan (Table 9) issuers over time. We use measures of firm size, leverage, and profitability from Compustat and report the results in Table 8. For this test, we can use the long time series available from both Compustat and Mergent. We capture three downturns and use indicators for NBER recessions to identify periods of economic and financial market strain. The results in Table 8 show that bond issuers *in recessions*, compared to other periods, are large in terms of sales, assets, and employees (columns 1–3). The effects are sizable: the typical issuer is about 30–50 percent larger in recessions. The pattern appears similar across the three sample recessions but is most pronounced in the GFC. Table 8 further shows that issuers do not differ in terms of leverage between recessions and normal times (column 4) and that profitability (EBITDA to sales) is higher in two of the three recessions (column 5). These results confirm the strength of those firms that issue bonds in recessions: these are large, profitable firms, even beyond the pattern for bond issuers in normal times, and thus they may be one factor that makes the U.S. bond market more resilient during financial crises and economic downturns. The last two columns show that rated issuers are not more common in recessions (they always dominate) but that more bond issues were rated as investment-grade in the two earlier recessions. This further supports the idea that bond issuers are healthy firms.

Table 9 repeats the same set of tests for loan issuers that appear in both DealScan and Compustat. Here, the general pattern is that differences across periods, in terms of issuer size, profitability, or rating status, are small and statistically insignificant. Taken together, Tables 6 and 8 indicate that the relative stability of the bond market in part reflects the creditworthiness of a subset of large, stable firms that tend to favor bonds.

A related question is the ability of new issuers to enter the bond market. If the bond market caters to large, established firms, perhaps new issuers are rare, especially in bad times. We examine this by

Table 8. Characteristics of Bond Issuers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Sales (log)	Assets (log)	Employees (log)	Book Leverage	EBITDA to Sales	Inv.-Grade Issue	Rated Issue
Mean	8.633	9.147	1.884	0.503	0.147	0.810	0.878
2001 Recession	**0.360****	**0.369****	**−0.062**	**−0.008**	**0.020****	**0.096****	**0.018**
	(0.151)	(0.153)	(0.250)	(0.23)	(0.008)	(0.045)	(0.044)
GFC Recession	**0.573*****	**0.481*****	**0.554*****	**−0.012**	**0.031****	**0.153*****	**−0.045**
	(0.121)	(0.112)	(0.132)	(0.020)	(0.007)	(0.026)	(0.034)
COVID Recession	**0.381*****	**0.257****	**0.456***	**−0.042**	**−0.013**	**−0.016**	**−0.040**
	(0.142)	(0.130)	(0.245)	(0.038)	(0.009)	(0.028)	(0.026)
Linear Time Trend	**0.122*****	**0.116*****	**0.052**	**−0.020*****	**0.000**	**0.012**	**−0.011**
	(0.030)	(0.029)	(0.036)	(0.005)	(0.002)	(0.008)	(0.007)
Quadratic Time Trend	**−0.002**	**−0.001**	**−0.000**	**0.001*****	**0.000**	**0.000**	**0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,739	4,743	4,477	4,743	4,729	4,158	4,743
R-squared	0.191	0.192	0.245	0.122	0.038	0.118	0.025
Fixed Effects	FF12	FF12	FF12	FF12	FF12	FF12	FF12
Clusters	Issuer	Issuer	Issuer	Issuer	Issuer	Issuer	Issuer

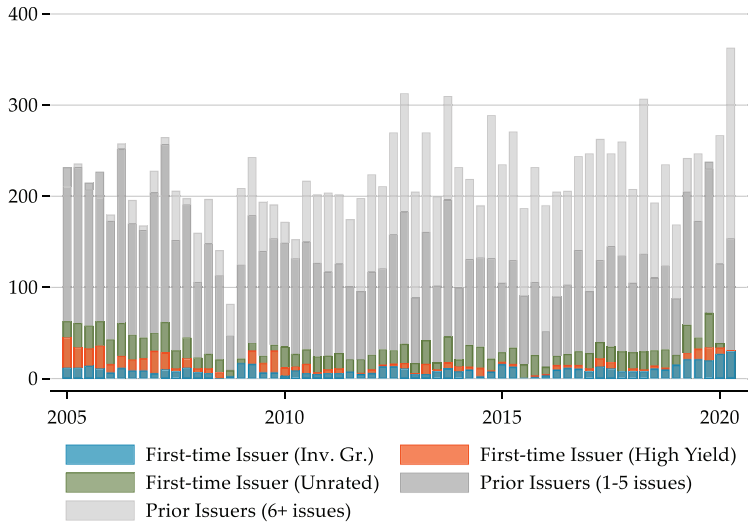
Note: This table presents regression results for bond issuers. Bond data from Mergent is matched to firm data from Compustat using CUSIP numbers. The panel covers nonfinancial issuers, 2000–20. Recession dates are based on NBER data (March–November 2001; December 2007–June 2009; February 2020–end of sample). Book Leverage refers to debt over book assets. Each observation is one bond. Investment-Grade Issue refers to BBB–/Baa3 or better, and Rated Issue refers to a nonmissing rating. Fixed effects are included for each Fama-French industry (12). * denotes significance at the 10 percent level, ** at 5 percent and *** at 1 percent. Standard deviations are reported below coefficients.

Table 9. Characteristics of Loan Issuers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Sales (log)	Assets (log)	Employees (log)	Book Leverage	EBITDA to Sales	Inv.-Grade Issue	Rated Issue
Mean	6.631	6.904	0.856	0.462	0.109	0.470	0.308
2001 Recession	**0.198**	**0.481**	**0.882**	**0.051**	**0.071**	**0.461*** **	**0.085**
	(0.578)	(0.490)	(0.603)	(0.085)	(0.113)	(0.192)	(0.100)
GFC Recession	**0.503***	**0.501***	**0.294**	**–0.052**	**0.043****	**–0.190***	**0.009**
	(0.294)	(0.281)	(0.300)	(0.048)	(0.018)	(0.103)	(0.098)
COVID-19 Recession	**0.210**	**0.256**	**0.282**	**0.072**	**0.048**	**–0.238**	**–0.093**
	(0.322)	(0.325)	(0.308)	(0.064)	(0.039)	(0.198)	(0.080)
Linear Time Trend	**0.110**	**0.115**	**0.135**	**0.013**	**0.024**	**0.065***	**0.028**
	(0.071)	(0.070)	(0.083)	(0.013)	(0.023)	(0.034)	(0.019)
Quadratic Time Trend	**–0.000**	**–0.000**	**–0.003**	**–0.000**	**–0.000***	**–0.003***	**–0.002**
	(0.001)	(0.000)	(0.004)	(0.001)	(0.000)	(0.002)	(0.001)
Observations	2,295	2,301	2,210	2,301	2.299	709	2,301
R-squared	0.263	0.281	0.261	0.070	0.106	0.162	0.085
Fixed Effects	FF12	FF12	FF12	FF12	FF12	FF12	FF12
Clusters	Issuer	Issuer	Issuer	Issuer	Issuer	Issuer	Issuer

Note: This table presents regression results for bond issuers. Loan data from DealScan are matched to firm data from Compustat using CUSIP numbers. The panel covers nonfinancial issuers, 1995–2020. Recession dates are based on NBER data (March–November 2001; December 2007–June 2009; February 2020–end of sample). Book Leverage refers to debt over book assets. Each observation is one loan. Investment-Grade Issue refers to BBB–/Baa3 or better, and Rated Issue refers to a nonmissing rating. Fixed effects are included for each Fama-French industry (12). * denotes significance at the 10 percent level, ** at 5 percent, and *** at 1 percent. Standard deviations are reported below coefficients.

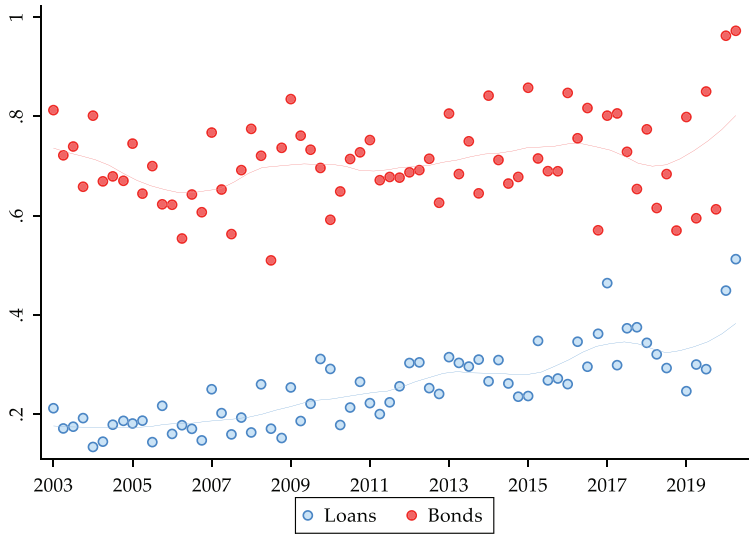
Figure 13. Bond Issuer Composition



Note: This figure plots the split of issuers in five groups: first-time bond issuers with investment-grade ratings (blue, bottom), first-time issuers with high-yield ratings (orange, second from bottom), first-time issuers without ratings (green, third from bottom), repeat issuers with up to five prior issues since 2001 (dark gray, second from top), and prior issuers with more than five prior issues since 2001 (light gray, top). The data are described in Table 1.

dividing bond issuers into those with and without prior bond issues. Quarterly shares are presented in Figure 13. New issuers are subdivided into investment-grade, high-yield, and unrated categories. Repeat issuers are separated by number of prior issues (since 2001), 1–5 and 6 or more. In all quarters of 2005:Q1–2020:Q2, new issuers appear in the market. The low point is 2008:Q4, when a handful of new issuers reached the market, but this is also by far the lowest issuance quarter in the 15-year period. New issuers with investment-grade ratings are common in 2020, highlighting the strength of this segment in this crisis. Overall, Figure 13 suggests that the bond market remains open for new issuers at all times, as long as they are of sufficient quality. This suggests an important caveat to the traditional understanding of the bank-borrower relationship as a mechanism for increasing access to financing for firms (Petersen and Rajan 1994; Berger and Udell 1995; Houston and James 1996): when banks

Figure 14. The Frequency of Rated and Unrated Issues



Note: This figure shows the fraction of newly issued bonds and loans that have a credit rating each quarter. The sample runs from 2003:Q1 to 2020:Q2. Loans (blue) includes term loans. Bonds (red) excludes convertible bonds. See Table 1 for summary statistics.

have limited ability to lend, relationships may not help those who need it the most, and arm's-length lending (where credit ratings play a role) instead becomes more important.

We provide further information on issue properties in Figure 14, which reports the quarterly share of rated issuers in our loan and bond samples, respectively. Several empirical patterns stand out. First, the rated share is always high in the bond market and low in the loan market. The bond market relies heavily on credit ratings (especially the investment-grade category, as Figure 6 demonstrates). In contrast, less than one third of loans are rated in most of the sample quarters. Second, there is a positive trend in the loan market, perhaps related to the increasing share of institutional loans, for which the market relies on credit ratings. Last, the first two quarters of 2020 saw record shares of rated assets in both markets, with as much as half of new loans and almost all bonds being rated.

5.3 Credit Supply—Who Buys Corporate Bonds?

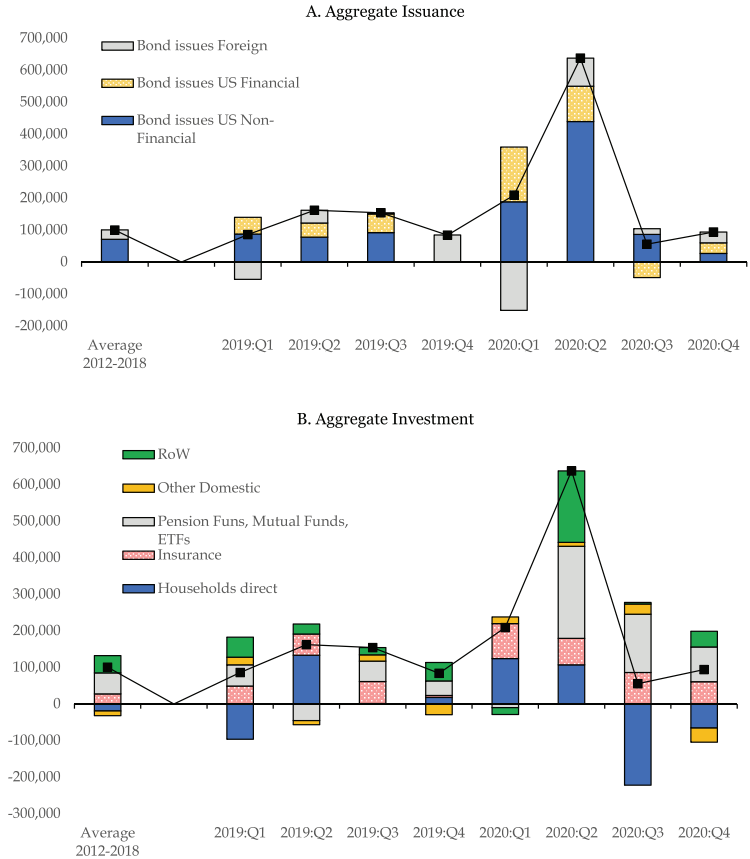
Our regression results in Table 5 show that flows into bond mutual funds are a strong determinant of bond issuance. This result suggests that an important credit supply factor affects bond issuance during financial crises and economic downturns. The notion that the development of institutional investors can contribute to the development of capital markets has been formulated by Scharfstein (2018), who develops a model that endogenizes the extent to which savings are intermediated through banks or capital markets. Scharfstein (2018) also presents suggestive evidence on the link between pension savings and bond and equity market development. Similarly, Niggemann and Rocholl (2010) show that reforms intended to increase pension fund assets lead to increases in stock and bond issuance.

