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INTERNATIONAL JOURNAL OF CENTRAL BANKING

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International Journal of Central Banking

The Effects of Borrower-Based Macroprudential Policy: An Empirical Application to Korea[*]

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The effects of borrower-based macroprudential policy (BB-MaPP) measures in the form of mandatory caps on loan-to-value (LTV) and debt-service-to-income (DSTI) ratios in the Korean real estate market are investigated using a sign-identified structural vector autoregressive (SVAR) model. Sign restrictions are drawn from a small open-economy dynamic stochastic general equilibrium (DSGE) model with collateralizable housing. While empirical results suggest only moderate effects of monetary policy on house prices in Korea, BB-MaPP measures have been successful in curbing real household credit and real house price growth. A historical decomposition also emphasizes the advantages of a targeted approach toward macroprudential regulation.

JEL Codes: E32, E44, E58, G28.

1. Introduction

In the wake of the global financial crisis, a large number of countries started to introduce macroprudential policies to counteract the buildup of financial imbalances. Especially boom-bust cycles in asset markets were identified as important predictors of upcoming financial distress. However, with the disastrous consequences of the financial crisis fresh in mind, doubt spread that the existing policy

mix of monetary and microprudential instruments was enough to cope with these unsustainable buildups in asset markets, promoting the emergence of a macroprudential policy toolkit within many central banks. Residential housing—as the most important collateral of households—was identified as one of the main targets of these measures.[1] Nevertheless, the limited experience puts a huge constraint on investigating the effectiveness of macroprudential policies in curbing financial cycles. Most studies rely on either calibrated or estimated models or resort to cross-country panels. The first method imposes a large number of assumptions on the data-generating process, while the latter approach suffers potentially from endogeneity issues and a lack of comparability of macroprudential measures throughout countries.

In this paper, I follow Peersman and Straub (2009) and Sá and Wieladek (2015) by identifying a structural vector autoregressive (SVAR) model via sign restrictions drawn from a dynamic stochastic general equilibrium (DSGE) model. Using an SVAR model circumvents possible endogeneity issues, while structural identification via sign restrictions is based on the economic reasoning of a microfounded model without imposing its exact structure. In particular, a small open economy that allows for collateralizable housing is modeled for the Korean economy. The latter presents an interesting case study, as (i) mandatory caps on loan-to-value (LTV) ratios had already been implemented as early as 2002, followed later on by caps on debt-service-to-income (DSTI) ratios, and (ii) these borrower-based macroprudential policies (BB-MaPP) experienced a relatively high degree of time variation. Drawing robust sign restrictions from the model, I propose an identification for, among others, a BB-MaPP shock. Results from the SVAR analysis suggest that an exogenous tightening in these borrower-based measures is indeed effective in that it leads to lower real house prices and real household credit.

The use of BB-MaPP measures is generally motivated by the disastrous economic effects that credit booms can have if they go bust

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[1]According to the International Monetary Fund's Global Macroprudential Policy Instruments Database, the number of countries that implemented some form of maximum LTV ratios increased from 10 in 2000 to 44 in 2013 for the 119 countries under investigation (for DSTI ratios, that number increased from 4 to 26).

(see, e.g., Schularick and Taylor 2012). In particular, the housing sector is perceived to be susceptible to initiating these malicious boom-bust cycles due to real estate prominently featuring on households' balance sheets and, as a consequence thereof, its preeminent role as collateral. Initial positive effects on house prices following laxer lending conditions are amplified as borrowing constraints loosen, leading to a buildup of leverage (see, e.g., Mian and Sufi 2011). As soon as the upswing in house prices comes to a halt, the chance of households starting to default on their loans increases, as happened in the United States at the start of the Great Recession. In the DSGE model, this financial accelerator mechanism is introduced in the fashion of Iacoviello (2005). Until recently, the monetary policy response in most countries to these boom-bust cycles was one of "benign neglect." While acknowledging the possible disastrous effects of asset price busts, Bernanke and Gertler (1999, p. 43) conclude: "Given a strong commitment to stabilizing expected inflation, it is neither necessary nor desirable for monetary policy to respond to changes in asset prices, except to the extent that they help to forecast inflationary or deflationary pressure."[2]

The general stance of policymakers changed over time, but conventional monetary instruments are still discarded by most to curb boom-bust cycles in asset markets due to their economy-wide consequences and potential other deficiencies (Crowe et al. 2013). Depending on the specific target in mind, a wide array of macroprudential instruments has been proposed and implemented instead (for an overview, see Galati and Moessner 2013). In real estate markets, LTV and DSTI regulations are the dominant choices of policymakers. Both instruments target the demand side by restricting highly leveraged households from receiving mortgage credit. In theory, mandatory caps on these ratios tighten the borrowing constraints of targeted households, leading on aggregate to a reduction in mortgage credit and housing demand, ultimately pushing down house prices. By restricting the borrowing ability of impatient households

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[2]In their defense, the nominal interest rate is considered as the only monetary policy tool, abstracting from macroprudential measures that were generally not part of the policy mix at that time; for more anecdotical evidence, see Crowe et al. (2013).

in the model to a fraction of their available collateral and introducing a policy rule that governs this fraction depending on household credit growth in the economy, similar to Lambertini, Mendicino, and Punzi (2013), an LTV environment is mimicked.

This setup allows the identification of an exogenous variation of the prevalent LTV ratio and borrows from the growing literature studying the welfare effects of macroprudential measures within DSGE models. Closed-economy approaches stress the relevance of the origin of shocks (Kannan, Rabanal, and Scott 2012), the importance of coordination between monetary policy and macroprudential policy (Angelini, Neri, and Panetta 2011), different welfare effects for borrowers and savers (Lambertini, Mendicino, and Punzi 2013), and the cost-effectiveness of LTV regulations (Alpanda and Zubairy 2017) but also the potentially greater effectiveness of DSTI regulations over LTV regulations (Gelain, Lansing, and Mendicino 2013). Open-economy approaches demonstrate the positive effects of decentralization of macroprudential policy (Quint and Rabanal 2014) and their usefulness under capital inflow shocks (Unsal 2013). The model implemented here is closest to Funke and Paetz (2013, 2018) in that it unifies the small open-economy setup developed by Galí and Monacelli (2005) with the financial accelerator in Iacoviello (2005). However, I deviate from this literature in utilizing the model merely to motivate robust sign restrictions and, ultimately, let the data speak in the SVAR approach. With that in mind, I aim to answer the question as to whether LTV and DSTI regulations have been successful in curbing cycles in the Korean real estate market.

Following a strong increase in house prices and credit growth in the early 2000s, with the Asian financial crisis still fresh in mind, Korean authorities first introduced a mandatory cap on LTV ratios. A glance at figure 1 suggests that these measures reduced volatility in real estate markets dramatically. Still, with the background of extensive housing supply policies in the late 1980s aimed at closing the large housing supply-demand gap as well as the financial crisis, this could simply be a consequence of a calming in the Korean real estate market. It is therefore essential to extract an exogenous variation in those policy measures for any causal statement to be credible. Past empirical research mostly relies on panel data and finds that LTV and DSTI caps are able to curb credit growth (Lim et al. 2011) and house prices (Kuttner and Shim 2016), but much

Figure 1. House Price and Household Credit Growth in Korea
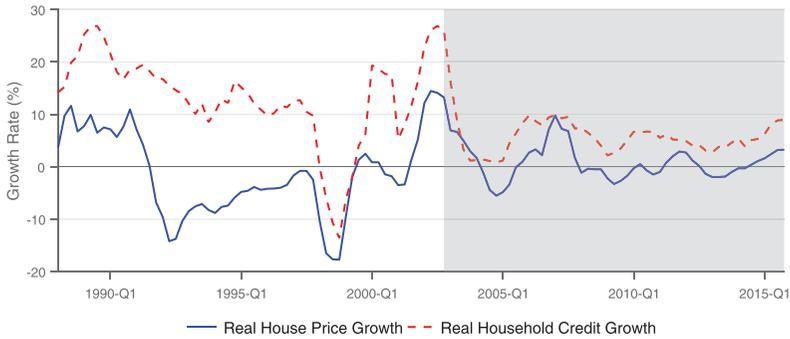
Source: Bank for International Settlements.
Notes: The figure displays the quarterly year-on-year growth rates. The gray-shaded area depicts the time period where BB-MaPP measures have been actively applied in real estate markets.

more so during boom phases (Claessens, Gosh, and Mihet 2013). Vandenbussche, Vogel, and Detragiache (2015), on the other hand, detect no significant effects on house prices, while Cerutti, Claessens, and Laeven (2017) stress regulation avoidance in the form of cross-border lending. Using Korean household data, Igan and Kang (2011) provide evidence of the effectiveness of LTV and DSTI regulations in delaying property purchase decisions, but only tighter LTV ratios push down price expectations. Only recently, there have been time-series approaches that generally support the effectiveness of macro-prudential measures (Tillmann 2015) but also warn of contractionary economy-wide consequences (Kim and Mehrotra 2018). Both studies rely solely on zero restrictions, a restrictive identification strategy which is often not theoretically justifiable. The empirical novelty of my approach lies in the use of sign restrictions and the utilization of a newly compiled BB-MaPP index that is able to quantify changes in average regulation in Korea.[3]

While Kim and Mehrotra (2018) distinguish between macro-prudential and monetary policy shocks, assigning a structural

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[3]Towbin and Weber (2016) also use sign restrictions to identify an LTV shock, but utilize actual LTV ratios for the United States, not macroprudential regulations.

identification to multiple shocks is more straightforward with sign restrictions. Thus, in addition to the BB-MaPP shock, I also uniquely identify a monetary policy shock, a housing demand shock, and a technology shock. Besides providing further insights, imposing additional sign restrictions helps pin down the structural shocks of interest (Paustian 2007). All four identified shocks turn out to have a more or less important influence on the Korean real estate cycle. Taking into account that BB-MaPP measures are generally targeted toward certain types of borrowers or specific areas, the comparably small quantitative average effect on the whole economy can translate into huge effects for affected households. The monetary policy shock, on the other hand, has only a surprisingly small and statistically not significant effect on house prices. This result can be reconciled with a smaller interest rate sensitivity of housing demand under tight downpayment requirements (Calza, Monacelli, and Stracca 2013). In contrast to Kim and Mehrotra (2018), economy-wide consequences are more persistent for the monetary policy shock, endorsing the targeted BB-MaPP measures in terms of cost-effectiveness.[4] The main results are also robust to splitting the BB-MaPP index into an LTV and DSTI index, alternative identification strategies, and different prior specifications. Overall, the comparably low volatility in real house prices and real household credit growth seen in figure 1 since 2002 in Korea might at least be partially due to the implementation of BB-MaPP measures.

The remainder of this paper is structured as follows: the next section outlines the DSGE model. In section 3, the econometric framework and data are described and a short overview of the Korean housing sector is given. Results of the empirical application are presented in section 4, while section 5 concludes.

2.   The Model

The aim of the model is to produce impulse responses that allow for a robust sign identification of the impact responses in an empirical application. Under this premise, the model tries to capture

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[4]Other potential costs of these BB-MaPP measures, such as leakages to the unregulated sector, regulatory arbitrage, and unwanted distributional effects, are ignored due to a lack of data availability.

the main mechanisms of LTV regulations and conventional monetary policy without trying to match moments of the Korean economy, keeping it as parsimonious as possible. Building on the small open-economy setup by Galí and Monacelli (2005), each single country is assumed to be negligibly small, such that foreign variables are exogenous. It is also assumed that the law of one price holds for all individual goods. In order to introduce LTV ratios into the model, the domestic economy is inhabited by patient and impatient house-holds, who exhibit different discount factors, following Kiyotaki and Moore (1997). Impatient households always borrow, but they face a borrowing constraint which depends on the collateral they own and the prevalent LTV environment. As in Iacoviello (2005), both households demand consumption goods as well as real estate. They further allocate time to work in each of the two sectors. A model similar in vein is presented in Funke and Paetz (2013). The notation is as follows: a subscript h refers to the home economy, i refers to an individual foreign economy, and f refers to the continuum of foreign economies. A superscript i refers to a variable from country i's perspective, no subscript indicates a steady-state value, while a small letter with a hat is a variable in log-deviations from its steady state. In the following, the main features of the model are described and further details can be found in the appendix.

2.1   Households

2.1.1   Borrowers

The economy is inhabited by a fraction ω of impatient households (borrowers) and a fraction $(1-\omega)$ of patient households (savers). The representative impatient household spends income from allocating time to work in each of the two sectors on either nondurable consumption goods, C_t^b, or durable goods, D_t^b,[5] and maximizes

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_b^t \left\{ \log C_t^b + \gamma_t \log D_t^b - \frac{(N_{c,t}^b)^{1+\varphi}}{1+\varphi} - \frac{(N_{d,t}^b)^{1+\varphi}}{1+\varphi} \right\}, \quad (1)$$

where β_b is the borrower's discount factor, φ is the inverse of the Frisch elasticity of labor supply, $N_{j,t}$ denotes hours worked in sector

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[5]I use housing and durables interchangeably here.

$j = \{c, d\}$, and the stochastic weight, γ_t, enables housing demand (or, synonymous, preference) shocks to be modeled. Durable goods are different from nondurable goods in two ways: (i) they depreciate over time, $D_t^b = (1 - \delta)D_{t-1}^b + I_{d,t}^b$, with depreciation rate δ and new housing investment, $I_{d,t}^b$, while nondurable goods, C_t^b, vanish completely each period, and (ii) they constitute collateral which the impatient household borrows against. The composite consumption index (an equivalent consumption index is defined for durable goods) is given by

$$C_t^b = \left[(1 - \alpha_c)^{\frac{1}{\eta_c}}(C_{h,t}^b)^{\frac{\eta_c - 1}{\eta_c}} + \alpha_c^{\frac{1}{\eta_c}}(C_{f,t}^b)^{\frac{\eta_c - 1}{\eta_c}}\right]^{\frac{\eta_c}{\eta_c - 1}}, \qquad (2)$$

where $\alpha_c \in [0, 1]$ is an index of openness of the economy and η_j is a measure of substitutability between domestic and foreign non-durable goods. Households can choose from a variety of goods in the domestic economy and in each foreign economy as well as between different foreign economies.[6]

The budget constraint of borrowers in real terms (units of non-durable goods) is given by

$$C_t^b + q_t I_{d,t}^b + R_{t-1}\frac{b_{h,t-1}^b}{\Pi_{c,t}} = b_{h,t}^b + \frac{W_{c,t}^b}{P_{c,t}}N_{c,t}^b + \frac{W_{d,t}^b}{P_{c,t}}N_{d,t}^b, \qquad (3)$$

where $q_t = \frac{P_{d,t}}{P_{c,t}}$ is the relative price of durable and nondurable goods, $\Pi_{c,t} = \frac{P_{c,t}}{P_{c,t-1}}$ is gross consumer price index (CPI) inflation, $b_{h,t}^b$ is the stock of real domestic debt, R_t is the gross nominal interest rate, and $\frac{W_{j,t}^b}{P_{c,t}}$ is the real wage rate in sector $j = \{c, d\}$.

Due to the lower discount factor of impatient households, borrowers will never save ($b_{h,t}^b > 0 \ \forall t$). As in Kiyotaki and Moore (1997), an endogenous limit is set to the amount of borrowing which depends on the expected future value of the stock of durables. Thus, the collateral constraint is given in real terms by

$$R_t b_{h,t}^b \leq m_t(1 - \delta)\mathbb{E}_t[q_{t+1}D_t^b\Pi_{c,t+1}] \qquad (4)$$

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[6]These consumption indexes are all given by constant elasticity of substitution (CES) functions as in Funke and Paetz (2013).

with m_t being the time-varying maximum LTV ratio. The chosen discount factor ensures that the borrowing constraint is binding in steady state and the neighborhood thereof. This mechanism enables the effect of an exogenous variation in the LTV ratio on the household's behavior to be examined.

In comparison with nonconstrained households, the first-order conditions of the borrower's maximization problem differ in two ways: (i) the marginal utility of nondurable consumption additionally depends on the relaxation of the collateral constraint and (ii) the marginal utility of current consumption exceeds the marginal gain of shifting consumption to the next period.[7]

2.1.2 Savers

The utility function and demand schedules of patient households are analogous to those of impatient households. However, there are three main differences between patient and impatient households.

First, patient households always save and therefore do not face any borrowing constraint. Second, savers are able to trade bonds internationally on incomplete markets. Third, savers are the sole owners of firms and therefore generate income from profits ($PR_{j,t}^s$ with $j = \{c, d\}$). Thus, the saver's budget constraint in real terms (units of nondurable goods) reads

$$C_t^s + q_t I_{d,t}^s + R_{t-1} \frac{b_{h,t-1}^s}{\Pi_{c,t}} + R_{t-1}^* \Xi(\mathcal{E}_{t-1} b_{f,t-1}^*) \frac{\mathcal{E}_t b_{f,t-1}^*}{\Pi_{c,t}}$$

$$= b_{h,t}^s + \mathcal{E}_t b_{f,t}^* + \frac{W_{c,t}^s}{P_{c,t}} N_{c,t}^s + \frac{W_{d,t}^s}{P_{c,t}} N_{d,t}^s + PR_{c,t}^s + q_t PR_{d,t}^s, \quad (5)$$

where R_{t-1}^* is the nominal gross foreign interest rate; $b_{f,t}^*$ is a basket of foreign bonds denoted in the respective foreign country's currency; $\mathcal{E}_t$ is the basket of nominal exchange rates, where the price of country i's currency is denoted in terms of domestic currency; $\Xi(\mathcal{E}_t b_{f,t}^*)$ are international intermediation costs; and the other terms are analogous to the borrower's problem. In order to abstract from complete international risk sharing, international intermediation costs

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[7]For an extensive discussion of the role of collateral constraints in DSGE models, see Monacelli (2009).

are introduced such that the servicing costs increase with the amount of foreign debt.[8] Under this setup, an uncovered interest rate parity holds except for a wedge due to the intermediation costs.

2.2 Firms

To allow for sticky prices in the model, intermediate goods are produced by a continuum of monopolistically competitive wholesale firms. These intermediate goods are then aggregated by retailers to produce final goods using a CES production function

$$Y_{j,t} = \left(\int_0^1 Y_{j,t}(k)^{\frac{\varepsilon_j - 1}{\varepsilon_j}} \, dk \right)^{\frac{\varepsilon_j}{\varepsilon_j - 1}}, \quad j = c, d, \tag{6}$$

where $Y_{j,t}$ is aggregate output in sector j.

Production of differentiated intermediate goods follows a linear technology with labor as the only input factor,

$$Y_{j,t}(k) = A_{j,t} N_{j,t}(k), \quad j = c, d, \tag{7}$$

where $A_{j,t}$ denotes sector-specific, stochastic labor productivity.

The monopolistically competitive intermediate firms set prices in a staggered fashion, following the scheme in Calvo (1983). A proportion of $(1 - \theta_j)$ randomly selected firms in sector j is able to reset prices in period t, while reoptimization is not possible for the remaining θ_j firms. Taking into account optimal price setting by each firm and the dynamics of the price index, a familiar-looking log-linearized Phillips curve can be derived for each sector:

$$\hat{\pi}_{j,h,t} = \beta \mathbb{E}_t \hat{\pi}_{j,h,t+1} + \kappa_j \hat{mc}_{j,h,t}, \quad j = c, d, \tag{8}$$

where $\kappa_j = \frac{(1-\theta_j)(1-\theta_j \beta_s)}{\theta_j}$ for $j = c, d$.

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[8]This modeling decision should not have a major impact on the results but is needed to circumvent unit-root behavior in the equilibrium dynamics (see Schmitt-Grohé and Uribe 2003).

2.3   Monetary Policy, Macroprudential Policy, and Shock Structure

As the primary goal of the Bank of Korea is price stability and it therefore adopts an inflation-targeting approach, the nominal interest rate is assumed to be pinned down by the Taylor principle,

$$R_t = R^{(1-\phi_r)} R_{t-1}^{\phi_r} \Pi_t^{(1-\phi_r)\phi_\pi} \varepsilon_t^{MP}, \tag{9}$$

where Π_t is gross inflation of all domestically consumed goods, ϕ_r is the persistence of the nominal interest rate, $\phi_\pi > 1$ gives the strength with which the nominal interest rate reacts to changes in inflation, and ε_t^m is a monetary policy shock with $\varepsilon_t^{MP} = \exp(e_t^{MP})$ and $e_t^{MP} \sim N(0, \sigma_{MP}^2)$.

Furthermore, similar to Lambertini, Mendicino, and Punzi (2013) or Rubio and Carrasco-Callego (2014), I impose a countercyclical rule on the LTV ratio, m_t, in the borrowing constraint of impatient households (4). The LTV ratio follows

$$m_t = m^{(1-\phi_m)} m_{t-1}^{\phi_m} \left(\frac{b_{h,t}^b}{b_{h,t-1}^b} \right)^{-(1-\phi_m)\phi_{LTV}} \varepsilon_t^{LTV}, \tag{10}$$

where ϕ_m is a smoothing parameter and ϕ_{LTV} is the policy parameter which defines the strength of the reaction of the LTV ratio toward changes in the growth of real domestic borrowing activity. To simplify matters, the LTV ratio changes continuously.[9] Analogous to the monetary policy shock, the stochastic component ε_t^{LTV} displays an exogenous variation in the LTV ratio that cannot be explained by changes in borrowing and is thus considered an LTV shock with $\varepsilon_t^{LTV} = \exp(e_t^{LTV})$ and $e_t^{LTV} \sim N(0, \sigma_{LTV}^2)$.

Two additional shocks are included in the model, namely a housing demand shock and a technology shock. As technology in the housing sector is to a large part invariable, I only allow for technology in the nondurables sector to be stochastic. Thus, households' weight

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[9]Funke and Paetz (2018) model an LTV ratio that only changes when a certain threshold of a target variable is exceeded; for the purpose of the present study, a continuous rule is chosen, as (i) interest lies only in impact responses of the model and (ii) a nonlinear rule would generate asymmetries in the responses, which data availability prohibits in the empirical application.

of housing in the utility function and the nondurables technology parameter evolves with

$$\gamma_t = \gamma^{(1-\phi_\gamma)}\gamma_{t-1}^{\phi_\gamma}\varepsilon_t^\gamma \qquad (11)$$

$$A_{c,t} = A_c^{(1-\phi_A)}A_{c,t-1}^{\phi_A}\varepsilon_t^A, \qquad (12)$$

where shocks are distributed according to $\varepsilon_t^k = \exp(e_t^k)$ and $e_t^k \sim N(0, \sigma_k^2)$ with $k = \gamma, A$.

2.4   Calibration

Similar to Peersman and Straub (2009) or Sá and Wieladek (2015), I specify ranges for the structural parameters according to a uniform distribution to mimic quarterly data. This allows for a relative agnostic calibration of the model. Before generating impulse response functions (IRFs), random values are drawn for each structural parameter following its assigned distribution. This process is repeated 10,000 times to cover a large part of the parameter space.

Some specifications displayed in table 1 are worthy of elaboration: the degree of openness is chosen to always be larger in the nondurables than in the durables sector, as residential housing is mainly traded domestically. Sectors also differ in the magnitude of price stickiness. Firms in the durables sector are allowed to change prices more frequently following Iacoviello and Neri (2010). They even assume fully flexible prices in the housing sector. The reasoning is twofold: (i) due to the large cost involved on a per-unit basis, the incentive to negotiate prices individually for each good is high, and (ii) houses are often priced for the first time when they are sold.

Elasticities of substitution between domestic goods and goods of foreign countries reflect price markups in steady state between 1.1 and 1.5, while elasticities of substitution between domestic and foreign goods imply higher markups, following Sá and Wieladek (2015). There is not much guidance in the literature on the policy parameter of the LTV rule. It is set conservatively to lie between 0 and 0.9, which encompasses the welfare-maximizing values proposed in Rubio and Carrasco-Callego (2014). The smoothing parameter of the rule is considered to be high, taking into account the noncontinuous changes in reality. Lastly, I attribute standard normal distributions

Table 1. Parameter Ranges

Parameter	Description	Parameter Range
β_s	Discount factor patient households	[0.975, 0.995]
β_b	Discount factor impatient households	[0.950, 0.970]
γ	Steady-state weight of housing pref. in utility	[0.2, 0.5]
δ	Depreciation durables	[0.005, 0.030]
α_c	Degree openness nondurables sector	[0.25, 0.50]
α_d	Degree openness durables sector	[0.05, 0.15]
$\varepsilon_c, \varepsilon_d$	EOS between domestic goods	[3, 11]
ζ_c, ζ_d	EOS between goods of different countries	[3, 11]
η_c, η_d	EOS between domestic and foreign goods	[1.5, 2.5]
ω	Fraction of borrowers	[0.15, 0.50]
$(1 - \theta_c)$	Prob. of readjusting prices (cons. goods)	[0.25, 0.50]
$(1 - \theta_d)$	Prob. of readjusting prices (durables)	[0.75, 0.90]
φ	Inverse of Frisch labor supply elasticity	[0.1, 3]
ϕ_π	Central bank reaction to domestic inflation	[1.25, 2.5]
ϕ_{LTV}	Reaction LTV ratio to credit growth	[0, 0.9]
$\phi_\tau, \phi_\gamma, \phi_A$	Smoothing parameters	[0.5, 0.9]
ϕ_m	Smoothing parameter LTV rule	[0.75, 0.95]
m	Steady-state LTV ratio	0.7
λ	International intermediation costs	[0.005, 0.050]
$\sigma^2_{LTV}, \sigma^2_\gamma,$ $\sigma^2_A, \sigma^2_{MP}$	Variance of log-linearized shocks	1

Note: Parameter ranges display the minimum value and maximum value of a uniform distribution; EOS: elasticity of substitution.

to all log-linearized shocks, since my interest lies only in qualitative responses.[10]

2.5   Impulse Responses and Sign Restrictions

The first column in figure 2 depicts a contractionary shock to the LTV ratio. On impact, the borrowing constraint of impatient households tightens, leading to a strong decrease in real borrowing activity. Impatient households lower their spending on housing as well as consumption. The decline in housing demand pushes down house prices. Compared with a model with fixed housing supply (e.g.,

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[10]Note that since the model is log-linearized, the shock size does not have an influence on the sign of the responses.

Figure 2. Impulse Response Functions from the Model
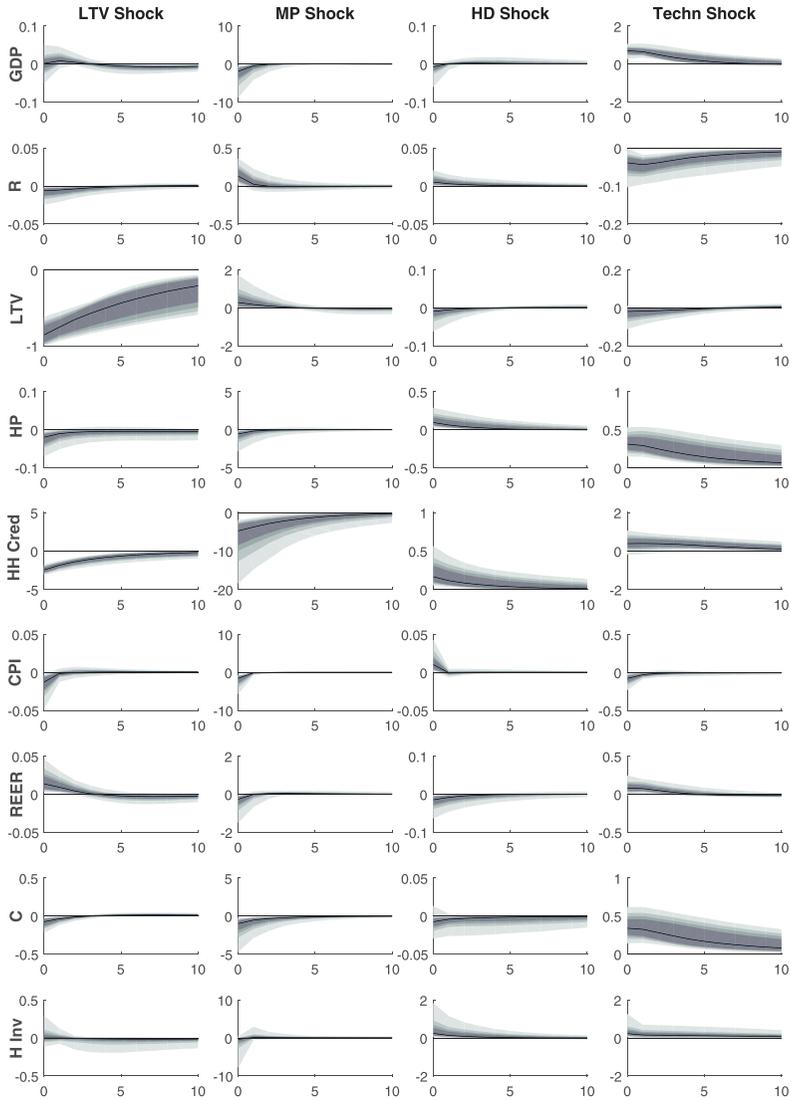
Notes: Each column represents a shock: LTV, monetary policy (MP), housing demand (HD), and a technology (Techn) shock. Each row gives the response of the respective variable: real GDP (GDP), short-term nominal interest rate (R), LTV ratio (LTV), real house prices (HP), real household credit (HH Cred), consumer price index (CPI), the real effective exchange rate (REER), consumption (C), and housing investment (H Inv). The solid line gives the median response, and the shaded areas, from dark to light, the 84-16, 90-10, 95-5, and 99.5-0.5 percentiles.

Iacoviello 2005), adjustments on the supply side due to lower marginal costs dampen the effect on house prices slightly. Due to the role of real estate as collateral and the lower price stickiness, house prices react more strongly than prices of consumption goods. Still, while aggregate consumption decreases unambiguously, the direction of overall housing investment is not clear: the more favorable price level induces patient households to substitute part of their nondurables with durables consumption. Declining price levels prompt the inflation-targeting central bank to lower the nominal interest rate, bringing about a depreciation of the domestic currency. Coupled with the decrease in prices, this leads to an increase in the real effective exchange rate (REER), i.e., higher price competitiveness.[11] Interestingly, real gross domestic product (GDP) can go in both directions as the increase in foreign demand counteracts the generally contractionary responses.

A contractionary monetary policy shock (second column in figure 2), through the increase in the nominal interest rate, tightens the borrowing constraint of impatient households. Their initial decrease in consumption of both types of goods is amplified via the collateral constraint channel but partially weakened by the countercyclical LTV rule. Following the same line of reasoning as in the LTV shock, patient households substitute consumption for housing. This time, however, the increase in the nominal interest rate leads to an appreciation of the domestic currency. While lower demand pushes down consumer prices, overall the economy still exhibits a loss in price competitiveness and, thus, a decrease in the REER and less foreign demand. In comparison with the LTV shock, real GDP drops unambiguously.

The two remaining shocks are included, as they are potential drivers of real estate cycles, either directly (housing demand shocks) or via synchronized business and real estate cycles (technology shocks). A positive housing demand shock (third column in figure 2) pushes up housing investment at the cost of consumption. The collateral

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[11]The REER is defined here such that an increase is equivalent to an improvement of domestic price competitiveness; also note that the decline in domestic prices is enough to push up the REER on impact even without the central bank's reaction.

Table 2. Sign Restriction

	BB-MaPP Shock	MP Shock	HD Shock	Techn Shock
REER	+	−	−	+
Real Res Inv		−	+	+
Inflation		−		−
Real Cons	−	−		+
BB-MaPP Index	+		+	
Interest Rate		+		
Real GDP				+
Real House Prices			+	
Real HH Credit				

Notes: Each column represents a shock: borrower-based macroprudential policy (BB-MaPP), monetary policy (MP), housing demand (HD), and a technology (Techn) shock. A "+" sign restricts the impact response for the variable to the respective shock to be non-negative for the first two quarters, while a "−" sign restricts the impact response of the variable of the respective shock to be non-positive for the first two quarters.

value of impatient households increases, amplified by the demand-driven boost in real house prices. Under some calibrations, their higher borrowing activity can even lead to an increase in nondurables consumption in line with Iacoviello and Neri (2010). Overall, consumer prices increase, triggering a rise in the nominal interest rate, leading to a decrease in the REER via the uncovered interest parity. Combined with the mitigating effect of the countercyclical LTV ratio on borrowing, the decrease in foreign demand might even dampen overall domestic production. A technology shock in the nondurables sector (fourth column in figure 2), on the other hand, is amplified by the open-economy setup as the declining price level coupled with lower nominal interest rates pushes up price competitiveness. Besides the direct increase in consumption, lower interest rates relax the borrowing constraint, initiating a demand-driven house price increase. Overall, we have a sharp increase in real domestic economic activity.

Table 2 depicts the sign restrictions that are imposed on the nine-variable Bayesian VAR (BVAR) for the first two quarters, all consistent with the DSGE model. Unique identification is achieved for all four shocks with the restrictions on the top five variables in the table above. The additional restrictions are imposed to pin down certain shocks more precisely. Thus, while, in general, the responses

of real house prices and real household credit are left unrestricted, this is not the case for the housing demand shock, since a positive reaction of house prices is deemed an important identifier here.[12] The LTV ratio is replaced by a more general borrower-based index, which also includes regulations on DSTI ratios. It is assumed that caps on LTV and DSTI ratios generally work in the same direction from a macroeconomic perspective and both fulfill the sign restrictions imposed.[13] From a practical perspective, merging the two policies allows for more time variation in the index. Note that an increase in this index is tantamount to a tightening of one of the policies, switching signs compared with the LTV ratio in the model. More detail on this index is given in the appendix.