We argue that the tendency of investors to sell assets perceived as risky in favor of purchasing safe assets (flight to safety) provides an effective hedge to bond issuance. The main point is that the typical investors in bonds (bond mutual funds, insurance companies, and pension funds) are crisis- and recession-resilient—especially when compared to commercial banks. The resiliency of those large bond investors reflects several patterns. First, important bond investors tend to pass through gains and losses to shareholders or policyholders. This avoids a dependence on equity cushions.[20] Second, these institutions invest in liquid assets and, compared to commercial banks, have balance sheets that do not become contaminated with nonperforming assets. As a result, bond investors keep the bond market open at the same time that bank lending grinds to a halt. That said, a large literature shows that individual mutual fund investment decisions are affected by outflows (e.g., Zhu 2021), and our regression results point to the role of aggregate flows.

Figure 15 displays quarterly flows in the bond market during the COVID-19 period, with the preceding period averages as a benchmark. Panel A displays aggregate net bond issuance, while panel B presents aggregate net bond investment. Clearly, for the

[20]Mutual funds, ETFs, and pension funds are accurately described as equity-free. Insurance companies *do* have equity, and they can be distressed (see, e.g., Becker and Ivashina 2015 and Koijen and Yogo 2015). However, a large part of insurance asset portfolios derives from pass-through policies, where inflows are closely connected with asset purchases.

Figure 15. Aggregate Bond Market Flows, 2012–20



Note: This figure shows flow of funds data for "Corporate and Foreign Bonds," based on Table F.213 in the US Flow of Funds accounts. Net quarterly flows, seasonally adjusted, are reported by issuer type (panel A) and by investor category (panel B). The scale is millions of dollars. Averages for the 2012:Q1–2018:Q4 period are reported, along with quarterly data for 2019 and 2020.

bond market to clear, aggregate net issuance should equal aggregate investment. The purpose of Figure 15 is to identify those investors that stepped in during the COVID-19 crisis and fulfilled the demand for credit. These flow of funds data include financial issuers (which we do not include in other tests), including structured assets such as mortgage-backed securities and foreign bond issuers in the U.S.

market. Panel A illustrates the major role that nonfinancial corporate entities played in the 2020 bond issuance peak. Panel B shows that both households and domestic institutions such as mutual funds, pension funds, and insurance companies contributed to the issuance peak as net buyers. U.S. banks (included in "Other Domestic" together with the public sector and a few other categories) did not play an important role in purchasing bonds issued during the COVID-19 period. This small role of banks may reflect regulatory changes that discourage banks from holding bonds (Bessembinder et al. 2018) or, more generally, the slowing of intermediating activities by banks during economic downturns and financial crises. Direct bond holdings of households declined in 2020:Q3, but the net for the year approaches zero. However, large inflows from households likely account for a large share of the expansion of mutual fund and ETF bond holdings. That is, it is likely that household investment in bonds—either directly or indirectly through mutual funds and ETFs—played a key role in the COVID-19 issuance boom.

Bond purchases by foreign investors ("Rest of the World," RoW) also played a large role in funding net issuance. This may reflect the relative safety of securities available in U.S. capital markets (e.g., Caballero, Farhi, and Gourinchas 2017) or of the currency itself (Farhi and Gabaix 2016; Corsetti and Marin 2020).

6. Conclusions

Financial markets can contribute to the development and propagation of recessions and crises. One important channel is limited access to funding for corporations: diminished access to funding can force companies to reduce employment and investment.

Given the central role of debt markets in funding corporations, disruption in the flow of new debt is a particularly important concern. In this paper, we examine the behavior of corporate debt in the context of the COVID-19 pandemic in 2020 and compare it to recent periods, including the Global Financial Crisis of 2008–09. We collect comprehensive issuance data for U.S. corporations in key debt markets: corporate bonds and leveraged (syndicated) loans. Descriptive statistics on loan and bond issuance at the weekly frequency show that bond issuance was more than twice as high in the COVID-19 period as in previous years. This abnormal issuance exceeded

$300 billion in the first half of 2020. In contrast, loan issuance was moderate or low.

The resilience of bond markets, especially relative to loan markets, may reflect several factors. First, bond issuers are on average much larger and of better credit quality than loan issuers. These firms may be more resilient in crises. Supporting evidence for this hypothesis includes depressed high-yield bond issuance in periods of crisis.

Second, frictions in the banking system have a greater impact on loan issuance than on bond issuance. In particular, leveraged financial institutions such as banks—subject to bank runs and debt overhang—are more important to loans than to bonds. In line with this institutional explanation, we document that inflows into bond mutual funds are associated with more bond issuance and, on the flip side, that stress in bank balance sheets predicts lower loan issuance.

Last, unconventional monetary policy and credit interventions may also play a role in the relative performance of corporate debt markets. Asset purchase programs may have a more direct effect on asset markets than on corporate lending, where the impact has to transfer through financial institutions, in which the interest rate environment, debt overhang, and other circumstances may reduce pass-through.

Appendix

This table lists the variables used in the tables and figures in this paper. FRED refers to the St. Louis Federal Reserve's data service, accessed at https://fred.stlouisfed.org/.

Variable	Data Source	Definition	Comment
Bond Number	SDC	Bonds issued each week; we drop withdrawn issues, convertibles, non-U.S. issues and bonds issued by the federal government, government agencies and local governments, and bonds issued by financial and utility firms	Weekly
Bond Value	SDC	(see Bond Number)	Weekly
Investment-Grade (IG) Bond	SDC	S&P and Moody's rating of BBB– or Baa1 or above; we use the lower of two ratings	Weekly number and value of issues calculated as above
High-Yield (HY) Bond	SDC	Bonds with at least one credit rating that are not investment-grade	Weekly number and value of issues calculated as above
Loan Number	DealScan	Accessed via Refinitiv. New term loans to U.S. borrowers. Deal purpose must be "General Purpose," "General Purpose/Refinance," "Working Capital," "Capital Expenditure," or "Equipment Upgrade/Construction"	Weekly
Loan Value	DealScan	See previous. Amount of new term loans plus changes in amount from amended term loans	Weekly
Investment-Grade (IG) Loan	DealScan	S&P and Moody's rating of BBB– or Baa1 or above. We use the lower of two ratings	Weekly number and value of issues calculated as above
High-Yield (HY) Loan	DealScan	Loans with at least one credit rating that are not investment-grade	Weekly number and value of issues calculated as above

Variable	Data Source	Definition	Comment
Treasury Bond Yield, 1yr	FRED	Yield to maturity of constant-maturity one-year Treasury bonds	Weekly
Treasury Bond Yield, 10yr	FRED	Yield to maturity of constant-maturity 10-year Treasury bonds	Weekly
Credit Spread	FRED	ICE BofA BBB US Corporate Index Option-Adjusted Spread, Percent, Weekly, Not Seasonally Adjusted	Weekly
Net Bond Mutual Fund Flow	ICI	Net flow into ETFs and mutual funds in the categories "IG bonds," "HY bonds," and "Mixed bonds," relative to the value of such funds and ETFs	Monthly
Nonperforming Loans	FRED	Nonperforming Commercial Loans (past due 90+ days plus nonaccrual) to Commercial Loans, Percent, Quarterly, Not Seasonally Adjusted	Quarterly
Global Financial Crisis	Table 3	September 15, 2008–September 30, 2009	Indicator variable
Federal Reserve 2008–13 Interventions	Table 3	Weeks with QE policy announcements	Indicator variable
COVID Crisis	Table 3	February 17, 2020–end of sample	Indicator variable
Federal Reserve 2020 Interventions	Table 3	Weeks with QE policy announcements	Indicator variable
2001 Recession	NBER	March–November 2001	Indicator variable
GFC Recession	NBER	December 2007–June 2009	Indicator variable
COVID Recession	NBER	February 2020–end of sample	Indicator variable
Sales (log)	Compustat	Sales, logarithm	Matched to issuers using CUSIP, lagged one year
Assets (log)	Compustat	Assets, logarithm	
Employees (log)	Compustat	Emp, logarithm	
Book Leverage	Compustat	(dlc+dltt)/at	
EBITDA to Sales	Compustat	oibdp/sales	
IG Issuer	Compustat	Baa3/BBB– or better issue credit rating	Indicator variable
Rated Issuer	Compustat	Nonmissing issue rating	Indicator variable

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Central Bank Credibility and Institutional Resilience*

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How central banks define their mission and how they are perceived by the public appears to have undergone a substantial shift since the Global Financial Crisis (GFC). Over the past 16 years, the persistence of unconventional monetary policy and subsequent return of inflation have diminished the credibility of central banks as measured, for example, by the gap between expectations and inflation performance. This paper explores whether a loss in confidence in central banks may lead to real institutional effects, hypothesizing that short-term declines in central bank credibility generate a fall in the institutional resilience of an economy. Using data from up to 107 developed and emerging market countries over 27 years, fashioning an explanation of the drivers of institutional resilience, and utilizing system-GMM, we find uniformly that decreased trust in central banks is associated with a significant lowering of resilience.

JEL Codes: E58, E42, O17.

1. Introduction

Academics and policymakers have recently rekindled their interest in economic and institutional resilience in the face of exogenous shocks (e.g., Brunnermeier 2021). Our study is squarely concerned with

*The authors wish to thank the Editors, an anonymous referee, and Michael Bordo, Richard Burdekin, Kristin Forbes, and Davide Romelli for comments on earlier drafts, as well as participants at the 2022 Asian Meeting of the Econometric Society in Shenzhen, China, for their suggestions, participants at a research seminar at Bournemouth University in 2022 for their insights, and Davide Romelli for sharing his data on central bank independence. Raw data are available from the authors on request. Corresponding author: psiklos@wlu.ca.

the role and impact of central banks in delivering both forms of resilience. Coming off a high point of more secure property rights and more liberal trade worldwide during the most recent wave of globalization, the series of global crises since the 2000s has slowed, or even reversed, many of these gains while at the same time emboldening populist voices (Devinney and Hartwell 2020; Wolf 2023).

As documented by Bordo and Siklos (2021), central banks were heavily affected in their institutional workings by the Global Financial Crisis (GFC). This was seen in calls throughout advanced economies to pull back some of the independence of central banks (Goodhart and Lastra 2018), changing how central banks defined their missions (Blinder 2010), how they communicated with the public (Horvath and Vasko 2016; Blinder et al. 2022), or how credible they were perceived as being vis-à-vis their inflationary targets (Bordo and Siklos 2021).

With emerging markets tending to overshoot their inflationary targets during the GFC and developed economies undershooting them until 2021, the credibility of central banks in terms of their ability to adhere to their central mandates, especially in weaker institutional environments, was threatened. Combined with the response to the crisis, the "whatever it takes" mentality of central bankers, and a willingness to take on new responsibilities (e.g., see Orphanides 2019), the stage was set for a combination of significant monetary interventions lacking an ex ante consensus on how they would play out or should be unwound.

A decline in central bank credibility is bound to have far-reaching ramifications. Indeed, links between inflation outcomes and the real economy continue to be debated (e.g., Coibion and Gorodnichenko 2015; Blinder 2018; Bernanke and Blanchard 2023). Elsewhere, inflation targeting is seen as crucial to maintaining this credibility but may become less effective if inflationary expectations become unmoored from monetary policy (e.g., CEPR 2013; Ehrmann 2021).

Based on the foregoing developments, this paper hypothesizes that short-term declines in central bank credibility (a flow variable) imply a parallel decline in the overall *trust* placed in central banks (with trust a slower-moving, institutional, or stock variable). If trust begins to ebb away from the central bank, this would likely be accompanied by a broader degradation of institutional quality and,

as a consequence, institutional resilience in an economy. We define "institutional resilience" as the capacity of a system to absorb a disturbance (Folke 2006; Brunnermeier 2021). Hence, resilience is not just about the strength of institutions, but also about adaptability to external shocks.

This paper extends the notion of institutional resilience one step further by extending a line of research found in Hartwell (2018a, 2018b, 2019) on the effects of monetary policy on institutions and marrying it with the research stream of Bordo and Siklos (2021) on central bank credibility and institutional resilience. More broadly, our paper stands at the intersection of three related literatures, namely the steering of inflation expectations; the trust in, credibility of, and confidence in central banks; and institutional strengths, weaknesses, and governance. We do not offer a new all-encompassing theory, instead fashioning an explanation of the drivers of institutional resilience. The novel contribution of this paper is to quantify—using a new and novel data set—the credibility and resilience links which have been left largely unexplored in the relevant literature. We provide new empirical evidence that strongly supports the notion that institutional resilience and economic performance are related. Methodologically, our work relies on dynamic panel (system generalized method of moments) and time-series models to estimate how changes in central bank credibility influence shifting institutional attributes.

Briefly, our results show that poorer central bank performance in terms of stated or implicit monetary goals significantly impacts institutional resilience. More precisely, we find that since the 1990s, each percent decline in a central bank's credibility corresponds with an average 3.6 percent drop in a country's institutional resilience. This result is robust to a variety of methodologies and to a split between pre- and post-GFC samples.