3.   Econometric Framework and Data

3.1   Estimation, Identification, and Data

Consider the following VAR(p) model:

$$Y_t = c + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + u_t, \tag{13}$$

where $Y_t = (y_{1,t}, y_{2,t}, \ldots, \ldots y_{n,t})'$ is an n-dimensional vector of endogenous variables, c is an n-dimensional vector of constants, A_k are $n \times n$ matrices of coefficients, and u_t is n-dimensional Gaussian white noise with covariance matrix $\mathbb{E}(u_t u_t') = \Psi$. Where n and p are of modest size, the number of coefficients to be estimated can already become large, leading to a curse-of-dimensionality problem. Bayesian VARs have become a popular choice to overcome this problem by "shrinking" coefficients toward some prior belief. I follow the idea of the Minnesota prior proposed by Litterman (1986) which

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[12]Iacoviello and Neri (2010) also name their housing preference shock "housing demand shock," precisely since it leads to an increase in house prices and housing investment; the sign-identified housing demand shock in Jarociński and Smets (2008) also imposes the restriction that house prices and residential investment move in the same direction.

[13]In reality, the transmission of the two regulations potentially exhibits differences; as shown, e.g., in Gelain, Lansing, and Mendicino (2013), with a hybrid borrowing constraint, labor supply is directly affected by the DSTI regulation; thus, in a robustness check, this assumption is relaxed and the effects of LTV and DSTI shocks are separated.

imposes the prior belief that most macroeconomic variables can be reasonably described to follow a random walk with drift. In general, the prior distribution of the coefficients is set to

$$
\mathbb{E}\left[(A_k)_{ij}\right] = \begin{cases} \delta_i, & j = i, k = 1 \\ 0, & \text{otherwise} \end{cases},
$$

$$
\text{Var}\left[(A_k)_{ij}\right] = \begin{cases} \frac{\lambda^2}{k^2}, & j = i \\ \frac{\lambda^2}{k^2}\frac{\sigma_i^2}{\sigma_j^2}, & \text{otherwise}, \end{cases} \tag{14}
$$

where $\delta_i = 1$ implies a random-walk prior. The hyperparameter λ controls the overall tightness of the prior: as $\lambda \to 0$, the prior belief becomes more and more important, dominating the actual data. For the constant, a diffuse prior is assumed. As the covariance matrix is assumed to be known in the original Minnesota prior, I follow Kadiyala and Karlsson (1997) by choosing a normal-Wishart prior that retains the general idea outlined above. In particular, the prior is implemented by adding dummy observations as in Bańbura, Giannone, and Reichlin (2010). This allows for easy extension of additional prior assumptions.[14]

The structural VAR model

$$
\mathcal{A}_0 Y_t = \nu + \mathcal{A}_1 Y_{t-1} + \cdots + \mathcal{A}_p Y_{t-p} + e_t \tag{15}
$$

with $e_t \sim N(0, I)$ as the structural innovations and the mapping $u_t = \mathcal{A}_0^{-1} e_t$ is then identified via sign restrictions pioneered by Faust (1998), Canova and Nicoló (2002), and Uhlig (2005). In order to identify $\mathcal{A}_0^{-1}$, the Cholesky decomposition of the covariance matrix, $\Psi = PP' = \mathcal{A}_0^{-1}\mathcal{A}_0^{-1'}$, delivers a solution which is multiplied by an orthogonal matrix Q, such that $\mathcal{A}_0^{-1} = PQ$ is not lower triangular.[15] Following Rubio-Ramírez, Waggoner, and Zha (2010), Q is

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[14]In general, it also has the computational advantage that inversion of a square matrix of dimension $np + 1$ instead of a square matrix of dimension $n(np + 1)$ is necessary.

[15]The solution $\mathcal{A}_0^{-1} = P$ is viable and often used but imposes a recursive structure; while it is often not justifiable from an economic perspective, in a robustness check later on this identification is utilized.

drawn from a QR decomposition of an n-dimensional square matrix of standard normal distributed random variables, which allows Q to be chosen randomly from the space of orthogonal matrices. Then, for each draw from the posterior, only the draws of Q are kept, which fulfill the identified signs from the DSGE model in table 2. Since there is an infinite amount of possible Q matrices, only set identification is achieved. To choose the "proper" impulse responses, I follow the median target (MT) method proposed by Fry and Pagan (2011). For each posterior draw, the orthogonal matrix Q is selected, which minimizes the distance of standardized impulse responses to the median response function over all Q-draws.[16]

The BVAR model contains nine endogenous variables: real GDP, the CPI, a real house price index, real loans to households, the REER, real residential investment, and real consumption, all included in logs, as well as a BB-MaPP index and a short-term nominal interest rate[17] included in levels. Additional details and sources are given in table A.1. The creation of the BB-MaPP index makes use of the fact that both regulations change quite frequently over the sample period. Similar to the idea of Igan and Kang (2011), an average value for the mandatory LTV and DSTI ratios is calculated. Then, using the min-max principle to make both policy ratios comparable, they are added with equal weighting. More details on the creation of this BB-MaPP index can be found in the appendix.

Before estimation, the Minnesota prior has to be specified. First of all, it is assumed that all variables besides the REER follow a random walk with drift, while the latter is specified by a white-noise process. This is in line with Bańbura, Giannone, and Reichlin (2010). I also lean on their work in calibrating the shrinkage parameter λ: for a pre-sample period going from 1991:Q1 to 1999:Q4, a benchmark in-sample fit is set by calculating the relative in-sample fit of ordinary least squares estimates of a small VAR only including real GDP, the CPI, and real household credit to a counterpart where

---

[16]Note that the median response function over all Q-draws itself lacks structural economic interpretation, as the responses at different horizons are likely to come from different draws of Q.

[17]Note that the central bank's base rate does not fall below 1.5 percent during the sample period such that zero lower bound considerations can be disregarded.

prior specifications are imposed exactly. Then, for the full VAR,[18] λ is chosen such that the relative fit for the variables of the small VAR comes as close as possible to the benchmark fit. This procedure ensures that Bayesian shrinkage increases with the size of the VAR. For the baseline setup, λ is equal to 0.16, while the hyperparameter for the constant, ε, is given a small value to impose a diffuse prior.

The BVAR is then estimated for the period 2000:Q1 to 2015:Q4, including four lags and drawing 500 times from the posterior. For each draw, the sign-restrictions algorithm is executed until 20 admissible draws[19] are found, whereby the "correct" model is identified via the MT method as described above.

3.2   Housing Sector and Housing Policies in Korea

For a long time, the Korean real estate sector was characterized by a shortage of residential housing. Along with economic growth came housing supply-side policies in the late 1980s that successfully closed the supply-demand gap in the Korean real estate sector. While real house prices peaked around 1990, the Two-Million Housing Drive policy measure effectively increased yearly housing construction in Korea from around 250,000 up to 550,000 units, bringing house prices down to an affordable level.

Nowadays, affordability of housing in Korea is comparable to other emerging and advanced economies (see, e.g., Kim and Park 2016). However, the government is still active in curbing housing cycles and making housing accessible to a larger part of the population. After the Asian financial crisis, a short-run decrease in housing supply coupled with the expansion of mortgage credit led to a surge in house prices. Besides tax changes, the macroprudential policies under investigation here were introduced in the form of mandatory LTV ratios in 2002 and, later on, mandatory DSTI ratios in 2005 to effectively reduce housing demand. As documented in table A.2,

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[18]The full VAR for the pre-sample period abstracts from the BB-MaPP index, as no such policies were implemented during this time; thus, the shrinkage parameter λ is possibly set too high, as the pre-sample full VAR only includes eight instead of nine variables.

[19]Due to the large amount of imposed sign restrictions, there are some "unlucky" posterior draws where the acceptance rate is very low; in these cases, the algorithm stops after 15 million draws of Q to reduce computation time.

Table 3. Korean Housing Sector Data

	2001–05	2006–10	2011–15
Residential Investment to GDP (%)	5.06	4.57	3.86
Housing Construction Permits	541,844	432,982	571,435
Housing Supply Ratio (%)	101.64	109.80	116.10
Owner-Occupancy Ratio (%)		55.40	53.70
Jeonse-Occupancy Ratio (%)		22.13	20.70
Rent-Occupancy Ratio (%)		19.56	22.77
House Affordability Index	67.50	64.17	56.34
Real House Price Growth (%)	3.86	0.99	1.02

Sources: Ministry of Land, Infrastructure and Transport; Bank of Korea; Korea Housing Finance Corporation; Bank for International Settlements.
Notes: The housing supply ratio is simply the number of dwellings to the number of households and is only reported up until 2014; owner-occupancy ratio, Jeonse-occupancy ratio, and rent-occupancy ratio are only available for the years 2006, 2008, 2010, 2012, and 2014; the house affordability index is defined as the debt service burden by the median income household purchasing the median priced house using a standard mortgage loan; all variables are given as annual averages.

these regulations were adjusted regularly based on characteristics of the borrower, the loan, or the region of the real estate. Korean authorities also engaged in housing finance policies and, lately, direct demand-side policies in the form of housing benefits. A summary of important residential housing statistics in Korea is given in table 3.

One peculiar feature of the Korean housing sector is the existence of Jeonse contracts. The tenant makes a large deposit upfront but does not pay any monthly rent. At the termination of the contract, the deposit is fully refunded. The landlord generates profit by investing the deposit. There are also mixtures of standard monthly rental contracts and Jeonse contracts. Around 20 percent of occupied households are under these Jeonse contracts (see table 3). Internationally compared, the owner-occupancy ratio is rather low, partially due to the existence of Jeonse contracts, which are often considered as a step toward home ownership. For ease of purpose, I will abstract from these peculiarities of the Korean housing sector in the following.

For a more comprehensive, up-to-date overview of the Korean residential housing sector, see Kim and Park (2016).

4.   Results

4.1   Baseline Results

For the baseline estimation, impulse responses to all four shocks are depicted in figure 3. A one-standard-deviation BB-MaPP shock (first column) increases the BB-MaPP index by about 0.015 on impact, equivalent to either an average decrease in the mandatory LTV ratio by 0.43 percentage point or a decrease in the mandatory DSTI ratio by 0.45 percentage point. At first glance, these shocks seem considerably small, but macroprudential measures in Korea are often targeted only toward specific groups of potential homebuyers or certain areas. Thus, while shocks might seem small on an average level, they can be quite substantial for individual borrowers. In 2009, for example, LTV regulations for house purchases above 600 million won in the metropolitan area were tightened by 10 percentage points, displaying a shock for affected borrowers multiple times more then those considered here. While the BB-MaPP shock dies out surprisingly fast, it effectively pushes down real household credit and house prices, both by about 0.3 percent at their peak. Credit reacts directly on impact and reaches its peak response after one year. House prices, possibly due to some stickiness (see, e.g., Merlo and Ortalo-Magné 2004 for empirical evidence on house price stickiness), only become negative after one quarter and exhibit their peak response after around six quarters.

Interestingly, the decrease in real residential investment is economically large but statistically only significant on impact at the 68 percent level. Depending on the region under consideration, responsiveness of housing supply may differ considerably. It is also not clear whether and how a decrease in housing demand affects investment decisions of existing homeowners regarding, e.g., maintenance or improvements. As imposed by the sign restrictions, real consumption decreases. The reasoning is twofold: (i) a tighter regulation prevents some homeowners from refinancing their mortgages with a smaller equity stake to antedate consumption and (ii) potential homebuyers affected by the regulation could be forced to reduce consumption in order to raise the demanded downpayment. In line with the decrease in residential investment and consumption, real GDP also declines but only significantly so for a short period of time.

Figure 3. Impulse Response Functions to the Baseline Sign-Identified BVAR
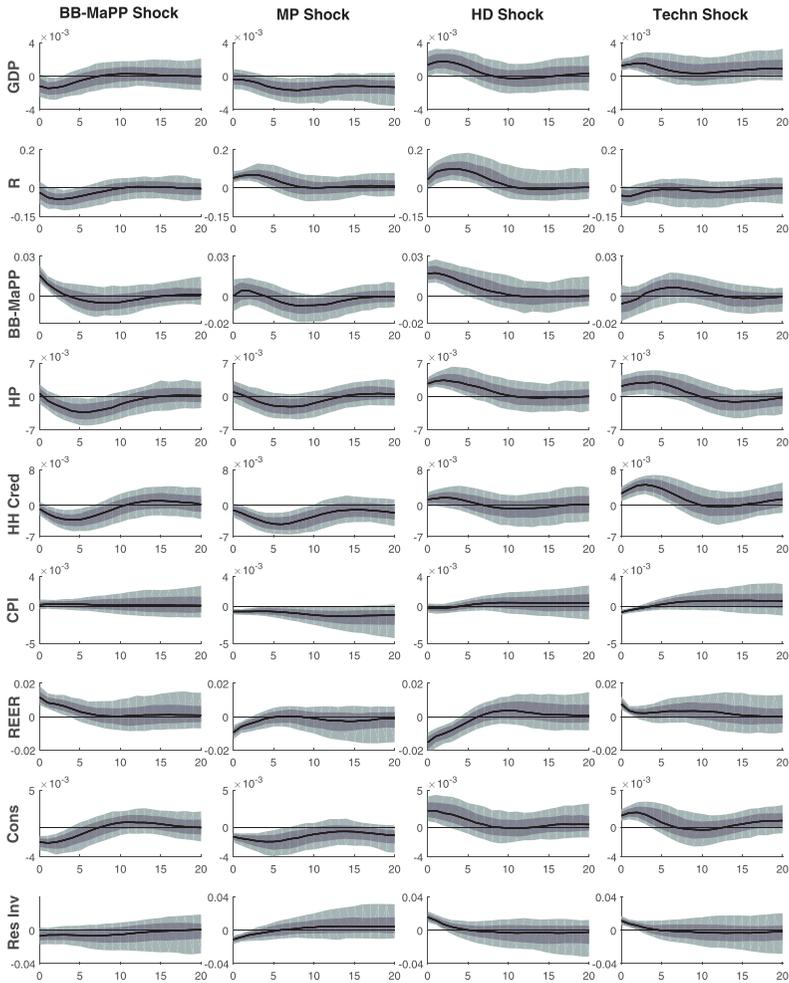
Notes: Each column represents a shock: borrower-based macroprudential policy (BB-MaPP), monetary policy (MP), housing demand (HD), and a technology (Techn) shock. Each row gives the response of the respective variable: real GDP (GDP), short-term nominal interest rate (R), borrower-based macroprudential policy (BB-MaPP) index, real house prices (HP), real household credit (HH Cred), consumer price index (CPI), the real effective exchange rate (REER), real consumption (Cons), and real residential investment (Res Inv). Gray shaded areas give the 68 percent and 90 percent credibility intervals.

The overall contractionary response to the BB-MaPP shock triggers an interest rate decrease, mitigating the overall effects on the real economy. Most empirical studies are silent on these potential costs of macroprudential regulations. One exception is Kim and Mehrotra (2018), who similarly observe a decline in overall economic activity, but a much more persistent one. Additionally, they find that consumer prices are negatively affected by a tightening of macroprudential regulations. Since they pool all types of macroprudential measures, this might indicate that the negative aggregate demand effects of macroprudential regulations besides BB-MaPP are comparably stronger.[20]

A monetary policy shock (second column in figure 3) first of all leads to an increase of the nominal short-term rate by 6 basis points on impact. This is rather small but in line with, e.g., the interest rate response in Uhlig (2005), which is much smaller in a sign-restrictions approach than with recursive identification. Most strikingly, house price responses to the contractionary monetary policy shock are comparably small and not significant at the 90 percent level. This result can be motivated by a decreasing interest rate sensitivity of housing demand for increasing downpayment requirements (see Calza, Monacelli, and Stracca 2013). On impact, real GDP does not react significantly but exhibits a sustained decline in contrast to its reaction to the BB-MaPP shock. Otherwise, responses go in the accustomed directions.

Another potentially important driver of real estate cycles is housing demand shocks (third column in figure 3). As house prices increase, housing wealth as well as the collateral capacity of constrained homeowners increases, which can explain the increase in consumption (see also Iacoviello and Neri 2010). Surprisingly so, the increase in household credit is not significant at the 90 percent level and comparably small, contradicting the idea that the increased collateral capacity is primarily responsible for the consumption hike. The effect of the housing demand shock is relatively short-lived, possibly due to the strong counteracting response of the interest rate and the BB-MaPP index. Technology shocks—as an important

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[20]The differences in responses to their study should be interpreted with some caution, as they estimate a panel SVAR with four countries (Korea is one of them) and use recursive identification.