The rest of the paper is organized as follows. The next section provides a literature review encompassing credibility, trust, and institutional resilience. There is an important thread linking these topics to each other that adds to our understanding of central bank resilience. A description of the data and the various methodologies employed precedes a discussion of the empirical results. The paper concludes with a summary, lessons learned, and potential for future research.

2. Literature Review

2.1 Central Bank Credibility

There is no universally accepted definition of credibility (see Cukierman 1986; Bordo and Siklos 2021; references therein). Ultimately, credibility is about the central bank delivering on its promise to keep inflation under control and delivering to the public on promises made (e.g., Cukierman 1986; Blinder 2004). Typically, such promises have centered on inflation performance. As a policy target, inflation has many advantages. First, its effects can be observed fairly quickly (e.g., monthly). More generally, as Borio (2019, p. 269) points out, "[P]rice and financial stability are inexorably linked. As concepts, they are joined at the hip."[1]

Almost all empirical attempts begin with the notion that deviations in observed inflation from some expectation can potentially lead to a loss of credibility.[2] Examples of studies in this vein include Cukierman (1986, 1992), Bodea and Hicks (2015), and Bordo and Siklos (2021). There is a fair amount of consensus in favor of a negative relationship between significant and persistent deviations in inflation from expectations and central bank credibility.[3]

The connection between central bank credibility and the adoption of inflation targeting (IT) is less clear-cut (e.g., see Filardo and Genberg 2010). On balance, the view is that, for at least two reasons, an IT policy regime provides the kind of discipline that enhances credibility (e.g., see Rose 2020) via demands for greater accountability. First, many central banks that are not explicitly mandated to meet a numerical inflation goal (e.g., U.S., euro area) mimic the behavior of the more formal version of a policy regime. Second, there are subtle differences in how IT regimes are defined, rendering

[1]There are lingering doubts about the strength of this connection (e.g., see Issing 2003). Nevertheless, many central banks have some or exclusive responsibilities for financial stability (e.g., Blot et al. 2015; Lombardi and Siklos 2016).

[2]An early example of this kind of definition used to operationalize the definition of credibility is Cukierman (1986).

[3]Data limitations often limit the body of empirical work in this area to professional forecasts or ones derived from developments in asset prices (e.g., fed funds futures or the equivalent), although this is changing, with household and firm expectations becoming used more frequently.

comparisons between IT and non-IT central banks difficult (e.g., Ehrmann 2021).

Keeping inflation within a defined range also serves to enhance the reputation of the monetary authority and "buys" the institution time, for example, in the event large shocks lead to departures from agreed-upon inflation objectives or financial market volatility rises sharply (e.g., see Hartwell 2018b).[4]

Existing credibility indicators ignore that institutions change slowly, as surveys of changes in central banking legislation (e.g., see Romelli 2021) or even monetary regimes (Unsal, Papageorgiou, and Garbers 2022) attest. Yet, there is a long-standing literature that associates governance with overall economic performance and even risk-taking (inter alia, see Clague et al. 1999, Butkiewicz and Yanikkaya 2006, and Kanagaretnam et al. 2019).[5]

2.2 Confidence and Trust in Monetary Institutions

Alesina and La Ferrara (2000) argue that the determinants of trust in society, a vital aim of institutions, are unclear. In a similar vein, but generalized to the entire economy, economic performance can also drive trust in political and economic institutions, with major crises such as the GFC diminishing trust substantially (Stevenson and Wolfers 2011). These suppositions are supported by political scientists (Citrin and Stoker 2018).

Less has been written about trust in central banks. Berggren et al. (2014) argue that central bank autonomy and societal trust

[4]There is, of course, another critical factor at play, namely how well the central bank communicates with markets and the public. Central bank communication is a separate branch of research that has emerged, especially after the GFC of 2008–09 significantly reduced central banks' room to manoeuvre their policy stance via changes in policy rates, combined with a growing need to explain why it was necessary to introduce unconventional monetary policies (UMP). A deeper analysis of the connection between communication, credibility, and institutional resilience is beyond the scope of this paper. However, see Blinder et al. (2008, 2022) and Orphanides (2019).

[5]At least in theory, deficiencies in central bank governance can be offset by appointing a conservative central banker, much like the conservative central banker is used to prevent politicians from favoring more inflation to exploit a Phillips curve trade-off (Rogoff 1985). Even if this is the case, there is no indication of how a conservative central banker can make the entire institution more resilient.

are positively related, albeit in a nonlinear manner.[6] One additional complication is that trust is an endogenous variable; that is, it is influenced by central bank independence but can also contribute to effectively raising it.[7]

There is some evidence of the effect of trust in a central bank. For example, Ehrmann, Soudan, and Stracca (2013) report an empirical connection between trust in the European Central Bank (ECB), a supranational institution, and economic performance. They link estimates of trust in the ECB, based on the Eurobarometer survey,[8] to trust in other European institutions as well as the public's views about the banking sector. Space limitations prevent a more detailed discussion of institutional trust in other central banks (see, however, Siklos 2002, 2017).

2.3 Institutional Resilience

Institutional resilience in society is impacted by both credibility and confidence. The most commonly agreed core of what makes an institution resilient is its ability to withstand shocks—or enable policymakers to respond to those shocks, as in Briguglio et al. (2009).[9] Goodhart and Lastra (2018) show that resilience (couched in terms of flexibility) and certainty (a key measure of confidence in a particular institution) trade off in a dynamic fashion. Moreover, as Zheng (2011, p. 298) notes, "political institutions that facilitate ex post flexibility in policy implementation will necessarily limit ex ante policy certainty."

[6]Space limitations prevent a discussion of the pros and cons of measuring central bank independence (de jure or de facto; e.g., see Masciandaro and Romelli 2018). We note that Adrian, Khan, and Menand (2024) have created a new index of central bank independence that explicitly incorporates governance indicators. The data, at the time of writing, are not yet available.

[7]Bjørnskov's (2011) result would suggest otherwise, as societal trust seems rather stable over time. An interfering variable may be the quality of the legal system, that is, the strength of the rule of law.

[8]https://europa.eu/eurobarometer/screen/home.

[9]Brunnermeier (2021) also links the concept of resilience to the statistical concept of impulse responses. Resilience also means adaptation in the ecological literature (Harkes and Novaczek 2002) but has also found a home in institutional economics, with ideas like Ostrom's (2010) need for institutional orders which collectively are able to facilitate adaptation (Aligica and Tarko 2014).

Resilience can run counter to the inherent attributes of institutions, namely their "relatively durable patterns of social interaction" (Steinberg 2009, p. 64). Hannaford (2018, p. 95) argues that "resilience is an entirely internal property of a system and relates to shifts between states rather than structural changes within the system." Bordo and Siklos (2021) construct a resilience index comprised of mostly system-wide economic attributes plausibly related to the ability of a system to withstand shocks, including governance and institutional attributes.

Generally, there is a consensus that an institutional system with a few institutions dominating is one which has more vulnerability than resilience. Moreover, a system which promotes poor policies also increases vulnerabilities (Kassab 2017). This is a crucial point to keep in mind for the examination below.

3. Methodology

3.1 Determining Confidence

We posit that confidence in a central bank consists of three components: a penalty for missing an inflation objective (explicit or implicit; TMISS); an indicator of monetary policy uncertainty (MPU); and a global component (GDEV). There is ample theory and evidence that some combinations of these three factors play decisive roles in determining confidence in the central bank (see, inter alia, Blinder 2000; Bordo and Siklos 2017; Levieuge, Lucotte, and Ringuedé 2018; or Cole and Martínez-García 2023). There is less agreement on how to define these concepts empirically. Our strategy consists in providing plausible definitions while investigating the sensitivity of the results to changes in some specifications. Confidence, expressed in equation form, is assumed to be an aggregation of the three components defined above:

$$CONF_{it} = \alpha TMISS_{it} + \beta MPU_{it} + \gamma GDEV_{it} + \varepsilon_{it}. \qquad (1)$$

Equation (1), defined for country i at time t, is expressed linearly and has an inverse interpretation, mainly that higher values of this

variable signify less confidence due to poor performance on the part of the central bank.[10]

Not all deviations from some numerical target (TMISS) need signal a loss of credibility, since it is reasonable to assume that policymakers and the public will tolerate some errors as inevitable, temporary, or even uncontrollable by the central bank. Therefore, it seems reasonable to penalize an institution for misses over the medium term rather than to penalize any period-by-period deviations. The larger and more persistent the misses over business cycle frequencies, the greater the loss of confidence in a central bank's ability to deliver an inflation objective. This leads us to write the following specifications where the subscript identifying a country in question (i.e., i) is dropped to economize on notation:

$$TMISS_t = \begin{cases} 0 & (2a) \\ (\tilde{\pi}^e_{t+1} - \tilde{\pi}^*_t)^2 & (2b) \end{cases}$$

$$\text{IF } \tilde{\pi}^*_{t,t-2} - \theta \leq \tilde{\pi}^e_{t+1} \leq \tilde{\pi}^*_{t,t-2} + \theta \quad (2a')$$

$$\text{IF } \tilde{\pi}^*_{t,t-2} - \theta > \tilde{\pi}^e_{t+1} > \tilde{\pi}^*_{t,t-2} + \theta \quad (2b')$$

$$\tilde{\pi}^*_t = \tilde{\pi}^*_t - \lambda_0 F(\dot{y}_t) - \lambda_1 F(\dot{\varepsilon}_t). \quad (3)$$

In Equations (2) and (3), π_t is annual inflation at time t.[11] TMISS implies no loss of credibility (implicitly for country i) as long as expected inflation (π^e_{t+1}) is within the bounds given by Equation (2a). Otherwise, a quadratic element kicks in which penalizes misses in an inflation objective ($\tilde{\pi}^*_t$) relative to one-year-ahead expectations ($\tilde{\pi}^e_{t+1}$).[12] The tolerance ranges (i.e., θ) given in Equations (2a)

[10]Of course, other functional forms are possible and interaction effects can also be added. We leave these, and other extensions, for future research in part because the results below are robust to a wide variety of econometric approaches.

[11]The choice of annual inflation is dictated by data availability for many of the institutional variables being considered. See Section 4.

[12]In the interests of a sensitivity analysis, we can apply the quadratic penalty (i.e., Equation (2b)) even within the target range (not all IT central banks adopt a target range). Alternatively, we can use the absolute value of inflation misses, that is, $(\tilde{\pi}^e_{t+1} - \tilde{\pi}^*_t)$. Still another possibility is to assume that confidence losses

and (2b) are determined according to how inflation expectations behave relative to observed inflation. TMISS is based on past performance and the two-year horizon is chosen since it is traditionally the time it takes for monetary policy decisions at time t to fully impact inflation in future.[13] We also consider, as a sensitivity test of our results, a longer reaction interval of five years. Our conclusions are unchanged. To distinguish the year-over-year inflation rate (π_t) from the two-year performance metric, we define such inflation performance as $\tilde{\pi}_t$.

When a central bank follows an explicit inflation target, $\tilde{\pi}_t^*$ is directly observable. The evidence is that the permissible range of misses around a central numerical inflation objective is generally smaller in advanced economies (AEs) than in emerging market economies (EMEs) (Levieuge, Lucotte, and Ringuedé 2018; Bordo and Siklos 2021). Hence, we set θ equal to ± 1 percent for AEs and ± 2 percent for EMEs. Notice that Equation (2a) treats a miss within the IT range as "bygones are bygones," which results in TMISS $= 0$, with credibility unaffected (Bicchal 2022).[14] Clearly, there is an element of arbitrariness in such definitions that cannot be avoided but the chosen ranges are consistent with how inflation target ranges are defined in practice as between AEs and EMEs (e.g., see Siklos 2017).

Observed inflation need not, of course, fluctuate symmetrically around the target over time. Hence, the central bank is penalized in the same manner whether inflation is too low or too high. Alternative specifications to replace TMISS do not yield different conclusions, and this is confirmed with experimentation (not shown) with alternatives to Equations (2a) and (2b) along the lines just described.

When the target range is not explicitly defined, a simple approach is to rely on, say, a five-year moving average of inflation,

follow an S-shaped function, again absolute value. For each one of these alternatives symmetry around the target is assumed, which, again, is also consistent with how inflation target ranges have been defined in practice.

[13] Indeed, many central banks explicitly refer to the two-year horizon when explaining the transmission process of monetary policy.

[14] Interestingly, the Fed's adoption of average inflation targeting suggests that the past does matter, since inflation below target for years is supposed to provide the central bank with some latitude to exceed a medium-term inflation objective, thereby making up for past misses.

that is, $\tilde{\pi}_{t,t-5}$. This has the advantage of being a metric that is easily comparable with the one specified for central banks where an explicit numerical objective is available.[15] Although the number of potential candidates for Equation (3) is large, experimentation reveals few notable differences between the simplest (i.e., a moving average) adopted in the empirical results below and a more sophisticated version.

Next, we argue that confidence in the central banking institution is adversely impacted by uncertainty generated by the conduct of monetary policy. There is general agreement that uncertainty has detrimental economic effects (Baker, Bloom, and Davis 2016). We consider that there are at least two elements that contribute to determining the level of monetary policy uncertainty. We posit that forecast errors in inflation and real GDP growth combine to generate monetary policy uncertainty. Theory has also focused attention on these variables as the main drivers in the policymakers' loss function.