Figure 4. Historical Decomposition

Real House Prices

Real HH Credit
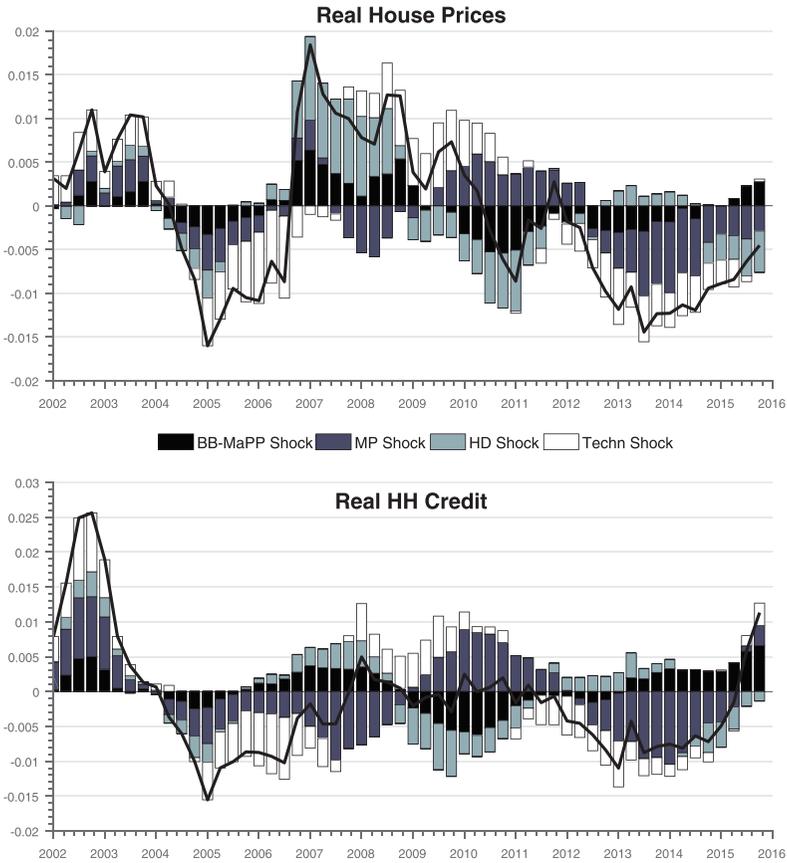
Notes: The solid line depicts the log-deviation of real house prices and real household credit, respectively, from their deterministic paths. The residual that comprises the five unidentified shocks in the BVAR is not reported to improve visibility.

driver of business cycle fluctuations—also contribute significantly to housing variables. These responses should capture part of the interdependency between real estate and business cycles.[21]

Figure 4 displays the historical decomposition of real house prices and real household credit, starting with the introduction of LTV

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[21]House prices are generally procyclical, while residential investment leads the business cycle (see, e.g., Morris and Heathcote 2005).

regulations in 2002. The bars depict the historical contribution of each shock to deviations of the two time series from their deterministic path, i.e., the path the time series would have followed if no shocks had taken place. As is common, only the median contribution of each shock in each period is considered. For better visibility, the five unidentified "residual" shocks are ignored.[22] The following results should be taken with some caution, as the potential influence of the initial conditions as well as estimation uncertainty are ignored.

First, all four shocks contribute importantly to the evolution of the two time series. While housing demand shocks drove the small housing boom starting at the end of 2006, a tightening in macroprudential measures was co-responsible for a decrease in house prices and household credit afterward. At the same time, loose monetary policy in reaction to a weakening domestic economy during the ongoing global financial crisis worked in the opposing direction in the Korean housing market. This demonstrates the advantage of the targeted approach of BB-MaPP measures. According to the historical decomposition, house prices would have been 0.5 percent higher without the regulations. Considering that the three tightening measures in 2009 were all targeted only toward the Seoul metropolitan area and, especially, the speculative zones therein, the contribution to house prices within these areas was possibly much larger. At the current end of the sample, the role of housing demand seems to have diminished, while the influence of the two policy tools increased. A unification of the LTV and DSTI regulations, tantamount to an overall loosening of the policies, already takes effect in that it pushes both housing-sector variables.

All things considered, the baseline SVAR suggests that BB-MaPP measures are effective in curbing real estate cycles when deployed at the right time. Nevertheless, these targeted policies have economy-wide effects in the short run, although not as sustained as conventional monetary policy.

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[22]At times, these shocks can have a large impact, but do not allow for any structural interpretation.

4.2 Robustness Checks

In the following, results are tested for the robustness toward splitting the BB-MaPP index, alternative identifications, as well as additional prior information. To keep the analysis concise, only impulse responses for the BB-MaPP shock and the monetary policy shock are presented.

4.2.1 Splitting the BB-MaPP Index

One concern regarding the baseline results is the merging of LTV and DSTI regulations into one BB-MaPP index. While the assumption of similar effects of these two policies is common to increase time-series variation (see, e.g., Tillmann 2015, Cerutti, Claessens, and Laeven 2017, or Kim and Mehrotra 2018), previous research has shown that their effects might differ (see, e.g., Igan and Kang 2011 or Claessens, Gosh, and Mihet 2013). Gelain, Lansing, and Mendicino (2013), e.g., argue that DSTI caps might be superior in stabilizing household debt and house prices, since the latter are generally more volatile than income, in line with the empirical results in Claessens, Gosh, and Mihet (2013). Thus, in the following, I split the BB-MaPP index into an LTV and a DSTI index as described in the appendix.

Figure 5 reports the impulse responses to a one-standard-deviation LTV shock (A) and to a one-standard-deviation DSTI shock (B).[23] On impact, the shocks lead to a tightening of the LTV ratio by 0.79 percentage point and a tightening of the DSTI ratio by 0.47 percentage point. For most variables, responses are virtually identical, giving justification to the consolidated index used in the baseline setup. The most striking difference is the considerably stronger response of household credit in the case of the LTV shock. In line with this, Igan and Kang (2011) find stronger demand effects of LTV regulations than of DSTI regulations utilizing survey data. However, at odds with the present impulse response functions, they only detect a dampening in house prices expectations after stricter

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[23]Changes in the impulse responses of the other shocks are negligible and are therefore not reported.

Figure 5. BVAR IRFs with LTV Ratio vs. DSTI Ratio

A. LTV Index   B. DSTI Index
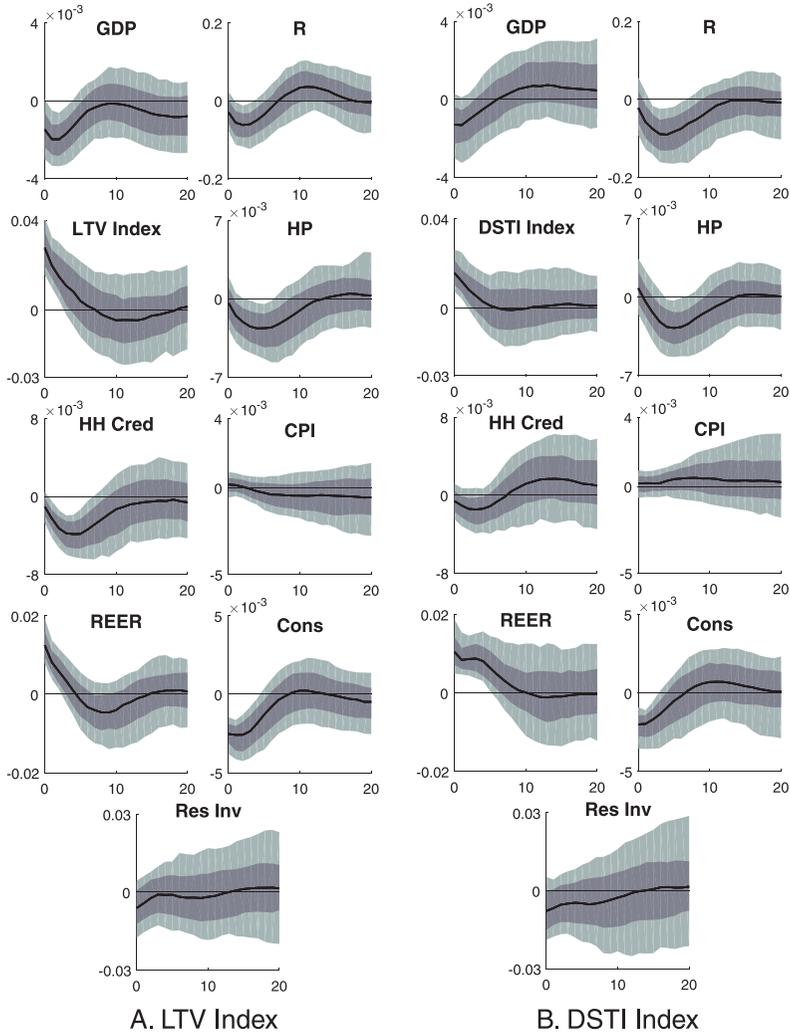
Notes: See note in figure 3. The BB-MaPP index is replaced by the LTV index in panel A and the DSTI index in panel B; a description of these indexes is given in the appendix.

caps on LTV ratios.[24] An alternative explanation could be a stronger decline in mortgage equity withdrawals by existing homeowners to finance consumption, which would also explain the slightly more marked reaction of real consumption in the case of the LTV shock. The stronger reaction of household credit following an LTV regulation also leads to a somewhat more pronounced fall in overall economic activity.

While I provide evidence for a similar reaction following both policies, results should be taken with some caution, as time-series variation is reduced to 11 changes in the LTV index and 10 changes in the DSTI index. Furthermore, DSTI regulations, at least in the beginning, were targeted to more specific types of borrowers—mostly in the speculative zones—while a wider audience was subject to LTV regulations in Korea. Differences in the effectiveness of the two regulations also boil down to the calibration of the measures and whether the targeted borrowers actually become constrained, which cannot be tested with the available data.

4.2.2 Alternative Identifications

To complement previous findings, a traditional recursive identification similar to Kim and Mehrotra (2018) is implemented. The approach follows Bernanke, Boivin, and Eliasz (2005) in dividing the variables into "slow-moving," "fast-moving," and shock variables. To keep matters simple, only a monetary policy and a BB-MaPP shock are identified, where the latter is ordered first as in Kim and Mehrotra (2018). Following Bańbura, Giannone, and Reichlin (2010), zero restrictions are imposed on the impact responses of the "slow-moving" variables—real GDP, real house prices, the CPI, real consumption, and real residential investment—while real household credit and the real effective exchange rate are considered to be "fast moving."

Impulse responses in figure 6 are mostly comparable to the ones from the sign-identified BVAR in figure 3, at least from a qualitative perspective. Real household credit as well as real house prices decline

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[24]Igan and Kang (2011) argue that DSTI ratios are more closely related to the affordability channel: following a tighter regulation, only richer households with a lower price sensitivity qualify for a mortgage loan such that, despite the lower demand, the willingness to pay does not decrease.

Figure 6. BVAR IRFs with Recursive Identification

A. BB-MaPP Shock   B. MP Shock
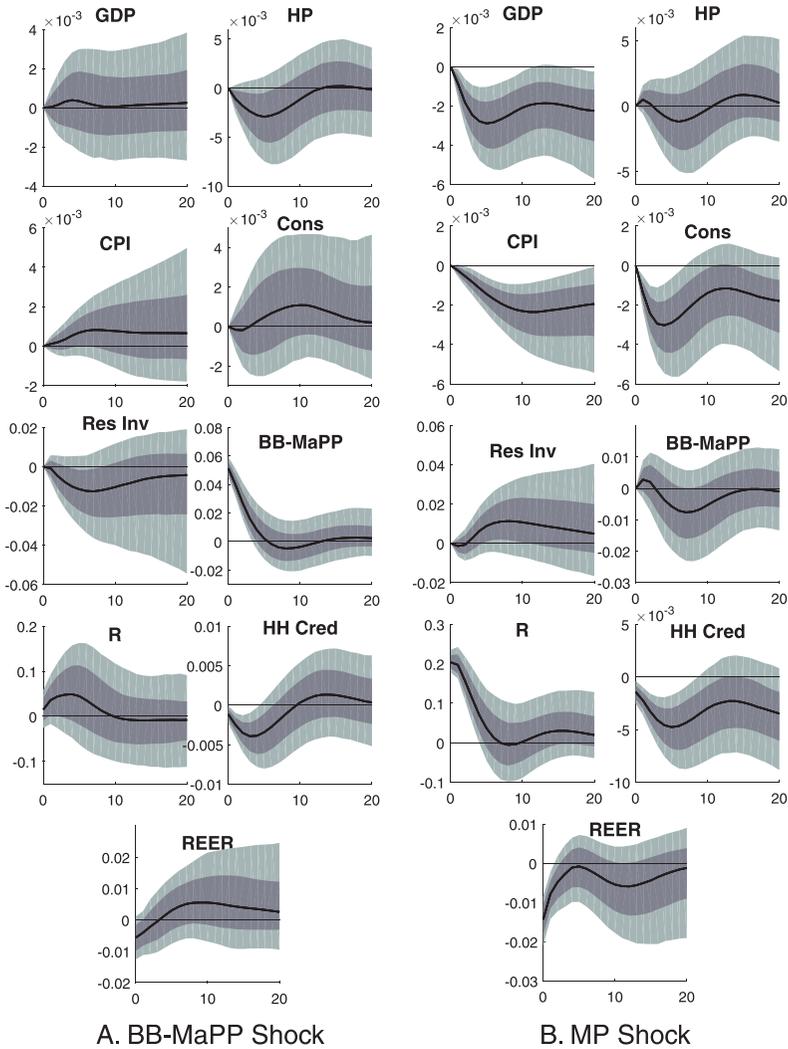
Notes: See note in figure 3. The BVAR is recursively identified using a Cholesky decomposition: GDP, HP, CPI, Cons, and Res Inv are defined as "slow-moving" variables, while HH Cred and REER are defined as "fast-moving" variables. The BB-MaPP shock is ordered before the MP shock.

Table 4. Alternative Sign Restriction

	BB-MaPP Shock	MP Shock	HD Shock	Techn Shock
Real Res Inv		−	+	+
Inflation		−		−
Real Cons	−	−		+
BB-MaPP Index	+		+	
Interest Rate	−	+	+	−
Real GDP				+
Real House Prices			+	
Real HH Credit				
REER				

Notes: Each column represents a shock: borrower-based macroprudential policy (BB-MaPP), monetary policy (MP), housing demand (HD), and a technology (Techn) shock. A "+" sign restricts the impact response for the variable to the respective shock to be non-negative for the first two quarters, while a "−" sign restricts the impact response of the variable of the respective shock to be non-positive for the first two quarters.

after a contractionary BB-MaPP shock, although the latter response is only significant at the one-standard-deviation level. In the recursive identification, the effect of monetary policy on house prices is completely muted. The real effective exchange rate drops on impact, as imposed in the sign-identified approach for the monetary policy shock, but moves in the "wrong" direction for the BB-MaPP shock. This indicates that the negative sign imposed above might be debatable. Lastly, and in contrast to the findings of Kim and Mehrotra (2018), GDP is not affected by the macroprudential measures at all.

While in line with the model, the recursive identification rejects the imposed sign on the REER for the BB-MaPP shock. Additionally, empirical evidence suggests that the connection between macroeconomic fundamentals and exchange rates might be unstable over time (see, e.g., Bacchetta and van Wincoop 2013 or Fratzscher et al. 2015). Table 4 presents alternative sign restrictions consistent with the model that uniquely identify the four shocks without restricting the REER.

Figure 7 presents the impulse responses for the BB-MaPP and the monetary policy shock. Differences between these and the baseline results are mostly negligible. The reaction of house prices and household credit following a BB-MaPP shock are somewhat smaller,

Figure 7. BVAR IRFs with Alternative Sign Restrictions
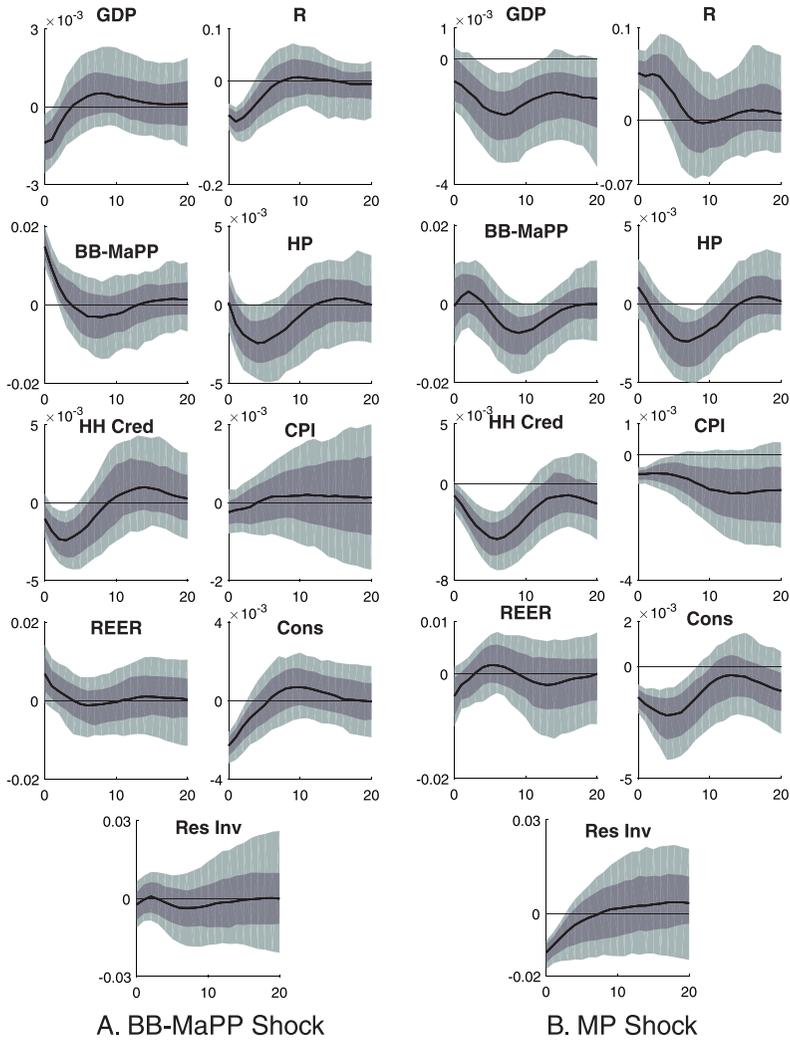
Notes: See note in figure 3. The alternative sign restrictions imposed are given in table 4.

while there is no significant feedback to residential investment anymore. This can be rationalized by a stronger decline of the interest rate, which is now imposed by a sign restriction. Importantly, the REER still moves in the same direction as proposed by the model.

Besides the smaller reaction of the REER, responses to the monetary policy shock are virtually the same as in the baseline identification. Overall, figure 7 reinforces previous results and shows that these are not driven by the restriction on the REER, but warn against giving too strong a weight to the exact quantitative reaction of the variables of interest.

4.2.3 Additional Prior Information

In forecasting exercises, adding additional prior information generally improves the precision of the results (see, e.g., Bańbura, Giannone, and Reichlin 2010). Therefore, I further add two popular modifications to the standard Minnesota prior: the sum-of-coefficients (SOC) prior and the co-persistence (COP) prior.

The SOC prior, proposed by Doan, Litterman, and Sims (1984), shrinks the long-run relationship in an error-correction representation of the BVAR in (13), $(I - A_1 - \cdots - A_p)$, toward zero. This "inexact differencing" imposes a unit root on each variable, y_t, but also rules out cointegration in the limit. To control for this shortcoming, Sims (1993) proposed the co-persistence prior. This prior imposes the belief that the dynamic behavior of the model is well presented by a no-change forecast. The idea is to bring the prior belief toward a form with unit-root nonstationarity in all variables but still allowing for possible cointegration relationships. Both priors can be easily added to the dummy observations (see, e.g., Bloor and Matheson 2010).[25] To abstract from the influence of a change in the overall tightness of the prior, λ is fixed at 0.16, the value of the baseline setup.[26]

Impulse responses for different prior specifications are reported in figure 8 for the BB-MaPP and the monetary policy shock. In general, differences in the results are of a qualitative, not a quantitative, nature. The COP prior on its own mostly mimics the baseline impulse responses. The SOC prior, on the other hand, imposes more

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[25]The tightness of the priors is set to 10λ as Bańbura, Giannone, and Reichlin (2010) do for the SOC prior; Bloor and Matheson (2010) show that forecasting performance in their model is robust to different specifications.

[26]The in-sample fitting procedure described in section 3.1 would suggest a looser prior when including the additional prior information; however, results are nearly identical to the ones presented here.

Figure 8. BVAR IRFs with Alternative Prior Information
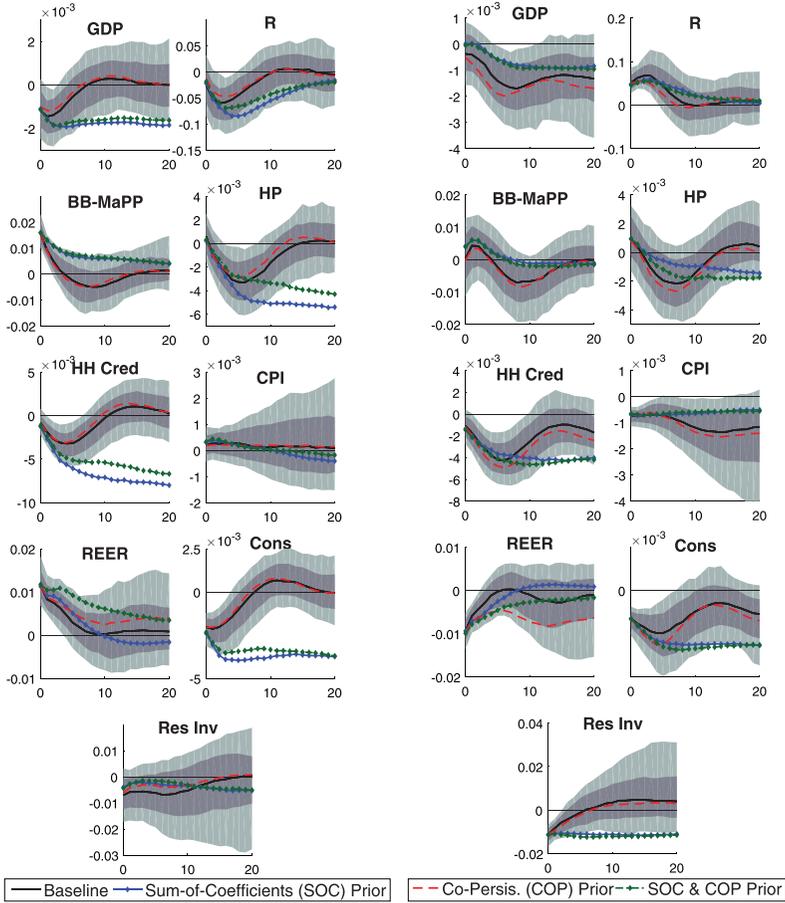
A. BB-MaPP Shock   B. MP Shock

Note: See note in figure 3.

persistent responses but also introduces more posterior draws with explosive roots. Consequently, the higher persistence in the response of the BB-MaPP index after a BB-MaPP shock is followed by a stronger and more sustained contraction in household credit and house prices, triggering more substantial losses in GDP and consumption. Not surprisingly, the combined prior is dominated by the influence of the SOC prior and therefore largely follows its responses.

In general, the main results are independent of the choice of prior. However, as the inclusion of the COP and, especially, the SOC prior leads to more posterior draws which exhibit explosive roots, results in this subsection should be taken with a grain of salt. At least in the relatively small sample under investigation, conclusions drawn from the simple Minnesota prior seem to be more reliable.

5.   Conclusion

In this paper, I estimate a sign-identified Bayesian SVAR model to analyze the effects of mandatory caps on LTV and DSTI ratios in the Korean real estate market. The sign restrictions are drawn from an agnostically calibrated small open-economy DSGE model that allows housing to be collateralizable. Results suggest that BB-MaPP measures, in effect since 2002 in Korea, have been successful in curbing real estate cycles in the form of household credit and house prices. Contractionary monetary policy shocks have only moderate effects on real house prices, in accordance with a weaker collateral constraints channel under strict downpayment requirements. A historical decomposition indicates that BB-MaPP measures helped in keeping the housing boom around the outbreak of the global financial crisis in check, while at the same time a loose monetary policy was able to stimulate the overall economy. Taken together, these results point to BB-MaPP regulations being a potentially important factor in the relatively stable house prices in Korea since their inception and emphasize the advantages of a targeted approach toward regulation. The study adds to the rather new branch of literature investigating macroprudential regulations empirically. By concentrating on a country with comparably long experience of BB-MaPP regulations, the construction of a new BB-MaPP index allows for the application of a VAR approach, thus circumventing potential problems of endogeneity inherent in previous panel data approaches.

The importance of investigating these regulations is obvious. A wide array of macroprudential policies has been proposed to dampen boom-bust cycles in asset markets, especially in real estate markets. Thus, understanding which policies are successful under which circumstances is crucial in defining the optimal policy mix. While this study makes a point for the implementation of mandatory LTV and DSTI regulations in real estate markets, a few shortcomings must be

taken into account. First of all, results might not be directly transferable to other countries due to the peculiarities of the Korean housing market, such as Jeonse contracts and a rather active housing supply policy preceding the sample period under investigation. Secondly, by aggregating over the whole country, the study ignores possible heterogeneous effects of the regulations. Thirdly, potentially undesirable distributional effects are ignored. Lastly, the influence of tightening and loosening periods on real estate markets might be different.

These shortcomings already set the ground for possible future research. Nonlinearities with respect to the direction or timing of policies could be taken into account. With more granular data, the investigation of distributional effects of these regulations might also be possible. In general, data limitation is the most relevant confining factor of empirical research on macroprudential policies. However, in line with the growing international experience with macroprudential policies, this factor should become less of an obstacle.

Appendix

A.1 Additional Details on the Model

A.1.1 Households' First-Order Conditions

Impatient households maximize utility in (1) subject to the budget constraint (3) and the binding borrowing constraint (4), leading to the following first-order conditions (FOCs):[27]

$$q_t = \gamma_t \frac{C_t^b}{D_t^b} + m_t(1-\delta)\psi_t \mathbb{E}_t[q_{t+1}\Pi_{c,t+1}] + \beta_b(1-\delta)\mathbb{E}_t\left[\frac{C_t^b}{C_{t+1}^b}q_{t+1}\right] \tag{A.1}$$

$$R_t\psi_t = 1 - \beta_b\mathbb{E}_t\left[\frac{C_t^b}{C_{t+1}^b}\frac{R_t}{\Pi_{c,t+1}}\right] \tag{A.2}$$

$$\frac{W_{j,t}^b}{P_{c,t}} = C_t^b(N_{j,t}^b)^\varphi, \quad j = c, d, \tag{A.3}$$

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[27]Note that the multipliers on the constraints (1) and (3) are defined as λ_t^b and $\lambda_t^b\psi_t$; ψ_t can then be interpreted as the marginal value of borrowing.

where (A.1) equates the marginal utility of nondurable consumption to the shadow value of durable services, equation (A.2) is a Euler equation incorporating the shadow value of borrowing of constrained households, and equation (A.3) links the real wage to the marginal rate of substitution between consumption and leisure in both sectors.

Patient households do not face a borrowing constraint and, thus, maximize utility subject only to their budget constraint:

$$q_t = \gamma_t \frac{C_t^s}{D_t^s} + \beta_s(1-\delta)\mathbb{E}_t\left[\frac{C_t^s}{C_{t+1}^s}q_{t+1}\right] \tag{A.4}$$

$$1 = \beta_s\mathbb{E}_t\left[\frac{C_t^s}{C_{t+1}^s}\frac{R_t}{\Pi_{c,t+1}}\right] \tag{A.5}$$

$$\frac{W_{j,t}^s}{P_{c,t}} = C_t^s(N_{j,t}^s)^\varphi, \quad j = c,d \tag{A.6}$$

$$1 = \beta_s\mathbb{E}_t\left[\frac{C_t^s}{C_{t+1}^s}\frac{\mathcal{E}_{t+1}}{\mathcal{E}_t}\frac{R_t^*\Xi(\mathcal{E}_tb_{f,t}^*)}{\Pi_{c,t+1}}\right]. \tag{A.7}$$

Conditions (A.4–A.6) are the same as for impatient households when $\psi_t = 0$. The last condition in equation (A.7) equates marginal utility of consumption today with discounted marginal utility of consumption in the next period by saving in the international bonds market.

A.1.2 Inflation, Exchange Rate, and the Terms of Trade

The bilateral terms of trade in sector j between the domestic economy and country are given by i as $S_{j,i,t} = \frac{P_{j,i,t}}{P_{j,h,t}}$. Log-linearizing the price index around a symmetric steady-state satisfying purchasing power parity (PPP) and using the effective terms of trade, inflation in sector j can be expressed as

$$\hat{\pi}_{j,t} = \hat{\pi}_{j,h,t} + \alpha_j\Delta\hat{s}_{j,t}, \quad j = c,d. \tag{A.8}$$

Consumer prices, therefore, depend additionally on the terms of trade scaled by the openness of sector j compared with a closed economy.

Under the assumption that the law of one price holds for all individual goods, the price of imported goods is given in log-linearized form by

$$\hat{p}_{j,f,t} = \hat{e}_t + \hat{p}^*_{j,t}, \quad j = c, d, \tag{A.9}$$

where $\hat{e}_t$ is the nominal effective exchange rate (price of foreign currency in terms of domestic currency) and $\hat{p}^*_{j,t} = \int_0^1 \hat{p}^i_{j,i,t} di$ is the world price index.

Now, further define the bilateral real exchange rate for good i in sector j as $\mathcal{F}_{j,i,t} = \frac{\mathcal{E}_{i,t} P^i_{j,t}}{P_{j,t}}$, such that it becomes cheaper to consume good i in sector j domestically when $\mathcal{F}_{j,i,t}$ increases. Log-linearizing, integrating over all goods i, and using the derived expressions in (A.8) and (A.9), sector j's real effective exchange rate (REER) in log-deviation from its steady state reads

$$\hat{f}_{j,t} = (1 - \alpha_j)\hat{s}_{j,t}, \quad j = c, d. \tag{A.10}$$

The real effective exchange rate for the whole economy, $\hat{f}_t$, can then be derived as a weighted average over both sectors.

A.1.3 Incomplete International Asset Markets

In order to avoid unit-root behavior in the equilibrium dynamics due to an exogenously given interest rate on incomplete international asset markets, a debt-elastic interest rate is introduced on international bonds. Then, under the assumption that foreign consumers exhibit an FOC on foreign borrowing similar to equation (A.5) and zero steady-state foreign debt, the change in domestic consumption of savers can be linked to foreign consumption in log-linearized form by

$$\mathbb{E}_t \Delta \hat{c}^s_{t+1} = \mathbb{E}_t \Delta \hat{c}^*_{t+1} + (1 - \alpha_c)\mathbb{E}_t \Delta \hat{s}_{c,t+1} + \lambda \tilde{b}_{f,t}, \tag{A.11}$$

where $\tilde{b}_{f,t}$ is the absolute deviation of foreign debt converted to domestic currency from its zero steady state and λ displays the intermediation cost parameter.

Aggregating budget constraints over both households, foreign debt evolves according to

$$\tilde{b}_{f,t} = \frac{1}{\beta_s}\tilde{b}_{f,t-1} + C(\hat{c}_t - \hat{y}_{c,t}) + q\delta D(\hat{\imath}_{d,t} - \hat{y}_{d,t}), \qquad (A.12)$$

where log-deviations from steady-state production are given by $\hat{y}_{j,t}$, $\hat{\imath}_{d,t}$ represents log-deviations from steady-state durables investment, and C and $q\delta D$ depict steady-state values of real consumption in the nondurables and durables sector.

A.1.4 Aggregation

Aggregate goods market clearing of domestic production in both sectors requires

$$Y_{c,t}(k) = C_{h,t}(k) + \int_0^1 C_{h,t}^i(k)di \qquad (A.13)$$

$$Y_{d,t}(k) = I_{d,h,t}(k) + \int_0^1 I_{d,t}^i(k)di. \qquad (A.14)$$

Under the assumption of symmetric preferences across countries, taking into account the demand schedules of domestic and foreign households, as well as aggregate production in sector j in (6), a similar derivation as in Galí and Monacelli (2005) gives

$$\hat{y}_{c,t} = (1 - \alpha_c)\hat{c}_t + \alpha_c\hat{c}_t^* + \vartheta_c\hat{s}_{c,t} \qquad (A.15)$$

$$\hat{y}_{d,t} = (1 - \alpha_d)\hat{\imath}_{d,t} + \alpha_d\hat{\imath}_{d,t}^* + \vartheta_d\hat{s}_{d,t}, \qquad (A.16)$$

where $\vartheta_j = \zeta_j + \eta_j(1 - \alpha_j)$. Thus, aggregate domestic production in sector j depends on changes in domestic and foreign consumption, but also on changes in the terms of trade.

Aggregate real output is given by $Y_t = \frac{P_{c,h,t}}{P_{h,t}}Y_{c,t} + \frac{P_{d,h,t}}{P_{h,t}}Y_{d,t}$, where the producer price index is defined as $P_{h,t} = (1 - \tau)P_{c,h,t} + \tau P_{d,h,t}$, with τ being the steady-state share of housing in aggregate production. Aggregate production in log-linearized form can then be shown to follow

$$\hat{y}_t = \frac{C}{Y}\lambda_y\hat{y}_{c,t} + q\frac{\delta D}{Y}\lambda_y\hat{y}_{d,t}, \qquad (A.17)$$

where $\lambda_y = [(1 - \tau) + \tau q]^{-1}$.