We hypothesize that the larger the unexpected deviations from observed inflation and real GDP growth, the less confident forecasts are about the evolution of these two variables over time. This will undoubtedly contribute to raising monetary policy uncertainty from the central bank's standpoint.[16]

We next estimate monetary policy uncertainty (MPU) as follows, again dropping the country subscript (i) to simplify notation:

$$MPU_t = \sum[(\pi^e_{t+1} - \pi_{t-1})^2 + (\dot{y}^e_{t+1} - \dot{y}_{t+1})^2], \tag{4}$$

where all the terms were previously defined. Note that forecast errors are evaluated relative to last year's observed inflation and real GDP growth, since contemporaneous values may not be observed at the

[15]One can either set it equal to that adopted in a comparable economy or estimate an implicit inflation objective for a non-IT central bank (e.g., via some filtering algorithm based on past performance). This is the approach adopted, for example, by Parkin (2014).

[16]For an example of this kind of approach to estimating MPU for the U.S., see Husted, Rogers, and Sun (2020). The alternative of using text analysis from news sources for a large number of countries, let alone data collected for over 170 countries as we have done, is impractical.

time uncertainty is evaluated. Equal weighting is given to inflation volatility and output growth volatility.[17]

The third component of confidence in central bank performance summarizes how the role of global shocks, considered an external threat to a domestic inflation target, are accounted for. Reintroducing the subscript identifying country i:

$$GDEV_{it} = \pi_{it-1} - \delta_i \pi^G_{t-1}. \tag{5}$$

The global factor dictates that confidence in the central bank requires an adjustment to domestic inflation rates due to incomplete pass-through effects from exchange rate changes (e.g., à la Forbes, Hjortsoe, and Nenova 2018). It is shown here as the gap between domestic inflation last period, used because of the lag in obtaining external inflation rates (e.g., main trading partners or some combination of external inflation rates), and last period's "global" inflation rate (i.e., π^G_{t-1}), measured as the average of the inflation rate of the United States and the European Union.[18] The coefficient δ reflects a view about the pass-through effects of external inflation.[19] Equation (5) asserts that a central bank in country i gets a boost

[17]Since both elements of Equation (4) point in the same direction for increasing uncertainty, and central bankers generally care about both metrics, this seemed to us a more plausible strategy than assuming alternative weights. Data limitations also mean that MPU can only be evaluated for a small set of forecasts. We rely on the forecasts from the World Economic Outlook (WEO). The historical data are available from https://www.imf.org/external/pubs/ft/weo/data/WEOhistorical.xlsx. We also used, for shorter samples, OECD Main Economic Outlook projections, Oxford Economics, and Consensus forecasts. However, the number of available countries and sample spans were much shorter for these other data sets. The paper's main conclusions seem unaffected by combining alternative forecasts with ones from the IMF.

[18]The European Union inflation rate is calculated based on all Member States as of that year.

[19]Once again, other specifications are possible. For example, the openness of an economy, the kind of exchange rate regime, and barriers to trade are also plausible alternatives. Another option is to regress domestic on global inflation and possibly allow for some time variation in the estimates of δ, or even assume that some form of cointegration between domestic and foreign inflation rates is possible, and use the error-correction term to capture pass-through effects. Each alternative is potentially problematic since the researcher takes a view concerning specific factors that drive inflation and this may cloud our estimates of the role of external shocks.

in confidence if it outperforms (i.e., has lower inflation than) global inflation.[20]

3.2 Determining Institutional Resilience

As previously noted, overall institutional resilience in an economy can be thought of as a combination of political and economic institutional resilience. We combine the following salutary aspects of an institutional order which can help to absorb shocks:

- *Property Rights*: In theory, a country with higher levels of property rights should instill confidence in citizens during times of crisis; similarly, the ability to trade, manage, and dispose of one's own property should allow for adjustment mechanisms to work more efficiently in times of crisis, lessening the pain felt due to an exogenous shock. Property rights are expressed here as "contract-intensive money" (Clague et al. 1999); that is, the proportion of money held inside the formal banking sector.
- *Exchange Rate Type:* The more flexible a country's exchange rate regime is, the greater should be the ability to adjust to external shocks.[21] We use the Ilzetzki, Reinhart, and Rogoff (2019) definition of exchange rate regimes here, with higher values of their numerical classification indicating more flexible exchange rates.
- *External Openness*: This element is made up of two parts. Both a country's openness to trade and its openness to capital movements should allow for more rapid adjustments in the economy. We utilize the standard measure of trade openness (exports and imports as a percentage of GDP) and the Chinn-Ito (2008) indicator of financial openness to capture these metrics.

[20]The development of each of these subcomponents of the confidence indicator is shown in Appendix A, broken out by geographic groupings.

[21]Whether, or how much, a floating exchange rate actually insulates an economy from shocks does, however, remain debated. For example, Devereux, Engel, and Tille (2003) find that exchange rate pass-through is low. Indeed, a variety of other exchange-rate-related puzzles have generated a growing literature. Since this is outside the scope of our study, we refer readers to, for example, Rey (2013), Gopinath et al. (2020), and Itskhoki and Mukhin (2021) for additional details.

The foregoing metrics have all been given equal weighting in the composite indicator (i.e., summed and divided by four) and then normalized between 0 and 1. The assumption behind this aggregation is that each of these subcomponents has a beneficial effect on resilience—meaning the most flexible of systems (taken here to be the most resilient) would have a score, after normalization, of 1 and the least flexible would have a score of 0.

Three specific attributes of a country's political system are also viewed as contributing to resilience. Our variable choices are inspired by a large literature in political science and economics that has relied on our chosen metrics.[22] They are: the *extent of democracy* (as captured in the Polity "democracy" indicator), based on the theory that democracy can enable the transfers necessary to cushion the pain of economic shocks (Margalit 2019); *executive constraints*, essentially capturing the veto points in a polity, as a guard against bad economic policies (Arezki and Brückner 2010; Besley and Mueller 2018); and *government expenditures to GDP* (Bordo and Siklos 2021), as a measure of rigidity of the economy (i.e., responses determined based on budgetary cycles rather than price signals). Both democracy and executive constraints, taken from the Polity 5 database, are expected to have a positive relationship with institutional resilience, while the size of government should correlate negatively. We aggregate the (normalized) values of these three measures by adding democracy and executive constraints and subtracting out the size of government.

The overall institutional resilience measure (RES) is defined as a linear combination of the economic and political components of resilience. Both components are equally weighted due the absence of theoretical exposition on which component *should* be given more weighting. We are aware of the so-called "hierarchy of institutions" argument of Acemoglu, Johnson, and Robinson (2005) but prefer to remain agnostic on this question and leave it to future research.

The model that is confronted with the data is written

$$RES_{it} = f\big(\widehat{CONFIDENCE}_{it}, MACRO_{it}, INSTITUTIONS_{it}, ATTRIBUTES_{it}, CRISES_{it}\big). \tag{6}$$

[22]See https://www.systemicpeace.org/index.html, where both the raw data and publications associated with these data are available.

As in Equation (1), CONFIDENCE is the confidence which a country, i, holds in a central bank at time t. A country with less confidence or trust in its central bank is less likely to be resilient. The hat over the CONFIDENCE variable highlights that it is estimated separately.

The list of covariates, their theorized relationship with overall resilience, and data sources are shown in Table 1 and explained further below. The MACRO vector in Equation (6) refers to a vector of macroeconomic and country-specific variables which are separate from those which lead directly to resilience but which are likely to make an institutional system more resilient.[23] The INSTITUTIONS vector encompasses institutional volatility, including changes in underlying institutions such as property rights and democracy, added to capture how unstable institutions may affect resilience. ATTRIBUTES represent inherent traits of an economy unrelated to macroeconomics or related only peripherally, including land area, stocks of human capital, or resource abundance. Finally, CRISES is a constructed measure of "excess crises," using the cumulative total of financial/monetary/currency crises that a country has faced (taken from the Laeven and Valencia (2018) database) less the crises faced by the United States (proxying for global common shocks).[24]

We implement three model selection techniques to provide a more robust representation of the effects of central bank credibility. The methodologies applied are as follows:

[23]Inflation, as measured by annual change in consumer prices, is included in the list of plausible covariates. Readers will note that it is also a component of the confidence indicator. There is, however, not necessarily any collinearity either theoretically or econometrically. From a theoretical standpoint, the confidence indicator is constructed using actual performance of inflation measured against preset metrics (or theorized metrics) and thus is a distance variable. The distance performance of a central bank is not related to the underlying change in inflation, as the targets vary across countries and inflation is but one component of the distance variable. Econometrically, there is almost no correlation between the inflation metric and the confidence metric, with a simple correlation of 0.015 between the two. Finally, the model selection process, as will be shown below, consistently drops inflation as an explanator so that it does not even appear in the baseline specification.

[24]Within the database this means, for example, that during 2001, when the world was in a recession, the number of "excess" crises for any country would be 0, as it was a common shock.

Table 1. Covariates of Resilience

Variable [Mnemonic]	Source	Reasoning/Effect on Resilience
Arable Land (Hectares per Person) [ARABLELAND]	WorldBank WDI	More land area available for productive purposes (especially agriculture) can correlate with institutional resilience, in providing a basis for growth. Conversely, it may also trap countries in an agrarian mentality, harming resilience
Central Bank Independence [CBI]	Romelli (2021)	A more independent central bank should be more flexible and resilient than one which is beholden to the ruling government
Central Government Debt as a Percentage of GDP [DEBT]	IMF	Governments which are highly indebted have less fiscal space in the face of a crisis and thus are likely to display low institutional resilience
Conflict [CONFLICT]	UCDP/PRIO Armed Conflict Dataset Version 21.1	Conflict can presage the breakdown of institutions or at least their reordering, and thus we expect the presence of armed conflict to be negatively correlated with institutional resilience
Employment Growth in Percent [EMPG]	The Conference Board Total Economy Database	A business cycle measure; countries with abundant jobs and the ability to create them are likely to see more institutional resilience
Excess Crises [EXCESS CRISIS]	Authors' calculations based on Laeven and Valencia (2020)	Coded as the number of crises above and beyond crises which have occurred in the United States. Each additional, nonglobal crisis can weaken institutions and make them less resilient
Financial Risk [FINRR]	ICRG	Coded from 0 to 100, with higher numbers indicating lower risk. Countries which have more fragile macroeconomic conditions overall are likely to have less resilient institutions, especially in the face of exogenous shocks
Foreign Direct Investment, Net Inflows (Percentage of GDP) [FDI]	World Bank WDI	The presence of funding coming from outside one's own borders acts as a supplement to internal funding and can provide a safety net in times of crisis
GDP Growth [GDPGUSD]	World Bank WDI	Countries which are growing may be able to absorb more shocks than economically fragile ones
Real GDP Growth Forecasts	IMF	Used in combination with real GDP growth data to estimate forecast errors. See Equation (4)

Table 1. (Continued)

Variable [Mnemonic]	Source	Reasoning/Effect on Resilience
Human Capital [HC]	Penn World Tables	Measured as a human capital index based on the average years of schooling; we would expect countries with higher levels of educated workers to be more resilient, in terms of both institutions and economy
Inflation, Consumer Prices (Annual Percent) – [INF]	World Bank WDI	The presence of escalating prices can seriously undermine both political and economic institutions (Hartwell 2018a)
Inflation Forecasts (One Year Ahead)	IMF	Used together with inflation to estimate inflation forecast errors. See Equation (4)
Informal Output (Percentage of Official GDP) [INFORMALITY]	Elgin et al. (2021)	A dynamic general equilibrium (DGE) model-based estimate of the informal output of each country. Countries with large informal sectors may have weak formal institutional resilience; however, the presence of a large informal sector may also contribute to resilience via diversity and redundancies
Political Institutions Volatility, Three-Month [POLVOL]	Authors' calculations from Polity IV data	The three-month rolling standard deviation of the Polity indicator. Countries with erratic commitment to democracy are likely to see erosion of both political and economic institutional resilience over time
Population Growth, Percent [POPG]	World Bank WDI	Like land, population growth can signal a deeper pool of resources to draw upon in case of a crisis; it may also signal more inclusive rather than extractive institutions
Property Rights Volatility, Three-Month [PTYRIGHTS]	Authors' calculations from IMF data	The three-month rolling standard deviation of contract-intensive money. Countries with erratic enforcement of property rights are likely to see erosion of both political and economic institutional resilience
Resource Rents as a Percentage of GDP [TOTALNATURALRE-SOURCE]	World Bank WDI	Countries which are more reliant on natural resources are tied to commodity cycles and likely to be less resilient than countries which are well-diversified

(i) Bayesian Model Averaging (BMA)

(ii) Stepwise (Backward) Regressions; and

(iii) Lasso Regressions

The BMA approach utilized here is the "exact BMA" originally devised by Leamer (1978) and programmed by De Luca and Magnus (2011), combining "prior beliefs on the unknown elements of the model with the additional information coming from the data," weighting each individual model by its posterior probability (ibid., p. 521). Our priors are small indeed, leaving the model space open (and computationally intensive) for various combinations. In order to choose variables for the model, De Luca and Magnus (2011), following Barbieri and Berger (2004), suggest a median probability rule of retaining model variables which display an absolute t-ratio of greater than 1 (corresponding to a posterior inclusion probability of 0.5). We prefer to set a more stringent limit of a posterior inclusion probability of 0.75, in the vein of Jeffreys (1961), Kass and Raftery (1995), and Mutshinda, Finkel, and Irwin (2013), corresponding to a "strong" probability.

Next, we also utilize stepwise regression; the backward approach we use here starts with all explanatory variables in the model and then eliminates them one by one based on statistical significance. Given the well-known issues with stepwise regression (Thompson 1995; Smith 2018), we treat these results with caution, and only as a robustness test for the BMA regressions, and set a strict criterion of a t-stat of 2.54 (i.e., at the 1 percent significance level) to keep a variable through for the next model.

Lasso regression (Tibshirani 1996) is a penalized least-squares regression which shrinks the coefficients of variables based on their significance (theoretically zeroing-out insignificant coefficients and allowing for estimation using nonzero coefficients). Lasso is effective and widely used when there are a large number of covariates, and the fact that it retains variables within the model estimation means it avoids many of the issues with stepwise regressions.

Once we have settled on a list of covariates from the theoretically plausible set of determinants, identification of the impact of credibility and institutional resilience is achieved by fashioning a system-GMM approach, operationalizing Equation (6) as

$$Y_{it} = \alpha \widehat{CONFIDENCE}_{it} + \beta X_{it-1} + \varepsilon_{it}, \tag{7}$$

where Y is, as noted above, institutional resilience, *CONFIDENCE* is our constructed measure of confidence in a central bank, X is the lagged vector of controls noted in Equation (6), encompassing macroeconomic variables, country attributes, institutional volatility, and a measure of crises, and the error term (ε) is specific for each country. System-GMM was chosen as it is a preferred estimation technique in a panel setting such as this, with large N and moderate T, and it also has the ability to allow for fixed effects and correct for serial correlation, as well as correcting for heteroskedasticity of unknown form via clustering on the country variable.[25] The lags were chosen to correct for the well-known persistence of inflation (e.g., see Fuhrer 2010; system-GMM also fits our identification strategy as it works well in the persistence of key variables; see Heid, Langer, and Larch 2012) and to satisfy the identification conditions as checked by commonly utilized diagnostics (the Hansen J-statistic and the AR(n) tests).

Finally, as discussed earlier, resilience in statistical terms can be evaluated in the form of responses to shocks; that is, relying on impulse response functions. Accordingly, we report results from the estimation of local projections (LPs), introduced by Jordà (2005); also see Barnichon and Brownlees (2019) and Plagborg-Møller and Wolf (2021). This is a widely used methodology to estimate impulse responses from vector autoregressions (VARs). The intuition behind the technique is that the impact of a shock in the current period (the impulse) can be traced out from forecasts of the dependent variable of interest in future (the response). We only report the responses to

[25]As a robustness test, not shown here, we also utilized a static panel fixed-effects model, absorbing country fixed effects. However, the short time span for most countries (an average t of 25 years) meant that Nickell bias was likely prevalent. Additionally, the manifest endogeneity of many of the variables became clear, as the human capital variable tended to absorb all of the significance in the equation. Results available from authors on request. In order to identify the model as shown in Equation (7), we use an instrumentation strategy which instruments the variables found significant in the model selection via their closest feasible lags, while variables found insignificant in the model selection process are included as instruments at their levels (all instruments are collapsed to avoid overfitting).

key determinants of central bank resilience, while others are available on request.

4. Data and Results

Because our empirical exercise relies on several institutional variables obtained from a variety of sources, it is natural to ask about the quality of the data employed. Space limitations prevent a detailed discussion. Fortunately, others have investigated the properties of the series employed here. IMF data are among the most widely used in empirical economics and there are regular reviews and assessments of the quality and reliability of the large number of time series collected (e.g., see the IMF's Dissemination Standards Bulletin Board).[26] The same comment applies to the World Development Indicators database.[27] Romelli (2021) is the source for the most recently updated central bank independence (CBI) data and comparisons are made with the other most widely used and available indices. Comparisons with other CBI metrics are also provided by the authors. Romelli's data also have the advantage of including a wider array of central bank characteristics and legal features than other indices that have been previously published. As a result, the data are relatively more robust to measurement errors. It is worth pointing out, however, that all such CBI indicators are de jure and not necessarily de facto measures (although it is not clear that this should induce a difference in the perception of central bank confidence unless there is a large gap between the two).

While several authors have constructed financial crises indicators and chronologies (e.g., Reinhart and Rogoff 2009; Schularick and Taylor 2012), the Laeven and Valencia (2020) data are among the most widely used (e.g., see Huynh and Uebelmesser 2024) and their chronology has the added advantage of being based on a broader

[26] https://dsbb.imf.org/dqrs/DQAF.

[27] "...a compilation of relevant, high-quality, and internationally comparable statistics..." (from https://datatopics.worldbank.org/world-development-indicators/stories/world-development-indicators-the-story.html). Also, see World Bank (2018).

definition of what constitutes a banking crisis than alternative indicators. The human capital series, from the Penn World Tables, is based on Barro and Lee's (2013), which is arguably the best known, but not the only indicator or measure of educational attainment.[28] The Polity data are considered "the most closely scrutinized data on political issues," while the same description applies to the ICRG database, which combines qualitative and quantitative risk metrics and covers well over 100 countries (e.g., see Levieuge, Lucotte, and Pradines-Jobet 2019, and references therein). In a similar vein, the data on armed conflict come from the gold standard in this area, the UCDP/PRIO Armed Conflict Dataset from Uppsala University, covering all armed conflicts from 1946 to 2022 where at least one party is a state actor. The extent of a country's informal economy is taken from Elgin et al. (2021), who have created a database which has strong cross-country and time-series coverage and which far outpaces other data on informality. Other data sources consulted include the OECD (Main Economic Indicators, Economic Outlook), the BIS, and the Conference Board. All are routinely used in empirical research.

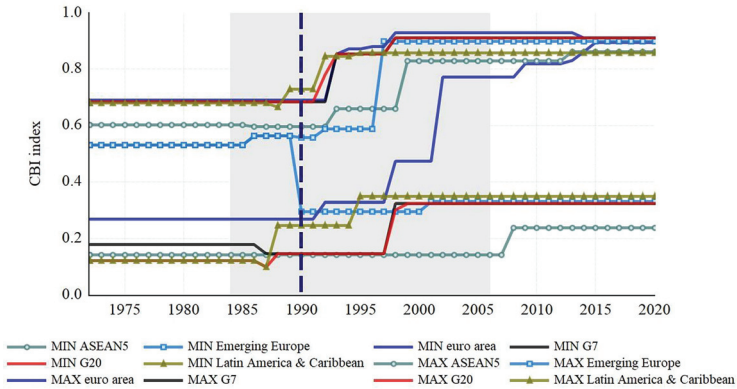
All estimation was conducted at an annual frequency (summary statistics can be found in Appendix B). When we maximize the number of covariates included in estimation, the econometric results discussed in reality encompass the period starting from 1990, and this does not reflect the lags utilized in Equation (6).[29] Nevertheless, several series have been available since the early 1960s. We provide some discussion of these data in the next section. The countries in the data set represent around 80 percent of global GDP,[30] while differences in inflation performance between all potential countries and the ones that remain when Equation (6) is estimated are very small. Our econometric estimates are based on a data set which varies between 92 countries at a minimum and 107 countries as the maximum, with a mode of 100 countries; the differing number of

[28]Fraumeni (2015) provides a comparison of alternative human capital indicators relative to the Barro and Lee measure. The study does not reach a firm conclusion about whether one indicator is superior to the others.

[29]As a result, plots shown in Figure 2 show data for the sample from 1992 to 2019, capturing the use of lags in the model.

[30]See https://g20.org/.

Figure 1. Central Bank Independence



Note: Based on annual data from Romelli (2021). The shaded area is the period of the Great Moderation (1984–2006). The minimum value for the CBI index is 0, the maximum is 1. Data are available from dromelli.github.io/cbidata/index.html. There is some overlap between certain country groupings (i.e., G7 and G20; G20 and Latin America and Caribbean; G7, G20, and euro area). Appendix D provides more details about the countries included in each country group and where overlap exists. The total number of non-overlapping countries included in the figure is 79. The vertical line is drawn at 1990, which dates the start of the sample used in most of the econometric results presented in Tables 2 and 3.

countries across specifications is due to data availability on covariates (see Appendix C for the list of countries by model selection method). Regardless, the large coverage here gives us hope that we are capturing the true effects of the relationship.

4.1 A Few Stylized Facts

Figures 1 and 2 provide a few stylized facts. Figure 1 illustrates the indicator of overall central bank independence (CBI) used since the early 1970s for several country groupings. CBI has often been used to assess the performance of monetary authorities across a wide range of macrofinancial and institutional variables, including inflation, real GDP growth, and transparency and accountability.[31] We

[31]There is no let-up in investigations of links between CBI and macroeconomic and institutional performance. Readers are asked to consult, for example, Dincer

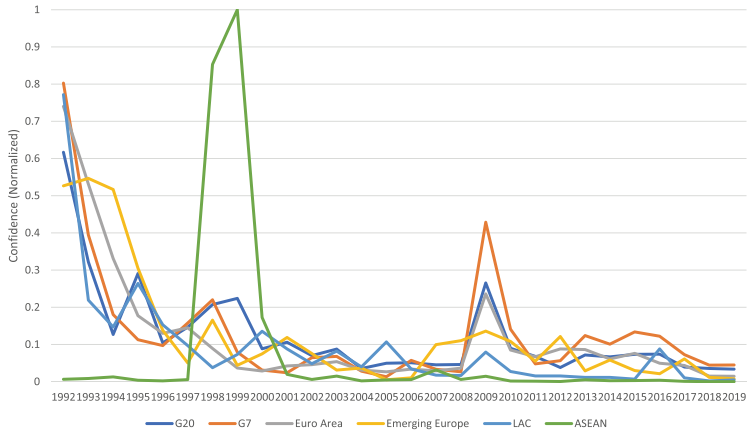
use the country groupings defined by the IMF in its WEO publication to estimate average levels of independence (see Appendix D for details). The shaded area highlights the era of the Great Moderation as a benchmark.

While there is a general tendency for CBI to rise over time there remains considerable heterogeneity across various regions of the world. Indeed, the gap between highest (MAX) and lowest (MIN) levels of CBI has widened over time in most regions of the globe shown in Figure 1. Using a vertical line, Figure 1 also identifies when the sample begins for the econometric tests reported below. Prior to the 1990s there is little variation in CBI over time between country groups. This also partly explains why the results shown in the tables to follow (Tables 3 and 4) pertain to the last three decades of data (i.e., 1990–2020). Moreover, while the tests below were conducted for longer samples, there is also a loss of data as several of the series listed in Table 1 are not available for many countries before the 1990s and even more are missing before the 1980s. Finally, it is also worth pointing out that CBI was rising when the global economy was well into the period of the Great Moderation. On average, governments granted greater autonomy to monetary policymakers after inflation began to moderate and economic growth became less volatile. That said, the subsequent era of financial crises (i.e., the period since 2006) does not yet appear to suggest a reversal of fortune in CBI.

Figure 2 plots, for the sample used in the econometric testing below and for the same country groupings as in Figure 1, our measure of confidence in a central bank (CONF; see Equation (1)), which aggregates target misses (TMISS), monetary policy uncertainty (MPU), and the global factor (GDEV). As noted, a lower value of CONF translates into greater confidence in the central bank. Plots of the individual components can be found in Appendix A. Three notable features are seen in the plot. First, there is considerable heterogeneity in central bank confidence over time. Indeed, as

and Eichengreen (2014), Garriga and Rodriguez (2019), Romelli (2021), Adrian, Kahn, and Menand (2024), and references therein. While CBI plays an important role in the empirical work below, it is only one of several other components we argue can and should be employed to evaluate the performance and resilience of central banks.

Figure 2. Confidence in Central Banks



Note: See Figure 1 and Equation (1) for details. A lower level of CONF translates into greater confidence in the central bank.

might be expected, CONF is far more volatile than CBI. CONF in the G7 is generally much lower than elsewhere in the world although the ASEAN5, Latin America and the Caribbean, and indeed the G20, have overtaken the G7 for some years after the GFC. We also observe the spike in CONF among the richest economies (i.e., G7, euro area) during the GFC, which translates into a temporary, but large, drop in confidence in central banks. While CONF recovers post-GFC, it only comes close to pre-GFC levels by the end of the sample.