Table A.1. Data and Sources

Variable	Description	Source
GDP	Quarterly GDP at market prices, chained 2010 year prices, seasonally adjusted	Bank of Korea (BoK)
REER	Real effective exchange rate, 2010 = 100 (↑: increase in competitiveness)	Bank for International Settlements (BIS)
R	Overnight interbank call rate	BoK
BB-MaPP	Borrower-based MaPP index	See appendix
HP	Real residential property price index, 2010 = 100, seasonally adjusted	BIS
HH Cred	Real credit to households (outstanding), deflated by CPI, seasonally adjusted	BIS
CPI	Consumer price index, 2010 = 100, seasonally adjusted	BoK
C	Real household consumption, chained 2010 year prices, seasonally adjusted	BoK
Res Inv	Real residential investment, chained 2010 year prices, seasonally adjusted	BoK

A.2 Creation of a BB-MaPP Index

The starting point for the creation of a BB-MaPP index is to calculate an average regulatory LTV and DSTI ratio for the sample period. Building on the work by Igan and Kang (2011) and Shim et al. (2013), table A.2 depicts all changes in these regulations, starting with the inception of a mandatory LTV ratio in October 2002. Overall, there have been 11 changes in the LTV ratio (seven tightening actions and four loosening actions) and 10 changes in the DSTI ratio (six tightening actions and four loosening actions).

Since most of these changes are subject to certain characteristics of the borrower, the type of loan, or the real estate purchased, a weighting scheme is introduced in table A.3. Some of the values are directly taken from Igan and Kang (2011), while others are compiled using data from the Korea Housing Finance Corporation and the Korean Statistical Information Service. The general idea is to have an individual LTV and DSTI ratio for each possible combination of the given characteristics in table A.3 and the weight thereof. Weights depict the situation in Korea before the inception

Table A.2. LTV and DSTI Regulation Changes in Korea

Date	Type	Regulation Change	Direction
10/2002	LTV	60% for banks and insurance companies	Inception
05/2003	LTV	50% for house purchases in speculative zone with loan maturity of less than three years for banks and insurance companies	Tightening
10/2003	LTV	40% for apartments in speculative zones with loan maturity of 10 years and less for banks and insurance companies	Tightening
03/2004	LTV	70% in all regions for loan maturities of more than 10 years and amortized payments for all institutions	Loosening
06/2005	LTV	40% for house purchases with value above 600 million won in speculative zones with loan maturity of 10 years and less for banks and insurance companies	Tightening
08/2005	DSTI	40% for house purchases in speculative zones for singles less than 30 years or married couples where the spouse is in debt for all institutions	Inception
03/2006	DSTI	40% for house purchases with value above 600 million won in speculative zones for all institutions	Tightening
11/2006	LTV	50% for house purchases with value above 600 million won in speculative zones for all institutions	Tightening
11/2006	DSTI	40% for house purchases in speculative zones for all institutions	Tightening
02/2007	DSTI	40% to 60% for house purchases with value less than 600 million won for banks	Tightening
08/2007	DSTI	40% to 70% for nonbank financial institutions	Tightening
11/2008	LTV DSTI	All areas except the three Gangam districts removed from list of speculative zones	Loosening
07/2009	LTV	50% for house purchases with value above 600 million won in metropolitan area for banks	Tightening
09/2009	DSTI	40% for the three Gangam districts removed from the list of speculative zones, 50% for nonspeculative zones in Seoul, 60% for other metropolitan area for banks	Tightening
10/2009	LTV	Expand regulation to metropolitan area for all institutions	Tightening
08/2010	DSTI	Exemption of house purchases in nonspeculative zone in metropolitan area if debtor owns less than two houses for all institutions (until end of March 2011)	Loosening
05/2012	LTV DSTI	Three Gangam restricts removed from the list of speculative zones	Loosening
08/2014	LTV DSTI	70% LTV ratio and 60% DSTI ratio (unification)	Loosening

Table A.3. Weighting Scheme for BB-MaPP Index

	Loan Characteristic	Weight
Institution	Banks and insurance companies	0.80
	Nonbanks	0.20
Region	Seoul metropolitan area	0.48
	Nonmetropolitan area	0.52
Region 2	Speculative area (weight within Seoul metr. area)	0.70
	Nonspeculative area (weight within Seoul metr. area)	0.30
Maturity	Loan maturity < 3 years	0.40
	Loan maturity 3–10 years	0.20
	Loan maturity > 10 years	0.40
House Price	< 600 million won	0.90
	> 600 million won	0.10
House Type	House	0.50
	Apartment	0.50
Loan Type	Amortized payment	0.40
	Balloon payment	0.60
Age	< 30 years and single and/or spouse in debt	0.15
	None of the above	0.85

Sources: Korea Housing Finance Corporation, Korean Statistical Information Service, Igan and Kang (2011).

of BB-MaPP measures in 2002, when possible, to avoid endogeneity problems. As a convention, LTV and DSTI ratios are set to 75 percent when no mandatory values are introduced.

In order to make LTV and DSTI ratios comparable, the min-max principle is used, where

$$LTV_t^{ind} = 1 - \frac{LTV_t - LTV_{min}}{LTV_{max} - LTV_{min}} \quad \text{and}$$

$$DSTI_t^{ind} = 1 - \frac{DSTI_t - DSTI_{min}}{DSTI_{max} - DSTI_{min}}$$

such that both indexes lie between zero and one, and a higher index is equivalent to a tighter regulation. Then, both indexes are combined by equal weighting so that the final borrower-based macroprudential index is given by

$$\text{BB-MaPP}_t^{ind} = 0.5 \cdot LTV_t^{ind} + 0.5 \cdot DSTI_t^{ind}.$$

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To Guide or Not to Guide? Quantitative Monetary Policy Tools and Macroeconomic Dynamics in China[*]

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This paper discusses the macroeconomic effects of China's quantity-based banking regulatory tool, "window guidance," introduced in 1998. Using an open-economy DSGE model that includes a commercial banking sector, we study the stabilizing effects of this nonstandard quantitative monetary policy tool and the implications of quantity-based versus price-based monetary policy instruments for welfare. The analyses are relevant to the current overhaul of Chinese monetary policy.

JEL Codes: C61, E32, E44, E52.

1. Introduction

China's monetary policy has been in flux in recent years. Broadly speaking, the central bank embraced a gradual switch from quantity-based measures to guide monetary policy toward a price-based

approach that gave more weight to interest rates and let liquidity levels be determined by the price, rather than volume, of capital. The change was intended to bring the People's Bank of China (PBoC) closer to the practices of its counterparts in advanced economies.

Since China is transitioning to a price-based monetary policy approach, the future roles of China's administrative and quantity-based monetary policy tools are an open question.[1] In the past, China's monetary policy has been predominantly quantitative in nature, and the use of quantitative tools has long been the norm in implementing China's monetary policy. In particular, the PBoC has relied on "lending quotas" known as "window guidance" to influence bank behavior. The origin of window guidance dates back to 1998 when the PBoC abolished its pure quantity-based credit plan, a direct control on the credit quantity of state-owned banks. Window guidance is formulated by the PBoC and uses moral suasion to get banks and other financial institutions to follow official PBoC lending guidelines. The lending guidance is communicated in regular monthly meetings with commercial banks. The window guidance policy tool primarily targets the big-four state-owned banks, but it also extends to joint-stock commercial banks and smaller local banks. What's more, in addition to aggregate/across-the-board quantitative guidance, the PBoC on occasion tries to steer lending to particular sectors of the economy. For example, the PBoC might impose limits on property-related loans or promote lending to preferred sectors such as small and medium-sized enterprises. In the past, window guidance has been regarded by observers as one of the PBOC's most effective policy tools (e.g., Fukumoto et al. 2010, Lardy 2005). Some of the success of window guidance in China can be attributed to Chinese political hierarchic structures. The governor of the PBoC ranks higher in the political pecking order than heads of the state-owned commercial banks.

This raises the question of what role window guidance should play in the future. The Chinese government's statements in this

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[1]For a review of the current overhaul of Chinese monetary policy and the next steps in transitioning to a modern and market-based monetary framework, see, e.g., Chen, Ren, and Zha (2018), He, Wang, and Yu (2015), Fernald, Spiegel, and Swanson (2014), and International Monetary Fund (2017b, pp. 34–40).

respect are inconclusive. It pledges to let markets play a decisive role in the economy, but the desire for more efficient allocation of capital clashes with the authority's reflexive instinct for control to prevent a slowdown in growth. Thus, the tension between reform and control is quite evident in China's current monetary policy overhaul. Against this background, we analyze the efficacy of window guidance in a calibrated dynamic stochastic general equilibrium (DSGE) framework. Chang et al. (2016), Dai, Minford, and Zhou (2015), Le et al. (2014), and Liu, Wang, and Xu (2017) have recently modeled China's monetary policy in DSGE models. However, none of these papers has addressed window guidance policy in the theoretical framework. We strive to close this gap with the present paper. To our knowledge, it is the first paper to provide an in-depth DSGE-based assessment of window guidance allowing insights into Chinese-style monetary policy transmission channels. We also evaluate the welfare implications of introducing window guidance as an additional monetary policy tool.

In the modeling framework, particular attention will be paid to the problem of eroding policy buffers. The erosion of policy buffers during the global financial crisis in many countries has made it more difficult to curtail the slowdown in growth through monetary stimulus. As this problem persisted, monetary policy-makers increasingly contemplated radical approaches to pull their economies out of zero lower bound quicksand. In this spirit, we assess window guidance as a nonstandard policy tool for an economy subject to rare, but highly damaging, disruptions and investigate its effects. We are thus addressing Blanchard's (2014) warning of "dark corners." This makes it possible to answer the question of whether the PBoC should retain the nonstandard window guidance toolkit to address situations in which the economy is in rare "bad" states and the PBoC is limited in the use of its policy interest rate.

The remainder of the paper is as follows. Section 2 presents descriptive evidence about China's window guidance policy. In section 3, a DSGE model with window guidance is presented. To give a sense of the magnitudes, section 4 calibrates the model and provides a set of numerical experiments. Section 5 discusses the pros and cons of window guidance from an international point of view. Section 6 concludes.

2. Window Guidance and Financial Intermediation in China

Following the narrative approach of Romer and Romer (1989, 2004), we summarize the episode-by-episode development of the PBoC's window guidance policy with the corresponding economic situation at that moment. This approach relies on the reading of the central bank's documents to infer additional information on the PBoC's intentions. The policy stance is identified and, in addition, the driving force of each policy movement is detected.[2] We study all issues of the "Quarterly Monetary Policy Report" (QMPR) from 2001 onward and construct an indicator for the window guidance policy stance.[3]

The PBoC's window guidance policy can be classified into five stances. Table 1 presents definitions of indicators corresponding to five different stances of window guidance. Online appendix A (available at http://www.ijcb.org) gives a quarter-by-quarter summary of stances of PBoC window guidance policy from the QMPR.

Our method of distilling the window guidance information contained in the PBoC publications gives the following timeline of the window guidance policy stance:

- *1998–2000:* The PBoC started to implement window guidance in 1998 in the wake of the Asian Financial Crisis. The PBoC sought to boost the economic growth by stimulating the supply of bank credit through an "encouraging" window guidance policy. The PBoC cautioned banks, however, about real estate lending; see Zhang and Ji (2012).
- *2001–02:* The PBoC gave "no explicit direction" on window guidance during this period.

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[2]Angrick and Yoshino (2018) have recently combined the narrative approach with computational linguistic methods to quantify the stance of window guidance.

[3]The quarterly publication has been released since 2001:Q1. Its purpose is to increase policy transparency and enhance communication with the general public. For the purposes of this discussion, the useful feature is that the PBoC has commented consistently on window guidance since 2001:Q4. When evaluating the PBoC reports, we have paid particular attention to a careful demarcation of window guidance statements from wider governmental policy objectives.

Table 1. Qualitative Window Guidance Policy Stances (1998:Q1–2016:Q2)

Indicator	Stance	Period	Definition
–2	Strongly Discouraging	2003:Q1–2004:Q4 2006:Q2–2008:Q2 2009:Q2–2010:Q1	QMPR explicitly discourages growth of total credit.
–1	Weakly Discouraging	2005:Q1–2006:Q1 2010:Q2–2012:Q2	QMPR states the target of optimizing credit structure, provides risk alerts, and/or mentions that banks should manage the pace of credit growth.
0	No Explicit Direction	2001:Q1–2002:Q4 2012:Q3–2014:Q2	QMPR only states the target of optimizing credit structure and separately listing the sectors that should be both discouraging and encouraging (differentiated approach to credit guidance) *or* no explicit direction of credit growth.
1	Weakly Encouraging	2014:Q3–2016:Q2	QMPR only lists sectors to be encouraged for the target of optimizing credit structure.
2	Strongly Encouraging	1998:Q1–2000:Q4 2008:Q3–2009:Q1	QMPR encourages the growth of total credit explicitly.

Sources: Author's classification based on the information from PBoC's QMPR and Zhang and Ji (2012).

- *2003–08:* The PBoC strengthened window guidance to curb accelerated growth in lending, particularly to the real estate sector. During this period, the PBoC expressed a "strongly discouraging" window guidance stance to cool credit growth (2003–04 and 2006 to mid-2008), and a "weakly discouraging" stance in 2005, when the PBoC guided banks to optimize the credit structure in light of falling consumer price index (CPI) inflation.

- *2008–09:* The onset of the global financial crisis in September 2008 adversely affected the Chinese economy. Facing

rapidly deteriorating economic growth, Chinese authorities introduced a 4-trillion-yuan stimulus plan, while the PBoC simultaneously removed all rigid constraints on commercial bank lending and adopted a window guidance policy that "strongly encouraged" banks to provide loans in the last quarter of 2008. The policy continued through mid-2009.

- *2009–10:* Surging bank lending, particularly to real estate investment, alerted the Chinese authorities to an emerging risk of overheating. The PBoC responded with a sharp policy reversal on window guidance to "strongly discourage" lending. It emphasized the role of banks in risk prevention and controling credit growth.

- *2010–12:* As credit growth gradually slowed in early 2010, the PBoC assumed a "weakly discouraging" window guidance stance. The PBoC encouraged banks to manage the pace and structure of credit supply and sought to discourage lending in overcapacity sectors.

- *2012–14:* While a production growth slowdown and overcapacity concerns prevented the PBoC from stating an explicit direction for credit growth under its window guidance stance, it was able to emphasize loan reallocation. Specifically, it said its target now was optimizing the credit structure and focused window guidance by sector. A "discouraging" stance was recommended for overcapacity sectors and an "encouraging" stance for policy sectors. The period marked the beginning of an era in which the PBoC emphasized the loan reallocation function of window guidance.

- *2014–16:* As economic growth slowed, the PBoC "encouraged" banks to lend more. The nuanced response of sector focus meant, however, that overcapacity sectors still received differentiated treatment and one-size-fits-all measures were eliminated.

Figure 1 shows four selected macroeconomic variables overlaid with the time-varying window guidance stance. (For figures in color, see the online version at http://www.ijcb.org.) The shifting intensity and focus of the window guidance policy stance reflects the business cycle in terms of the output gap, the change in the output gap, CPI inflation, and loan growth. The graphical evidence illustrates

Figure 1. Window Guidance Stance, Output Gap, CPI Inflation, and Loans
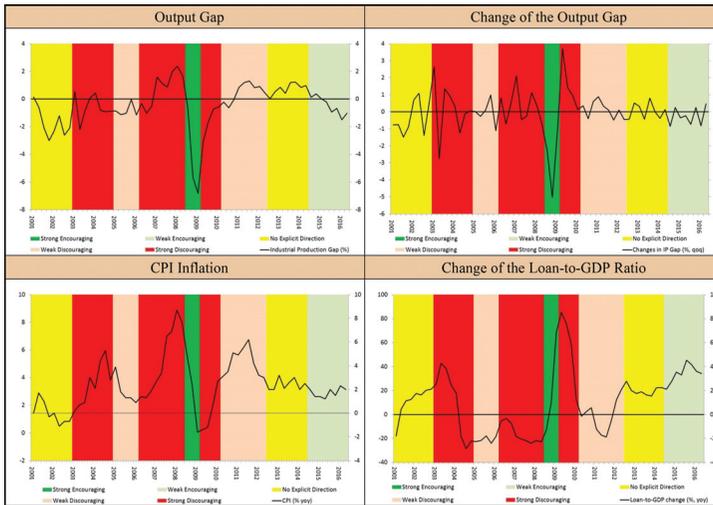
Sources: Authors' calculations based on information from PBoC and National Statistical Bureau of China.
Notes: The definitions of the quarterly variables are descibed in online appendix B. Here, we use the industrial-production-based output gap instead of the GDP-based output gap, because, at least in our view, the PBoC's loan-related policies have tended to focus mainly on industrial output growth.

that the window guidance stance is indeed countercyclical and thus aligned with the business cycle.