This same dispersion of our CONF variable can be seen on a country-by-country basis in Table 2, which displays the minimum and maximum of the raw (nonnormalized) confidence scores by each country used in the most expansive econometric estimation (see also below). While some countries have minima below zero (corresponding to lower-than-expected inflation performance), the more interesting metric is the maximum scores, which show by how much a country's central bank has missed its targets or how uncertain its policies have been. For the maxima shown in Table 2, the dispersion for advanced countries is tightly clustered, while countries such as Brazil have a maximum score of multiple millions and the Republic of Yemen has the worst-performing central bank globally, with

Table 2. Variation across Confidence and Resilience, by Country

Country	Raw Confidence Score			Resilience			Sample Period
	Std. Dev.	Min.	Max.	Std. Dev.	Min.	Max.	
Albania	4,537.56	–0.30	23,418.03	0.498	0.595	2.000	1993–2019
Algeria	135.01	–2.55	556.77	0.578	0.003	1.998	1992–2019
Angola	1,710.01	–56.55	5,594.50	0.200	0.701	1.475	2004–2019
Australia	2.96	–0.61	12.14	0.345	0.421	1.388	1992–2019
Austria	2.62	–0.62	11.53	0.220	0.472	1.201	1992–2019
Bahrain	25.97	–2.25	128.78	0.638	0.020	1.987	1992–2018
Bangladesh	3.75	1.52	16.93	0.534	0.051	1.758	1992–2019
Belgium	3.89	–0.77	16.87	0.622	0.000	1.964	1992–2019
Bolivia	447.60	1.50	2,388.94	0.625	0.096	1.953	1992–2019
Botswana	24.80	1.40	94.45	0.598	0.327	1.987	1992–2019
Brazil	780,699.50	2.36	4,115,369.00	0.474	0.474	1.997	1992–2019
Bulgaria	204,150.50	–1.31	1,072,750.00	0.337	0.950	2.000	1992–2019
Burkina Faso	246.26	–4.68	1,128.71	0.445	0.191	1.502	1992–2019
Cambodia	105.12	0.97	505.83	0.405	0.263	1.961	1996–2018
Cameroon	82.87	–1.69	351.11	0.341	0.232	1.353	1992–2019
Canada	2.45	–1.54	11.12	0.707	0.065	1.972	1992–2019
Chile	71.59	0.78	375.24	0.674	0.070	1.957	1992–2019
China	54.90	0.55	263.68	0.262	0.998	1.995	1992–2019
Colombia	54.84	1.25	220.26	0.276	0.130	1.117	1992–2019
Congo, Rep.	156,000,000.00	5.79	568,000,000.00	0.488	0.003	1.326	1992–2019
Costa Rica	111.73	0.06	414.90	0.387	0.198	1.635	1992–2019
Croatia	385,084.30	–0.79	1,963,973.00	0.544	0.000	1.998	1994–2019
Cyprus	78.00	0.26	341.95	0.370	0.631	2.000	1994–2019
Czech Republic	79.59	0.07	286.92	0.263	0.886	1.933	1993–2019
Denmark	3.98	–1.47	19.23	0.219	0.524	1.324	1992–2019

(*continued*)

Table 2. (Continued)

Country	Raw Confidence Score			Resilience			Sample Period
	Std. Dev.	Min.	Max.	Std. Dev.	Min.	Max.	
Dominican Republic	492.12	4.39	2,074.61	0.531	0.367	1.999	1992–2019
Egypt, Arab Rep.	51.47	0.19	202.19	0.570	0.001	1.999	1992–2019
Estonia	920.53	0.07	4,522.94	0.389	0.328	1.998	1994–2019
Ethiopia	568.61	9.13	2,130.15	0.340	0.363	1.540	2003–2019
Finland	7.00	–1.38	30.72	0.355	0.145	1.385	1992–2019
France	2.25	–1.23	8.90	0.325	0.877	1.999	1992–2019
Gabon	180.53	–2.00	822.36	0.257	0.823	2.000	1992–2019
Germany	3.95	–1.30	16.66	0.351	0.262	1.556	1992–2019
Ghana	401.53	6.16	1,468.94	0.381	0.538	2.000	1992–2019
Greece	13.00	–0.17	51.53	0.276	0.997	1.998	1992–2019
Guatemala	171.24	2.00	916.95	0.652	0.030	1.952	1992–2019
Hungary	77.01	1.02	394.84	0.450	0.115	1.999	1992–2019
India	16.71	1.29	66.30	0.460	0.178	1.996	1992–2019
Indonesia	399.63	1.20	1,648.86	0.748	0.000	1.905	1992–2019
Iran, Islamic Rep.	169.66	20.98	756.37	0.497	0.256	1.999	1992–2019
Ireland	10.88	–0.58	35.17	0.289	0.430	1.358	1992–2019
Italy	3.50	–0.84	15.02	0.397	0.088	1.394	1992–2019
Jamaica	1,632.54	1.82	8,545.20	0.391	0.208	1.706	1992–2019
Japan	40.74	–3.18	212.72	0.115	0.560	1.103	1992–2019
Jordan	60.52	–1.31	246.62	0.739	0.020	1.903	1992–2019
Kazakhstan	29.67	5.11	96.97	0.241	0.209	1.005	2007–2019
Kuwait	722.36	–0.12	3,750.19	0.560	0.144	1.989	1992–2019
Kyrgyz Republic	118.04	0.53	481.18	0.315	0.334	1.446	1997–2019
Latvia	158,398.50	0.89	792,339.30	0.546	0.187	1.828	1993–2019
Lithuania	146,222.10	–0.75	724,295.10	0.529	0.094	1.737	1993–2019
Malaysia	12.40	0.00	64.96	0.435	0.004	2.000	1992–2019
Mali	162.00	–1.78	750.44	0.376	0.504	1.714	1992–2019
Mauritius	11.07	0.08	48.87	0.621	0.049	1.954	1992–2019

(*continued*)

Table 2. (Continued)

Country	Raw Confidence Score			Resilience			Sample Period
	Std. Dev.	Min.	Max.	Std. Dev.	Min.	Max.	
Mexico	107.26	1.00	450.11	0.722	0.082	1.999	1992–2019
Moldova	620,067.00	4.75	2,435,056.00	0.387	0.670	1.996	1993–2019
Morocco	22.22	–1.71	105.25	0.506	0.007	1.997	1992–2019
Myanmar	661.33	0.41	2,608.47	0.232	0.760	1.563	2002–2019
Namibia	9.04	2.89	37.99	0.467	0.378	1.974	2004–2019
Netherlands	2.00	–1.28	6.79	0.370	0.072	1.331	1992–2019
New Zealand	2.62	–1.67	10.30	0.353	0.027	1.394	1992–2019
Niger	177.25	–1.36	696.28	0.555	0.002	1.895	1992–2019
Nigeria	600.87	8.94	2,439.02	0.464	0.435	1.802	1992–2019
Norway	2.52	–1.33	8.45	0.233	0.423	1.574	1992–2019
Pakistan	11.69	1.74	47.24	0.563	0.020	1.904	1992–2019
Paraguay	57.70	1.49	222.80	0.680	0.043	2.000	1992–2019
Peru	25,228.02	0.48	133,613.70	0.569	0.199	1.999	1992–2019
Philippines	28.85	1.11	156.96	0.701	0.077	1.958	1992–2019
Poland	5.97	–0.84	23.90	0.637	0.068	1.993	2000–2019
Portugal	2.64	–1.09	8.17	0.292	0.998	1.997	1992–2019
Qatar	137.15	0.82	616.54	0.699	0.025	1.928	1992–2019
Romania	7,978.41	–0.02	25,476.40	0.544	0.118	1.998	1992–2019
Russian Federation	76,310.87	1.57	388,413.50	0.289	0.872	1.798	1994–2019
Rwanda	69.95	6.04	314.98	0.725	0.002	1.996	1992–2019
Saudi Arabia	34.71	–2.05	163.90	0.445	0.255	1.633	1992–2019
Senegal	190.34	–1.96	751.22	0.648	0.064	1.888	1992–2019
Singapore	12.96	–2.48	48.18	0.693	0.013	1.998	1992–2019
Slovak Republic	33.09	0.70	161.12	0.353	0.753	1.895	1994–2019
Slovenia	106.02	–0.02	477.01	0.374	0.045	1.618	1994–2019
South Africa	10.36	2.31	50.09	0.723	0.015	1.999	1992–2019
South Korea	2.50	–0.58	9.32	0.654	0.048	1.967	1992–2019
Spain	4.28	–0.63	19.35	0.280	0.999	1.999	1992–2019
Sri Lanka	104.75	3.73	507.02	0.354	0.375	1.611	1992–2019
Sweden	3.90	–2.31	16.57	0.220	0.675	1.489	1992–2019

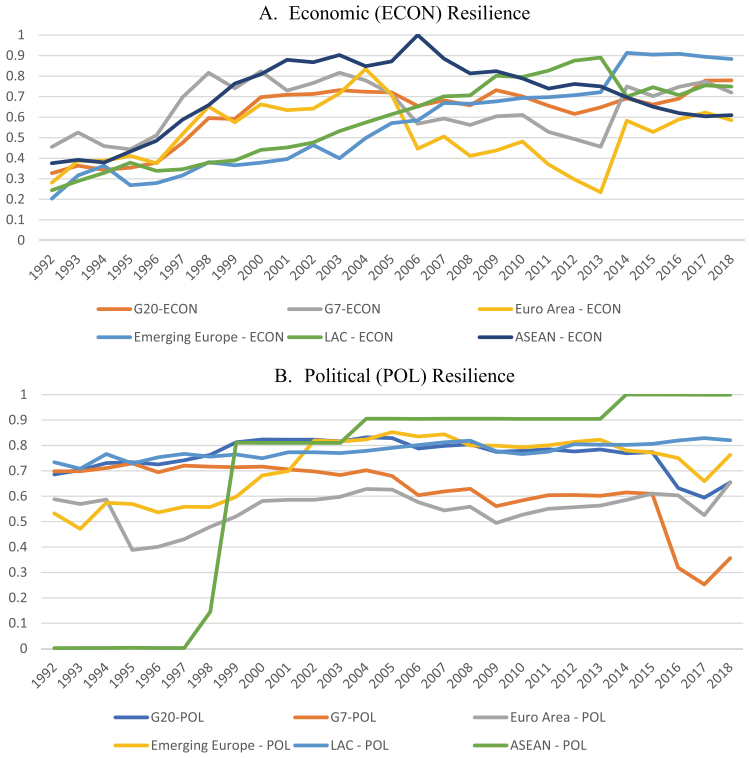
(*continued*)

Table 2. (Continued)

Country	Raw Confidence Score			Resilience			Sample Period
	Std. Dev.	Min.	Max.	Std. Dev.	Min.	Max.	
Tanzania	283.22	2.45	1,308.90	0.378	0.156	1.229	1992–2019
Thailand	15.41	–0.89	61.95	0.573	0.022	1.831	1992–2019
Togo	192.08	32.40	897.79	0.585	0.131	2.000	1992–2019
Trinidad and Tobago	33.17	2.62	151.07	0.512	0.252	2.000	1992–2018
Tunisia	5.98	0.84	27.22	0.551	0.001	2.000	1992–2019
Turkey	771.46	8.50	3,981.43	0.424	0.249	1.898	1992–2019
Uganda	60.66	–0.40	229.17	0.213	0.207	1.078	1995–2019
Ukraine	3,160,807.00	9.27	15,800,000.00	0.282	0.505	1.492	1994–2019
United Arab Emirates	53.49	1.59	181.81	0.318	0.700	1.955	2009–2019
United Kingdom	2.19	–1.26	9.75	0.291	0.884	1.986	1992–2019
United States	3.71	–0.64	16.98	0.340	0.782	1.847	1992–2019
Uruguay	2,141.47	3.89	11,278.23	0.528	0.087	1.999	1992–2019
Venezuela	270,000.50	35.43	715,338.80	0.224	0.574	1.532	2010–2016
Vietnam	782.92	–1.19	3,615.22	0.410	0.417	1.984	1997–2019
Yemen, Rep.	273,000,000,000,000,000.00	11.25	1,020,000,000,000,000,000.00	0.347	0.334	1.595	1994–2014
Zambia	7,697.03	18.12	30,181.63	0.649	0.197	1.880	1992–2019

Note: Equation (1) defines CONFIDENCE. In the estimation phase, CONFIDENCE is normalized for reasons explained in Section 4.1.

Figure 3. Economic and Political Resilience



Note: Resilience (RES) is defined in Equation (6). The discussion in Section 3.2 provides the details about the economic and political components of RES.

a maximum score of 1.02 quintillion.[32] These confidence indicators are also matched against the dispersion (maximum, minimum, standard deviation) in the normalized resilience indicators, which are far less disciplined by country type—put another way, it appears that countries can change their resilience substantially, and development level is not correlated with resilient policies.

Figure 3 puts the various inputs into resilience together into two parts: economic and political components of resilience. We plot

[32]The massive dispersion of these raw scores is another reason why the overall confidence indicator has been normalized.

levels of resilience for the same country groups as in Figures 1 and 2 for consistency. Resilience (RES in Equation (6)) is defined such that more confidence in central banks and greater institutional trust, as well as an improved ability to react to macroeconomic and financial shocks, define more resilience. On this score, levels of both economic and political resilience have risen over time, although the changes can be region- or country group-specific. Overall, there is a slow but noticeable downward trend since a major improvement took place in the mid-1990s, when positive institutional developments (e.g., more central bank independence) gathered pace and the Great Moderation was in full swing. There is a clear decline in economic resilience in the euro area associated with the sovereign debt crisis while many parts of the world, notably in emerging Europe and the G7, experience a rise. Nevertheless, there are signs of modest declines in this form of resilience following the GFC.

A similar pattern is seen in the political resilience indicator. However, we note a sharp rise in political resilience especially after the Asian financial crisis of 1997 and the drop in political resilience in the G7 after 2016,[33] while resilience in the euro area rises in the aftermath of the sovereign debt crisis. Finally, economic resilience is seen to improve toward the end of the sample. This development precisely captures the concept of resilience, namely the ability to withstand and recover from developments that have a negative impact on the public's confidence in central banks.

4.2 Results: Model Selection and Econometric Results

The results from the three model selection approaches are shown in Appendix E; the BMA analysis, comprising 65,536 unique models, indicated a parsimonious set of six control variables in addition to the lagged central bank credibility indicator, while the stepwise approach indicated only a slightly larger set of eight control variables and the Lasso approach took in nine covariates.

The results from the regressions relating institutional resilience to central bank confidence take these results into consideration and are shown in Table 3 for the system-GMM model. Given the

[33] We cannot determine, of course, whether this is triggered by the U.S. elections that year.

Table 3. System-GMM Results, Factors Affecting Institutional Resilience

	1	2	3	4	5
	BMA	**Stepwise**	**Lasso**	**Lasso**	**Lasso**
	SYS-GMM	**SYS-GMM**	**SYS-GMM**	**Pre-GFC (1990–2009)**	**Post-GFC (2010–19)**
CB Credibility	–0.35	–0.38	–0.39	–0.52	–0.73
	*3.15***	*2.81***	*2.84***	*2.73***	*2.07***
Property Rights Volatility	–8.64	–6.88	–6.57	–9.76	–9.42
	*2.41***	*2.16***	*2.05***	*1.43*	*1.30*
Central Government Debt	–0.001			NA	NA
	0.93				
Human Capital	–0.07	0.24	0.24	–0.06	
	0.62	*1.19*	*1.22*	*0.26*	
FDI	0.003		0.003	0.010	
	1.08		*1.02*	*0.83*	
Informality		0.02	0.02	0.02	0.010
		1.21	*1.26*	*1.70**	*0.69*
GDP Growth		0.03	0.03	0.01	
		*2.09***	*2.17***	*1.04*	
Population Growth		0.76	0.67	20.62	
		0.55	*0.56*	*2.64****	
Central Bank Independence (CBI)	0.71	0.74	0.66	0.25	–1.67
	*2.74****	*2.46***	*2.19***	*0.48*	*1.45*
Excess Crises	–0.08	–0.09	–0.09	–0.37	
	0.75	*0.65*	*0.73*	*2.16***	
Resource Rents		0.003	0.0001	–0.020	
		0.07	*0.02*	*2.04***	
Debt	NA	NA	NA	–0.003	0.002
				1.16	*0.86*
N	2,023	2,219	2,219	1,319	732
Number of Instruments	97	97	97	65	33
AR(n)	0.583	0.687	0.572	0.35	0.11
Hansen Statistic	0.45	0.325	0.334	0.554	0.214
Lag Structure	4 8 collapsed	4 8 collapsed	4 8 collapsed	8 10 collapsed	3 3 collapsed

Note: Absolute value of t-stats underneath the coefficients. *,**,*** denotes 10 percent, 5 percent, and 1 percent level of significance respectively. The AR(n) test gives the test of serial correlation for the first lag of the lag structure used.

similarities in the model selection process, for many of the GMM models the only changes are thus to be found in the instrumentation strategy, shifting according to the covariates found to be significant. Starting from the BMA analysis, our key variable of interest has a consistent result across all model selection criteria, with lower central bank credibility (manifested in a higher score) correlating strongly and significantly with lower institutional resilience. Across models, each percent increase in the central bank (non)confidence measure corresponds with an average 3.6 percent drop in institutional resilience.

For the remaining covariates, the results are uniform, with property rights volatility and government debt having a strong negative relationship; in terms of scale for property rights volatility, the highest amount of property rights volatility in the set (0.264, found in Ghana in 1964) corresponds to a drop of 57 percent in institutional resilience. Even when observed at its mean, the presence of property rights volatility results in an average 2 percent drop in resilience. In terms of positive influences on resilience, only GDP growth and central bank independence enter in as positive in two of the three regressions. The remaining determinants are all statistically insignificant.

4.3 Robustness Testing

These results point to a clear relationship between how key economic institutions perform and (lack of) institutional resilience, as, uniformly, a lack of central bank credibility correlates strongly and negatively with resilience. To see if these results are robust to changes in variables or methods, we undertake an extensive battery of robustness tests.

First, to rule out that a resilience effect is specific just to various years, we break out our sample into two time periods, a pre-GFC period (to 2009) and a post-GFC period (2010 onward) (last two columns of Table 3). As can be seen, the effect of central bank credibility is more statistically significant in the pre-GFC period, although it remains significant in both periods; perhaps of more interest is that so many plausible covariates drop out via the BMA model selection procedure in the post-GFC world, leaving central bank credibility, property rights volatility, debt, and central bank

independence as the only determinants of resilience. It must be noted that none of these has a positive effect on resilience, apart from a central bank which adheres to its stated policy goals. This second model also requires some caution in interpretation, as the only significant variable is the confidence variable; more importantly, the vast reduction in observations makes the system-GMM model more fragile, with serial correlation being rejected but only at the 11 percent level.

We replace covariates which are similar (and have high collinearity), but which could be capturing additional effects related to resilience, to see if the relationship between resilience and central bank credibility remains (Table 4). Given the stronger performance of central bank credibility in the Lasso model from Table 3, we have chosen to retain this variable set as the model to check robustness. In the first instance, column 1 shows the effects of replacing the human capital indicator from the Penn World Tables with another metric to proxy for human capital, namely mortality rates; high mortality is both a significant negative correlate with human capital and should have a deleterious effect on resilience. This model is even stronger than our baselines, with mortality having little effect but lack of central bank credibility continuing to have a significantly negative effect on resilience. A similar effect holds when we replace government debt with an overall indicator of "financial risk" (related to debt, current account, and other indicators of government finances; see Table 1), entering into the system-GMM (column 2) as also significant: as can be seen, the results of central bank credibility remain unchanged, albeit at a slightly smaller level of economic significance.

Building on the fact that perhaps the central bank itself is better the longer it is around, column 3 also includes a dummy if a country had a central bank pre-Second World War (i.e., 1939 or earlier). This variable will hopefully capture two possible effects: first, central banks which have been around for a much longer period have institutional memory in dealing with inflation; second, and perhaps more importantly, central banks which have existed for a hundred years might have already built up a store of credibility, meaning we would expect that countries which had a central bank pre-World War II would have more institutional resilience. However, rerunning the Lasso selection shows that this variable is insignificant, and so it is instead included as an additional instrument. In any event, this

Table 4. Robustness Tests

	1	2	3	4	5	6	7
	System-GMM	**System-GMM**	**System-GMM**	**System-GMM**	**System-GMM**	**Tobit (Lasso)**	**Tobit (BMA)**
CB Credibility	–0.38	–0.28	–0.37	–0.32	–0.30	–0.22	–0.21
	*3.43***	*2.89***	*2.83***	*2.53***	*2.38***	*3.45***	*3.25***
Property Rights Volatility	–2.91	–5.12	–3.02	–6.56	–9.90	–4.29	–3.46
	1.26	*1.94**	*1.25*	*1.95**	*3.09***	*3.70***	*3.18***
Human Capital		0.23	0.16	0.20	0.04	0.05	0.005
		1.42	*0.74*	*1.26*	*0.25*	*1.01*	*0.09*
Mortality	0.001						
	0.81						
FDI	0.0009	0.001	0.0003	0.003	0.0004	0.001	0.003
	0.35	*0.19*	*0.13*	*0.94*	*0.15*	*0.88*	*2.32***
GDP Growth	0.01	0.01	0.005	0.02	0.01	0.01	
	1.08	*1.08*	*0.60*	*2.31***	*1.35*	*2.10***	
Population Growth	1.76		0.87	0.46		0.19	
	0.87		*0.66*	*0.44*		*1.14*	
Central Bank Independence (CBI)	1.02	0.77	1.08	0.83	–0.22	0.03	0.08
	*3.71***	*2.71***	*3.30***	*3.10***	*0.44*	*0.19*	*0.46*
Informality	–0.006	0.01	0.005	0.01	0.01	0.003	
	0.75	*0.99*	*0.31*	*1.09*	*1.54*	*1.04*	
Excess Crises	–0.06		–0.05	0.04	–0.20	–0.12	–0.15
	0.37		*0.42*	*0.33*	*1.23*	*3.12***	*3.76***
Resource Rents	0.004		0.01	0.001		–0.001	
	0.76		*1.96***	*0.32*		*0.40*	

(*continued*)

Table 4. (Continued)

	1	2	3	4	5	6	7
	System-GMM	**System-GMM**	**System-GMM**	**System-GMM**	**System-GMM**	**Tobit (Lasso)**	**Tobit (BMA)**
Land Area			–1.21				
			*1.69**				
Financial Risk		0.03					
		*3.95****					
Years of a Central Bank				–0.001			
				0.51			
Debt					–0.009		–0.001
					*1.91**		*1.78**
CBI*Debt					0.01		
					*1.85**		
N	2,349	2,141	2,216	2,219	2,023	2,219	2,023
Number of Instruments	97	97	92	98	86		
AR(n)	0.237	0.4670	0.134	0.829	0.8710		
Hansen Statistic	0.18	0.351	0.202	0.285	0.295		
Lag Structure	4 8 collapse	4 8 collapse	4 8 collapse	4 8 collapse	5 8 collapse		

Note: Absolute value of t-stats underneath the coefficients. Column 3 uses pre-war central bank existence as an additional instrument, as it was insignificant in a rerun Lasso model selection test.

does not change the effects of lower confidence in central banks on institutional resilience. Similarly, perhaps it is not just if a bank has been in existence for a long time but how long, and we thus include a variable measuring the number of years a central bank has been in existence to capture more recent memory effects (column 4). The same result is obtained, with Years of a Central Bank entering in directly in the equation but not significant, drawing some minor significance from the credibility of the bank and its effect on institutional resilience (p=0.011). Keeping with this same theoretical line, we posit that perhaps it is how central banks handle their debt which is the key measure for resilience, and we find (column 5) that interacting CBI and levels of debt does show an improvement in resilience, as more independent central banks do contribute to higher levels of resilience via their management of debt. However, this result is significant only at the 10 percent level, and credibility remains a key determinant of resilience at the 5 percent level.

Given that the resilience indicator we utilize here is censored from left and right between the values of 0 and 2, we utilize a tobit regression in columns 6 and 7 for both the Lasso and BMA results respectively. As the tobit model does not account for endogeneity or fixed effects, these results should be interpreted more cautiously, and indeed, excess crises have much more of an effect here: we surmise this is the case because the underlying causes of crises are not used as instruments. In any event, while the magnitude of the resilience effect is smaller, the statistical significance of the central bank credibility variable remains strong.

Finally, a selection of impulse responses from estimated local projections are shown in Figure 4. We focus on the impact of shocks from four of the covariates shown in Tables 2 and 3 which have a consistently statistically significant impact on resilience, including central bank credibility, government debt, financial risk, and property rights volatility.[34] When the full data set is considered, central bank credibility is found to raise resilience at all lags.[35] However,

[34] Of course, we also examined the impact of other covariates (not shown). For example, CBI is found to raise resilience but only since 2010. This explains, perhaps, the mixed evidence reported above in relation to this variable.

[35] Given the span of the sample when all covariates are included and the annual frequency, five-year-ahead impulse responses are deemed to be sufficient.

Figure 4. Selected Impulse Responses from Local Projections

Note: Impulse responses for a one-unit shock in the variables shown on RESILIENCE. The black lines are the estimated impulse responses; the red lines are the 68 percent confidence bands. Credibility, debt, FINRR (Financial Risk), and PTYRIGHTS (property rights volatility) are explained in the text and in Table 1. EME, G7, and G20 are, respectively, the emerging market, Group of Seven and Group of Twenty economies in the data set. Estimates are for the full sample (i.e., starting in 1990). Depending on the variables included in the VAR (see Tables 3 and 4), between 83 and 85 countries are included.

the evidence is a little more mixed when only the EMEs are considered, although after one and four years, credibility does improve resilience. It appears that this link is more fragile than for the "rest of the world" (dominated by AEs) and this result parallels the one in

Bordo and Siklos (2021). Similarly, rising government debt reduces resilience, and this result holds even more strongly for the G20 economies, a mix of AEs and EMEs. Financial risk (see Table 1), when it translates into more financial fragility, also reduces resilience for all countries, including EMEs. Finally, the clearest effect comes from the property rights volatility variable, as a rise in this form of volatility unambiguously reduces resilience. Overall, the local projections shown generate results that mirror the regression results discussed above.

The bottom line is that central bank performance, as measured by credibility, and institutional factors, including central bank autonomy and the protection of property rights (to give two examples from a wide variety of indicators examined), robustly explain the resilience of monetary policy as defined in this study. This conclusion is a global one, although there is a small amount of evidence that the nexus between central bank resilience and its determinants may be relatively weaker in EMEs.

5. Conclusions

This paper examines the links from central bank credibility to trust to overall institutional resilience. In positing these links, extant research offers few clues on the factors affecting institutional resilience, preferring to offer instead what resilience encompasses. Building on this gap in the literature, we offer robust empirical evidence about what drives institutional resilience and let our data do the talking via several model selection methods. Applying dynamic panel models, we show that confidence in a central bank—expressed as a function of how good it is at its job, i.e., controlling inflation—is directly related to overall institutional resilience. In particular, the more a central bank loses confidence via missing inflation targets or veering from global trends, the more harm it does to overall institutional resilience in a particular country. Simply put, given the centrality of a central bank to a country's institutional system, both political and economic, the faltering of a central bank in its mission is bound to lead to a loss of resilience for the system.