Summarizing the above, it can be said that window guidance is a prominent quantity-based monetary instrument to the present day. It is repeatedly emphasized in the PBoC's monetary policy reports. How is the window guidance policy stance coordinated with other monetary policy instruments? Figure 2 shows the systematic pattern between window guidance and other monetary policy tools. When the window guidance stance is "encouraging," interest rates decrease, and vice versa. Furthermore, the PBoC usually raises the required reserve ratio during the period when the window guidance stance is "discouraging," and vice versa.[4] In other words, the price-based and quantity-based instruments are mutually coordinated.

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[4]Traditionally, the PBoC has steered reserve requirements to sterilize liquidity injections and withdrawals related to its interventions in the foreign exchange

Figure 2. Coordination between Window Guidance and Price-Based Monetary Policy Tools
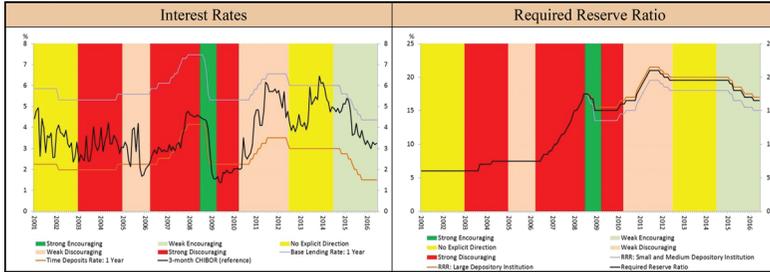
Sources: PBoC, CEIC, and authors' calculations.

It should be noted that we regard the evidence presented above as more descriptive than a rigorous statistical pursuit. In particular, we have so far not acknowledged the fact that the window guidance stance evolves endogenously with the state of the economy. Not only may the PBoC respond to incoming news about output and inflation by changing its policy stance, but shifts in its policy stance can also affect agents' expectations about the future evolution of the economy. Without isolating this systematic component of monetary policy, it is difficult to infer anything about the effectiveness of window guidance. In order to separate the "surprise" window guidance component from the "expected" window guidance component, one needs to control for the variation in economic fundamentals that the policy endogenously responds to. To do so we estimate the forward-looking Taylor rule $S_t = c + \beta_S S_{t-1} + \beta_\pi \pi^e_{t+1} + \beta_{gap} gap^e_{t+1} + \varepsilon_t$, where S_t is the the window guidance stance, π^e_{t+1} is the inflation expectation in the next period (proxied by the one-step-ahead AR(1) forecasts), gap^e_{t+1} is the industrial production-based output gap forecast for the next period (proxied by the one-step-ahead AR(1) forecasts), and ε_t is the error term. Then, the window guidance shocks can be calculated as $\hat{\varepsilon} = S_t - \hat{c} - \hat{\beta}_S S_{t-1} - \hat{\beta}_\pi \pi^e_{t+1} - \hat{\beta}_{gap} gap^e_{t+1}$.[5] What

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markets. For this reason, we omit the reserve requirement rate as a monetary policy tool from our closed-economy DSGE framework.

[5]In constructing the five-value window guidance policy stance variable and window guidance policy shock indicator, we would like to point out that, like

Table 2. The Correlation Coefficient of the Window Guidance Shock $\hat{\varepsilon}_t$ and Economic Variables

Variables	Correlation Coefficient
Output Gap	−0.1467
ΔOutput Gap	−0.5507
CPI Inflation	−0.0325
ΔLoan-to-GDP Ratio	−0.0666

Sources: Authors' calculations based on information from PBoC and National Statistical Bureau of China.
Note: The definitions of variables are described in online appendix B.

is the relationship between the two indicators S_t and $\hat{\varepsilon}_t$? The correlation coefficient and the rank correlation coefficient of S_t and $\hat{\varepsilon}_t$ are 0.623 and 0.806, respectively. In addition, the graph in online appendix C shows that in the change of each regime (stance), there is a jump and otherwise $\hat{\varepsilon}_t$ is roughly zero. This is confirmed by the bivariate Granger causality tests in online appendix D, which find unidirectional Granger causality from $\hat{\varepsilon}_t$ to S_t. Finally, the correlation coefficients of $\hat{\varepsilon}_t$ with the economic variables given in table 2. As expected, the results show that the PBoC employs window guidance policy in a countercyclical manner.

It is important to emphasize that providing a precise quantification of the role of window guidance shocks is an inherently difficult task. The bivariate correlations in table 2 focus only on part of a complex web of relationships. This comes with the caveat that other factors may simultaneously affect loans and output. Not taking these into account may lead to an upward bias in the estimated role of window guidance and loans in predicting the industrial production dynamics. As a robustness check, we have therefore also calculated four-variable VARs.[6] We find that the window guidance

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many other researchers, we need to measure and analyze concepts using an ordinal scale. Recent research by Schroder and Yitzhaki (2017) shows that, in theory, the cardinal statistical treatment of ordinal variables must be robust to increasing monotonic transformations of the ordinal scale. In headline terms, we find that the econometric results are largely robust to reasonable data transformations.

[6]The associated impulse response functions are available in online appendix E.

shock measure $\hat{\varepsilon}_t$ has incremental forecasting power for loans. Furthermore, loans have a significant influence on the development of inflation and the output gap. Conversely, there is no significant feedback from loans to the window guidance shock. Overall it appears that the PBoC's attempt at policy via suasion was successful. This result provides a rigorous statistical justification for the inclusion of nonstandard window guidance policies in our framework.

Finally, two China-specific aspects warrant a brief discussion. Chen, Ren, and Zha (2018) and Hachem and Song (2016) have recently highlighted the institutional asymmetry between state-owned and non-state-owned banks in China. For this reason, further information about the transmission channel of window guidance is provided in online appendix F showing the loans from the four major state-owned banks (the Bank of China, the China Construction Bank, the Agricultural Bank of China, and the Industrial and Commercial Bank of China) versus other banks. As expected, the general impression is that the state-owned banks are by and large more compliant with the window guidance policies than private banks. Nevertheless, both loans series point in the same direction. Another potentially important question is whether the impact of window guidance is the same for state-owned and non-state-owned firms. Figure G.1 in online appendix G indicates that the time-varying loan dynamics is broadly similar across state-owned and non-state-owned firms. However, the response for state-owned firms is more pronounced. In other words, to some degree an asymmetric impact exists which may exacerbate inefficiencies in resource allocation.[7]

While a descriptive empirical exploration of the application and efficacy of window guidance gives a sense of the transmission channels of window guidance, it does not provide evidence on specific effects from a window guidance stance. Isolating the effect of window guidance from complementary policies or other economic developments constitutes a significant empirical challenge and requires cautious interpretation. To address this difficulty, a large strand of

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[7]Chang et al. (2016) study the role of reserve requirements for China's macroeconomic stabilization in a two-sector DSGE model with state-owned enterprises (SOEs) and private-owned enterprises (POEs) having access to segmented credit markets. On this topic also see Buera, Kaboski, and Shin (2011), Hsieh and Klenow (2009), and Song, Stroesletten, and Zilibotti (2011).

literature on the impact of monetary policy employs New Keynesian general equilibrium DSGE modeling toolkits. In this tradition, we offer a structural interpretation of window guidance policy through the lens of a DSGE model for mainland China.

3. The DSGE Modeling Framework

To place monetary policy discussions in China in a coherent conceptual framework, we develop a DSGE framework that considers China's unique monetary transmission characteristics. The model is designed to be tractable to obtain intuitive results.

A large body of theoretical literature has arisen in recent years on incorporating financial features and the banking sector into DSGE models. In the strand represented by Gerali et al. (2010), the model economy features patient and impatient households, as well as entrepreneurs. Impatient households and entrepreneurs are collaterally constrained. Interest rates are set optimally by banks subject to quadratic adjustment costs, which makes their pricing decisions intertemporal. Here, we extend Gerali et al. (2010) by modeling a "semi-open" economy (Jeanne 2013). We assume world interest rates do not respond to Chinese economic conditions. Only tradables are produced and purchased both domestically and abroad. Both consumption and investment goods can be imported from abroad. The ratio of domestic and imported goods in the consumption and investment bundles depends on the relative prices. Despite baby steps toward liberalization, the Chinese capital account remains largely closed (e.g., private entities are not free to hold assets denominated in foreign currency). Instead, foreign assets, accumulated from positive current account balance, are exchanged for securities denominated in local currency by the PBoC.[8] Two consequences arise from

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[8]As a semi-open economy, the public sector in China has access to the international financial markets whereas the private sector cannot freely hold foreign assets. The Chinese government has recently sought to liberalize the country's capital account. Part of this effort includes the rollout of investment vehicles for foreigners wanting to invest in China and Chinese firms exploring overseas opportunities. While these measures represent incremental liberalizations of China's capital account, the pace of change has been slow. Extensive capital controls remain intact, limiting room for speculative maneuvering.

this arrangement. First, nominal exchange rate fluctuations, as well as any misalignment between foreign and domestic interest rates, are not reflected in the budget constraint of private agents—but they *do affect* the PBoC's profit/loss position. Second, the standard uncovered interest rate parity (UIP) may not hold in equilibrium, because arbitrage between domestic and foreign assets is administratively prohibited. The UIP condition is replaced by an equation that allows exchange rate to reflect only a small fraction of the ex ante spreads between the returns of domestic and foreign assets. This arrangement stabilizes exchange rate movements and nests two extreme cases—fully open and fully closed capital accounts. Several alternative microfounded setups may give rise to such a "distorted" no-arbitrage rule. Chang, Liu, and Spiegel (2015) model China's capital controls as a quadratic friction on the deviation of investor's portfolio choice between domestic bonds and foreign assets from an exogenous benchmark. If, instead, the cost of holding foreign bonds depends on the spread between return on domestic and return on foreign bonds, the modified UIP condition will take the same form as the one declared below. The same equation may be derived from an equilibrium in the foreign exchange market, whereas only a small fraction of participants are allowed to exchange foreign assets. The aggregate link between the ratio of foreign and domestic interest rates and nominal exchange rate would be proportional to the share of arbitrageurs in the market. Yet a third rationalization of the modified UIP condition may involve the PBoC's strategy to adjust the exchange rate very gradually, taking into account the difference between domestic and foreign bond return.

Crucially to our analysis, we expand the model of Gerali et al. (2010) by introducing occasionally binding constraints on credit activity. We implement this feature by augmenting the Euler equation of retail banks with a Lagrange multiplier that is positive when the constraint binds. This alters the optimal path of lending rates, and the effect is propagated through the economy. Gerali et al. (2010) feature multiple rigidities in factor, product, and financial markets, which are kept in the current model as well. While nominal and real rigidities constitute the core of a New Keynesian DSGE model, the choice of financial frictions warrants a brief discussion along the lines of Gerali et al. (2010). Both deposit and

lending branches possess certain market power over savers and borrowers, which gives rise to a markdown and a markup of retail interest rates in the model. The spreads on interest rates in China are comparatively high, suggesting an environment of limited competition, informational frictions, and difficult substitutability between products and competitors. By the same token, we also keep the adjustment costs on retail interest rates and capital adequacy. They may represent in a tractable way operational and regulatory costs, asymmetric information, and risks. Having intertemporally optimizing banks enables window guidance to affect bank lending on the entire transition path and not only on the binding dates. We let the magnitude of these frictions be determined by the Chinese financial-sector data. Because our central topic—window guidance practices—concerns bank lending to the corporate sector, unlike Gerali et al. (2010), we abstract from lending to households and from housing markets.

3.1 Households

Time is discrete and indexed by t. Households, indexed by j, maximize their lifetime utility, discounted by β_P^t subject to a usual budget constraint in real terms and a downward-sloping labor demand curve.

Their instantaneous utility depends *positively* on the difference between current consumption $c_t^P(j)$ and a fraction of aggregate lagged consumption c_{t-1}^P (due to habit formation) and *negatively* on hours worked $l_t(j)$. Individual consumption preferences are subject to an exogenous disturbance ϵ_t^z that follows an AR(1) process. Households supply differentiated labor input and receive in return wages that are sticky in nominal terms. Their income is formed from payroll $w_t l_t(j)$, dividends $t_t^P(j)$, and *real* gross interest income on last period's deposits $\frac{(1+r_{t-1}^d)d_{t-1}(j)}{\pi_t}$. Current income is reduced by the quadratic wage adjustment costs $\Omega(W_t(j), W_{t-1}(j)) = \frac{\kappa_w}{2}\left(\frac{W_t(j)}{W_{t-1}(j)} - \pi_{t-1}^{i_w}\right)^2 \frac{W_t(j)}{P_t}$, where W_t are nominal wages and $\pi_{t-1}^{i_w}$ is the wage indexation rule. Households use this income to buy consumption goods or save in new deposits $d_t(j)$. Inflation is denoted by π_t and nominal wage inflation is defined as $\pi_t^w = \frac{w_t}{w_{t-1}}\pi_t$.

$$\max_{c_t^P(j),d_t(j),l_t(j)} E_0 \sum_{t=0}^{\infty} \beta_P^t$$

$$\times \left[\left(\frac{1-a^P}{1-\xi^P} \right) \epsilon_t^z \left(c_t^P(j) - a^P c_{t-1}^P \right)^{1-\xi^P} - \frac{l_t(j)^{1+\phi}}{1+\phi} \right]$$

$$c_t^P(j) + d_t(j) \le w_t l_t(j) + \frac{\left(1+r_{t-1}^d\right) d_{t-1}(j)}{\pi_t}$$

$$- \Omega\left(W_t(j), W_{t-1}(j)\right) + t_t^P(j)$$

$$l_t(j) = \left(\frac{W_t(j)}{W_t} \right)^{-\epsilon_l} l_t,$$

where W_t and l_t are aggregate wage and hours worked, respectively. The first-order conditions (FOCs) with regard to $c_t^P(j), d_t(j), l_t(j)$ are

$$\left(1-a^P\right) \epsilon_t^z = \lambda_t^P \left(c_t^P(j) - a^P c_{t-1}^P \right)^{\xi^P} \tag{1}$$

$$\lambda_t^P = \beta_P \lambda_{t+1}^P \left(\frac{1+r_t^d}{\pi_{t+1}} \right) \tag{2}$$

$$\kappa_w \left(\pi_t^w - \pi_{t-1}^{i_w} \bar{\pi}^{1-i_w} \right) \pi_t^w = \beta E_t \left[\frac{\lambda_{t+1}^P}{\lambda_t^P} \kappa_w \left(\pi_{t+1}^w - \pi_t^{i_w} \bar{\pi}^{1-i_w} \right) \frac{\left(\pi_{t+1}^w\right)^2}{\pi_{t+1}} \right]$$

$$+ (1-\epsilon_l) l_t(j) + \epsilon_l \frac{l_t(j)^{1+\Phi}}{\lambda_t^P w_t}. \tag{3}$$

Equations (1) and (2) form the Euler equation, while (3) is a wage Phillips curve.