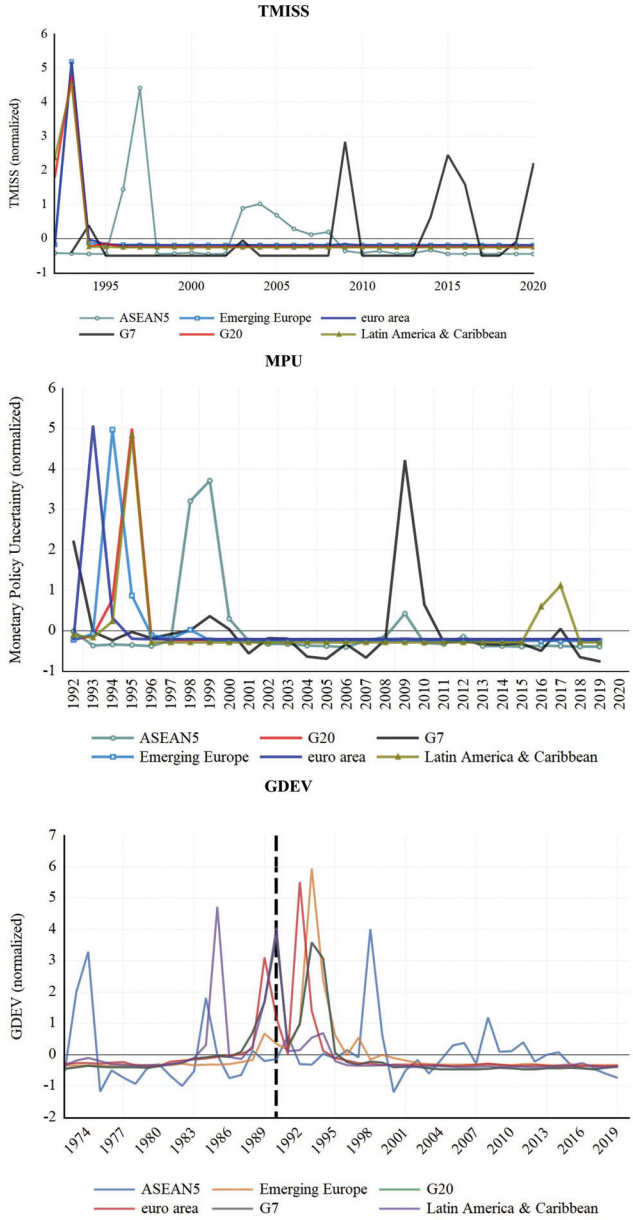
As noted earlier, there is very little to guide our path in theorizing what exactly drives resilience at either the economic or institutional level, making our identification strategy one of the first of (we hope)

a long line of attempts to isolate the relationship between central banks and their institutional environment. Indeed, we have shown a novel attempt to fashion empirical evidence for both confidence in the central bank and institutional resilience and one which builds on existing theories to guide the empirical approach. Accordingly, we invite other researchers to follow in "the wake of Magellan" and explore these issues much more deeply.[36]

Conviction is growing among academics and policymakers that institutional resilience is a critical ingredient not just for central banks but for society more generally. In part to enhance the robustness of our findings, we encourage the search for different ways to quantify institutional resilience at both the political and economic system level, drawing on other disciplines where resilience is an important characteristic, as well as more rigorously modeling the relationship between macroeconomic variables and overall institutional resilience. The attributes of confidence in a central bank could also be refined beyond the ex post measures we have utilized here, to include ex ante measures or to account for the endogeneity of political institutions and the central bank. In any event, given the importance of institutional resilience in a world buffeted by financial, macroeconomic, and now epidemiological shocks and military conflict, the search for the drivers of resilience should keep researchers busy for years to come.

[36]Thanks to Jon Oliva for this phrasing.

Appendix A. The Components of CONF: TMISS, MPU, and GDEV



Note: TMISS, MPU, and GDEV as defined in the text. The line at 1990 on the GDEV graph marks the year when econometric estimates begin.

Appendix B. Summary Statistics

Variable [Mnemonic]	n	Mean	Std. Dev.	Min.	Max.
Resilience [RESILIENCE]	5,117	1.032922	0.5454773	0	2
Confidence [CONF]	3,207	0.1333199	0.2396472	0	1
Controls					
Arable Land (Hectares per Person) [ARABLELAND]	8,877	0.2880	0.2868	0.00	3.30
Central Bank Independence [CBI]	5,519	0.5557	0.1747	0.10	0.93
Central Government Debt as a Percentage of GDP [DEBT]	6,904	48.2685	44.4778	0.00	547.78
Conflict [CONFLICT]	12,283	0.1395	0.3464	0.00	1.00
Employment Growth in Percent [EMPG]	9,209	2.5579	4.8899	–61.96	122.77
Excess Crises [EXCESS CRISIS]	12,283	0.0535	0.2530	0.00	3.00
Financial Risk [FINRR]	4,650	35.0981	8.3106	4.00	50.00
Foreign Direct Investment, Net Inflows (Percentage of GDP) [FDI]	7,035	3.4795	12.3347	–58.32	451.64
GDP Growth [GDPGUSD]	8,719	4.4090	7.6069	–66.66	147.73
Human Capital [HC]	8,337	2.0929	0.7329	1.01	4.35
Inflation, Consumer Prices (Annual, Percent) [INF]	7,071	25.1330	353.3735	–60.50	23,773.13
Informal Output (Percentage of Official GDP) [INFORMALITY]	4,313	31.4979	12.2854	7.97	67.66
Political Institutions Volatility, Three-Month [POLVOL]	8,628	0.4211	1.2674	0.00	9.24
Population Growth, Percent [POPG]	8,939	0.0192	0.1334	–3.20	6.83
Property Rights Volatility, Three-Month [PTYRIGHTS]	7,109	0.0152	0.0201	0.00	0.26
Resource Rents as a Percentage of GDP [TOTALNATURALRESOURCE]	7,299	7.4792	11.2917	0.00	87.51

Appendix C. Countries Included in the Econometric Estimation, by Method

BMA	Stepwise	Lasso
Albania	Albania	Albania
Algeria	Algeria	Algeria
Angola	Angola	Angola
Australia	Australia	Australia
Austria	Austria	Austria
Bahrain	Bahrain	Bahrain
Bangladesh	Bangladesh	Bangladesh
Belgium	Belgium	Belgium
Bolivia	Bolivia	Bolivia
Botswana	Botswana	Botswana
Brazil	Brazil	Brazil
Bulgaria	Bulgaria	Bulgaria
Burkina Faso	Burkina Faso	Burkina Faso
Cameroon	Cambodia	Cambodia
Canada	Cameroon	Cameroon
Chile	Canada	Canada
Colombia	Chile	Chile
Congo, Rep.	China	China
Costa Rica	Colombia	Colombia
Croatia	Congo, Rep.	Congo, Rep.
Cyprus	Costa Rica	Costa Rica
Czech Republic	Croatia	Croatia
Denmark	Cyprus	Cyprus
Dominican Republic	Czech Republic	Czech Republic
Estonia	Denmark	Denmark
Finland	Dominican Republic	Dominican Republic
France	Egypt, Arab Rep.	Egypt, Arab Rep.
Gabon	Estonia	Estonia
Germany	Ethiopia	Ethiopia
Ghana	Finland	Finland
Greece	France	France
Guatemala	Gabon	Gabon
Hungary	Germany	Germany
India	Ghana	Ghana
Indonesia	Greece	Greece
Iran, Islamic Rep.	Guatemala	Guatemala
Ireland	Hungary	Hungary
Italy	India	India
Jamaica	Indonesia	Indonesia
Japan	Iran, Islamic Rep.	Iran, Islamic Rep.
Jordan	Ireland	Ireland
Kazakhstan	Italy	Italy
Kuwait	Jamaica	Jamaica
Kyrgyz Republic	Japan	Japan
Latvia	Jordan	Jordan
Lithuania	Kazakhstan	Kazakhstan
Malaysia	Kuwait	Kuwait
Mali	Kyrgyz Republic	Kyrgyz Republic

BMA	Stepwise	Lasso
Mexico	Latvia	Latvia
Moldova	Lithuania	Lithuania
Morocco	Malaysia	Malaysia
Myanmar	Mali	Mali
Namibia	Mauritius	Mauritius
New Zealand	Mexico	Mexico
Niger	Moldova	Moldova
Nigeria	Morocco	Morocco
Norway	Myanmar	Myanmar
Pakistan	Namibia	Namibia
Paraguay	Netherlands	Netherlands
Peru	New Zealand	New Zealand
Poland	Niger	Niger
Portugal	Nigeria	Nigeria
Qatar	Norway	Norway
Romania	Pakistan	Pakistan
Russian Federation	Paraguay	Paraguay
Rwanda	Peru	Peru
Saudi Arabia	Philippines	Philippines
Senegal	Poland	Poland
Sierra Leone	Portugal	Portugal
Singapore	Qatar	Qatar
Slovak Republic	Romania	Romania
Slovenia	Russian Federation	Russian Federation
South Africa	Rwanda	Rwanda
South Korea	Saudi Arabia	Saudi Arabia
Spain	Senegal	Senegal
Sri Lanka	Singapore	Singapore
Sweden	Slovak Republic	Slovak Republic
Switzerland	Slovenia	Slovenia
Thailand	South Africa	South Africa
Togo	South Korea	South Korea
Trinidad and Tobago	Spain	Spain
Tunisia	Sri Lanka	Sri Lanka
Turkey	Sweden	Sweden
Uganda	Tanzania	Tanzania
Ukraine	Thailand	Thailand
United Kingdom	Togo	Togo
United States	Trinidad and Tobago	Trinidad and Tobago
Uruguay	Tunisia	Tunisia
Venezuela	Turkey	Turkey
Vietnam	Uganda	Uganda
Yemen, Rep.	Ukraine	Ukraine
Zambia	United Arab Emirates	United Arab Emirates
	United Kingdom	United Kingdom
	United States	United States
	Uruguay	Uruguay
	Venezuela	Venezuela
	Vietnam	Vietnam
	Yemen, Rep.	Yemen, Rep.
	Zambia	Zambia

Appendix D. Countries by Grouping in Figures 1 and 2 and Appendix A

Country Groups					
G7	G20	Latin America & Caribbean	ASEAN5	Emerging Europe	Euro Area
CAN	CAN	ATG	IDN	ALB	AUT
FRA	FRA	ABW	MYS	BLR	BEL
DEU	DEU	BHS	PHL	BIH	CYP
ITA	ITA	BRB	THA	BGR	EST
JPN	JPN	BOL	VNM	HVR	FIN
GBR	GBR	BRA		HUN	FRA
USA	USA	CHL		UVK	DEU
	AUS	COL		MDA	GRC
	MEX	CRI		MNE	IRL
	TUR	DMA		MKD	ITA
	RUS	DOM		POL	LVA
	CHN	ECU		ROM	LTU
	IND	SLV		RUS	LUX
	IDN	GRD		SRB	MLT
	SAU	GTM		TUR	NED
	ZAF	GUY		UKR	PRT
	KOR	HTI			SVK
	ARG	HND			SVN
	BRA	JAM			
		PAR			
		PER			
		SUR			
		TTO			
		URY			
		VEN			
		ARG			
		MEX			

Note: ISO-3 codes are used here to identify the countries. The country groupings are the ones used in Figures 1 and 2 and are obtained from the IMF's World Economic Outlook. Country codes that are underlined indicate countries that appear in more than one country group. See https://www.imf.org/en/Publications/WEO/weo-database/2023/October/select-aggr-data for the complete list of countries in each country group. We did not necessarily have data for all the countries in the country groupings shown, except G7, euro area, G20, and ASEAN5.

Appendix E. Results of the Model Selection Process, by Method

	1	2	3
Variables	**BMA**	**Stepwise**	**Lasso**
Arable Land (Hectares per Person)	–0.01		–0.08
	0.33		*1.96*
Central Bank Independence	0.34	0.26	0.52
	*4.81**	*4.70**	*7.63**
Central Government Debt as a Percentage of GDP	–0.001		–0.0003
	*2.33**		*0.81*
Conflict	–0.001		0.04
	0.13		*1.34*
Excess Crises	–0.12	–0.10	–0.11
	*2.76**	*3.00**	*3.07**
Foreign Direct Investment, Net Inflows (Percentage of GDP)	0.008	0.001	0.007
	*2.31**	*1.55*	*2.69**
GDP Growth	0.001	0.02	0.01
	0.37	*7.37**	*4.81**
Human Capital	0.04	0.27	0.27
	*1.44**	*22.22**	*18.74**
Inflation, Consumer Prices (Annual, Percent)	–0.00006		–0.0002
	0.29		*0.93*
Informal Output (Percentage of Official GDP)	0.0003	0.01	0.01
	0.37	*15.04**	*9.93**
Money Supply (M2) Growth	0.00006		0.0001
	0.11		*1.19*
Political Institutions Volatility, Three-Month	–0.0008		0.003
	0.19		*0.28*
Population Growth, Percent	0.006	0.42	0.34
	0.14	*2.47**	*2.10**
Property Rights Volatility, Three-Month	–4.46	–3.21	–3.39
	*5.12**	*4.12**	*4.00**
Resource Rents as a Percentage of GDP	–0.0001	0.004	0.002
	0.24	*3.60**	*2.02**

Note: Absolute value of the t-ratio shown under the estimated coefficient. * indicates variables which are included in the final model.

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