3.2   Entrepreneurs

Entrepreneurs, indexed by i, combine capital $k_t^E(i)$ that depreciates at rate δ, and labor $l_t(i)$, to produce a homogenous intermediate good in accordance with the standard Cobb-Douglas production function.[9] The production function is subject to an

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[9]The budget constraint of entrepreneurs expressed in terms of consumption goods and output is sold at producer prices. Thus, firm revenues should be discounted by a retail markup, x_t.

autoregressive total factor productivity (TFP) shock, A_t^e. The real price of capital is denoted by q_t^k. Capital utilization rate, $u_t(i)$, can also vary over time and is chosen every period by entrepreneurs. Capital utilization costs are determined by the quadratic function $\psi(u_t(i))$. The firms borrow $b_t(i)$ at nominal interest rate r_t^{bE}, to partially finance the purchase of productive capital and decide their consumption profile $c_t^E(i)$ to maximize lifetime utility from consumption, discounted by β_E^t. Borrowing is constrained by the total stock of capital.

$$\max_{c_t^E(i),b_t^E(i),k_t^E(i),u_t(i),l_t(i)} E_0 \sum_{t=0}^{\infty} \beta_E^t \left[\left(\frac{1-a^E}{1-\xi^E} \right) \left(c_t^E(i) - a^E c_{t-1}^E \right)^{1-\xi^E} \right]$$

$$c_t^E(i) + w_t l_t(i) + \frac{\left(1 + r_{t-1}^{bE}\right) b_{t-1}(i)}{\pi_t} + q_t^k k_t^E(i) + \psi(u_t(i)) k_{t-1}^E(i)$$

$$\leq \frac{y_t^E(i)}{x_t} + b_t(i) + q_t^k (1-\delta) k_{t-1}^E(i)$$

$$y_t^E(i) = A_t^e \left[u_t(i) k_{t-1}^E(i) \right]^{\alpha} l_t(i)^{1-\alpha} \tag{4}$$

$$\psi(u_t(i)) = \chi_0(u_t(i) - 1) + \frac{\chi_1}{2}(u_t(i) - 1)^2 \tag{5}$$

$$\left(1 + r_t^{bE}\right) b_t(i) \leq m_t^E E_t \left[q_{t+1}^k (1-\delta) k_t^E(i) \pi_{t+1} \right] \tag{6}$$

The first-order conditions of the entrepreneurs' problem w.r.t. $c_t^E(i), k_t^E(i), l_t(i), b_t(i), u_t(i)$ are

$$\left(1 - a^E\right) = \lambda_t^E \left(c_t^E(i) - a^E c_{t-1}^E \right)^{\xi^E} \tag{7}$$

$$\beta_E \lambda_{t+1}^E \left(q_{t+1}^k (1-\delta) + r^k(i) \right) - \psi(u_{t+1}(i))$$
$$+ \mu_t^E \left[m_t^E q_{t+1}^k (1-\delta) \pi_{t+1} \right] = \lambda_t^E q_t^k \tag{8}$$

$$r_t^k(i) k_t^E(i) = \alpha \frac{y_t^E(i)}{x_t} \tag{9}$$

$$w_t l_t = (1-\alpha) \nu \frac{y_t^E(i)}{x_t} \tag{10}$$

$$\lambda_t^E - \beta_E \lambda_{t+1}^E \left(\frac{1 + r_t^{bE}}{\pi_{t+1}} \right) = \mu_t^E \left(1 + r_t^{bE}\right) \tag{11}$$

$$r_t^k(i) = \chi_0 u_t(i) + \chi_1(u_t(i) - 1). \tag{12}$$

3.3   Central Bank

Inflation is the foremost goal of monetary policy in advanced economies. In China, the PBoC is mandated with maintaining overall stability. In other words, the PBoC may attach high priority to inflation fighting, but safeguarding high gross domestic product (GDP) growth rates is the top priority. In the modeling framework, the PBoC provides funds at the policy rate, r_t, and exchanges bonds denominated in foreign currency (D_t^*) for assets in local currency (D_t^{CB}).[10]

$$\Delta D_t^{CB} = S_t \Delta D_t^* \tag{13}$$

The Chinese capital account, as noted, is closed, so the usual UIP condition must be modified. The nominal exchange rate, S_t, reflects only partially the differences in interest rates at home and abroad, so

$$\frac{S_{t+1}}{S_t} = \left(\frac{1 + r_t}{1 + r_t^*} \right)^{\kappa^r}, 0 < \kappa^r \leq 1. \tag{14}$$

Monetary policy employs standard and nonstandard monetary tools. The standard monetary toolkit consists of a Taylor rule, whereby the PBoC sluggishly closes deviations of inflation from the long-run target rate and gaps between actual and potential output.

$$(1 + r_t) = (1 + \bar{r})^{(1-\phi_R)} (1 + r_{t-1})^{\phi_R} \left(\frac{\pi_t}{\bar{\pi}} \right)^{\phi_\pi (1-\phi_R)}$$

$$\times \left(\frac{y_t}{y_{t-1}} \right)^{\phi_y (1-\phi_R)} \epsilon_t^r \tag{15}$$

When these coefficients are positive, monetary policy is said to be countercyclical. The coefficient ϕ_R captures the degree of inertia in monetary policy, implying that the PBoC adjusts the interest rate gradually toward its target rate.

In modeling window guidance, the descriptive empirical evidence in section 2 strongly argues for nonlinearity in the use of window guidance. In that spirit, we augment the PBoC's toolkit with a

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[10]Exporters are obliged by law to exchange foreign assets with the central bank.

nonlinear window guidance instrument. The attraction of integrating nonlinearities into DSGE models is that they can produce rich medium-term dynamics useful in shaping policy.[11]

The window guidance policy instrument in the PBoC's toolbox is modeled as follows. We first assume that the central bank has the power to define and implement a lower bound B^{lb} and an upper bound B^{ub} on the stock of loans to entrepreneurs. Irrespective of the means to achieve its goal (moral suasion or administrative measures), these limits are respected by the commercial banks. The rules for B^{lb} and B^{ub} are assumed to be symmetric, hence only the lower bound is described below for brevity:

$$B^{lb} = \Delta^{lb}\overline{B}, \tag{16}$$

where $\bar{B}$ is the steady-state level of B. The fractions Δ^{lb} can be exogenously fixed by the monetary authority or can vary countercyclically with the business cycle stance, i.e., $\Delta^{lb} = \overline{\Delta}^{b}\left(\frac{Y}{\overline{Y}}\right)^{-\epsilon^{lb}}$, $\epsilon^{lb} \geq 0$. In other words, the window guidance reaction is a function of output alone. An important feature of the policy rule (16) is the assumed nonlinearity. We solve the model two ways: once assuming the loan constraint is slack (at first order) and once where the constraint is assumed to be occasionally binding.

Equation (16) can also be interpreted as an attempt to avoid the "dark corners" first noted by Blanchard (2014).[12] The nonstandard window guidance toolkit addresses situations in which the PBoC is limited in the use of its policy interest rate. Pointing out that standard Taylor rules lack this pronounced risk-avoidance property, Blanchard (2014) makes a strong case that macroeconomic policymakers should give high priority to avoiding dark corners and may have to resort to novel tools to do so.

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[11]Nonlinear monetary policy reaction function has been studied largely in reduced-form empirical work, but not in a structural model. See, for example, Brüggemann and Riedel (2011), Cukierman and Muscatelli (2008), and Lamarche and Koustas (2012).

[12]Bernanke and Reinhart (2004) recommend aggressive preemptive measures to avoid the complications raised by the zero lower bound. In that light, equation (16) aims at providing insurance for avoiding severe recessions. In such "dark corners," the focus upon output appears to be an appropriate description of the behavior of Chinese policymakers.

The next sections on commercial banks discuss how an occasionally binding window guidance constraint might affect bank behavior. Impulse response functions of the general equilibrium effect and the tradeoffs arising from the window guidance are explained in detail.

3.4 Wholesale Banking

The asset side of the wholesale bank sector comprises loans to firms (B_t) and central bank bonds denominated in the domestic currency (D_t^{CB}). On the liability side, wholesale banks combine deposits from households (D_t) and bank capital (K_t^b):

$$B_t + D_t^{CB} = D_t + K_t^b. \tag{17}$$

Their real net worth evolves as a law of motion,

$$\pi_t K_t^b = (1 - \delta^b) K_{t-1}^b + j_{t-1}^b, \tag{18}$$

where $\delta^b K_{t-1}^b$ is the per-period cost for managing bank capital and j_{t-1}^b is last period's *real* profits of financial intermediaries. To stabilize the capital adequacy ratio in the long run, it is necessary to introduce a (small) friction on the interbank market. The spread between loan rate (R_t^b) and deposit rate (R_t^d) should depend negatively on banks' leverage $\frac{K_t^b}{B_t}$. In the steady state, this margin disappears such that

$$R_t^b - R_t^d = -\kappa_{Kb} \left(\frac{K_t^b}{B_t} - \nu^b \right) \left(\frac{K_t^b}{B_t} \right)^2. \tag{19}$$

Following Gerali et al. (2010), we assume that deposit rates on the wholesale market are equal to the policy rate (r_t): $R_t^d = r_t$.

3.4.1 Retail Banking

Financial flows are channeled through an imperfectly competitive banking sector. Banks supply deposits and loans to their agents, and set interest rates on both deposits and loans to maximize profits. Retail banks supply slightly differentiated credit services, $b_t^E(j)$, to firms. Facing quadratic adjustment costs and taking into account the downward-sloping demand for loans, they set up interest rates

in a sticky manner. This gives rise to positive markup for interest rates on loans to firms $\left(r_t^b\right)$ over the interest rates prevailing on wholesale money market $\left(R_t^b\right)$. Sectoral profits are countercyclical in equilibrium. The objective of a retail lending bank is to maximize its profits, discounted by the consumption-based discount factor $\left(\Lambda_{0,t}^P\right)$:

$$
\max_{r_t^b(j)} E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P
$$

$$
\times \left[r_t^b(j) b_t^E(j) - R_t^b b_t^E(j) - \frac{\kappa_{bE}}{2} \left(\frac{r_t^b(j)}{r_{t-1}^b(j)} - 1 \right)^2 r_t^b b_t^E \right],
$$

where b_t^E is the average level of retail bank loans. The downward-sloping demand for loans is expressed as

$$
b_t^E(j) = \left(\frac{r_t^b(j)}{r_t^b} \right)^{-\epsilon^b} b_t^E, \tag{20}
$$

where ϵ^b is the elasticity of loan demand. The existence of a lower bound on loans to firms enters the commercial banks' model block via a Lagrange multiplier λ^B. Assuming a symmetric equilibrium, the FOC w.r.t. r_t^b is

$$
1 - \epsilon^b + \epsilon^b \frac{R_t^b}{r_t^b} - \kappa_b \left(\frac{r_t^b}{r_{t-1}^b} - 1 \right) \frac{r_t^b}{r_{t-1}^b}
$$

$$
+ \Lambda_{t,t+1}^P \kappa_b \left(\frac{r_{t+1}^b}{r_t^b} - 1 \right) \left(\frac{r_{t+1}^b}{r_t^b} \right)^2 \frac{b_{t+1}^E}{b_t^E} - \frac{\lambda^B \epsilon^b}{r_t^b} = 0. \tag{21}
$$

Following the Kuhn-Tucker necessary conditions for an optimum, one of two cases—(i) $\lambda^B = 0; b_t^E > b^{lb}$ or (ii) $\lambda^B > 0; b_t^E = b^{lb}$—must hold. The more binding the lower bound on credit, the greater the shadow price λ^B.

By (21), it follows that r_t^b should decline. The economic intuition here is that interest rates must be lower than in the unconstrained case in order to accommodate the increase in credit supply. Since the model assumes full rationality and perfect foresight, banks on impact anticipate that the constraint ultimately binds. Given that lending rates are sticky, banks react to these expectations in advance

by inducing a milder credit crunch than in the case without window guidance, and thus avoid spending time in a constrained regime that is more costly to them than an interior equilibrium.

3.4.2   Deposit Branch

The deposit branch supplies differentiated deposit services, $d_t^P(j)$, to patient households at interest rates, $r_t^d(j)$, that are lower than on the wholesale market due to their monopolistic power. Limited participation prevents households from transacting directly with the wholesale branch or with foreign lenders, or arbitraging away the markdown on retail deposit rates. The intertemporal optimization of a retail deposit bank is

$$\max_{r_t^d(j)} E_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \left[r_t d_t^P(j) - r_t^d(j) d_t^P(j) - \frac{\kappa_d}{2} \left(\frac{r_t^d(j)}{r_{t-1}^d(j)} - 1 \right)^2 r_t^d d_t \right],$$

where d_t is the average level of retail bank deposits. The upward-sloping demand for deposits is expressed as

$$d_t^P(j) = \left(\frac{r_t^d(j)}{r_t^d} \right)^{\epsilon^d} d_t. \tag{22}$$

Assuming a symmetric equilibrium, the FOCs w.r.t. r_t^d are

$$-1 + \epsilon^d - \epsilon^d \frac{r_t}{r_t^d} - \kappa_d \left(\frac{r_t^d}{r_{t-1}^d} - 1 \right) \frac{r_t^d}{r_{t-1}^d}$$

$$+ \Lambda_{t,t+1}^P \kappa_d \left(\frac{r_{t+1}^d}{r_t^d} - 1 \right) \left(\frac{r_{t+1}^d}{r_t^d} \right)^2 \frac{d_{t+1}}{d_t} = 0. \tag{23}$$

3.5   Retailers in the Goods Market

Retailers costlessly repackage homogenous domestic intermediate goods into differentiated final goods. They set up domestic prices subject to quadratic adjustment costs and a downward-sloping demand curve. A well-known New Keynesian Phillips curve for domestic inflation, π_t^H, emerges, i.e.,

$$1 - \epsilon^y + \frac{\epsilon^y}{x_t} - \kappa_p \left[\pi_t^H - \left(\pi_{t-1}^H \right)^\iota \left(\bar{\pi}^H \right)^{1-\iota} \right] \pi_t^H$$

$$+ \Lambda_{t,t+1}^P \kappa_p \left[\pi_{t+1}^H - \left(\pi_t^H \right)^\iota (\bar{\pi}^H)^{1-\iota} \right] \left(\pi_{t+1}^H \right)^2 \frac{Y_{t+1}}{Y_t} = 0. \tag{24}$$

The optimal bundle of domestic products, C_t^H, is combined with imported goods, C_t^F, with the objective to minimize costs. Denote the domestic price level relative to aggregate consumer prices as $p_t^H = P_t^H/P_t$ and the relative price of imported goods as $p_t^F = P_t^F/P_t$. Then

$$C_t = \left[(\eta^c)^{1/\epsilon^c} \left(C_t^H \right)^{\left(\epsilon^C - 1 \right)/\epsilon^C} \right.$$

$$\left. + (1 - \eta^c)^{1/\epsilon^c} \left(C_t^F \right)^{\left(\epsilon^C - 1 \right)/\epsilon^C} \right]^{\epsilon^C/\left(\epsilon^C - 1 \right)}, \tag{25}$$

and

$$1 = \eta^c \left(p_t^H \right)^{1-\epsilon^C} + (1 - \eta^c) \left(p_t^F \right)^{1-\epsilon^C}. \tag{26}$$

Optimization sets up the ratio of the two consumption bundles as a function of the relative prices (real effective exchange rate):

$$\frac{C_t^H}{C_t^F} = \frac{\eta^c}{1 - \eta^c} \left(\frac{P_t^H}{P_t^F} \right)^{-\epsilon^C}. \tag{27}$$

By analogy, aggregate investment prices and quantities, as well as the ratio of domestic to foreign investment goods are given by

$$1 = \eta^I \left(p_t^{I,H} \right)^{1-\epsilon^I} + \left(1 - \eta^I \right) \left(p_t^{I,F} \right)^{1-\epsilon^I}. \tag{28}$$

$$I_t = \left[(\eta^I)^{1/\epsilon^I} \left(I_t^H \right)^{\left(\epsilon^I - 1 \right)/\epsilon^I} + \left(1 - \eta^I \right)^{1/\epsilon^I} \left(I_t^F \right)^{\left(\epsilon^I - 1 \right)/\epsilon^I} \right]^{\epsilon^I/\left(\epsilon^I - 1 \right)}, \tag{29}$$

$$\frac{I_t^H}{I_t^F} = \frac{\eta^I}{1 - \eta^I} \left(\frac{P_t^H}{P_t^F} \right)^{-\epsilon^I}. \tag{30}$$

3.6 Net Exports

The volume of exports depends on the relative prices of domestic and foreign goods.

$$\frac{C_t^{H*}}{C_t^*} = \left(\frac{P_t^{H*}}{P_t^*}\right)^{-\epsilon^F} \tag{31}$$

The real effective exchange rate in the end determines the trade balance of the country by altering foreign demand for exports and domestic demand for imports.

3.7 Capital Producers

In the capital-goods-producing sector, producers buy old capital and convert it to new productive capital according to the law of motion $K_t = (1-\delta)K_{t-1} + \left(1 - \frac{\kappa_i}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right)I_t$. As in Gerali et al. (2010), producers of physical capital goods are used as a modeling device to make explicit the dependence of price of capital on lagged, contemporaneous, and future investment levels, (I_{t-1}, I_t, I_{t+1}), or Tobin's Q, which enters the borrowing constraint of entrepreneurs. During the upturn, rising capital prices relax the borrowing constraint of entrepreneurs, thus amplifying and propagating the initial shock. The FOC is as follows:

$$1 = q_t^K \left(1 - \frac{\kappa_i}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2 - \kappa_i \left(\frac{I_t}{I_{t-1}} - 1\right)\frac{I_t}{I_{t-1}}\right)$$
$$+ \Lambda_{t,t+1}^E q_{t+1}^K \kappa_i \left(\frac{I_{t+1}}{I_t} - 1\right)\left(\frac{I_{t+1}}{I_t}\right)^2. \tag{32}$$

3.8 Market Clearing

Budget constraints must be satisfied. Thus, wages should clear the labor market and the real effective exchange rates should achieve domestic market equilibrium. The two equations that close the system are $y_t^E = C_t^H + q_t^k I_t^H + C_t^{H*}$ and $C_t = c_t^P + c_t^E$.

4. Model Calibration, Impulse Response Functions, and Welfare Analysis

We next describe how we have chosen parameters for our model. The model is parameterized to match key features of the Chinese economy. Specifically, we partition the model parameters into two sets. The first set of parameters can be recovered from targeting great ratios and other first moments of data. The parameters in the second group, describing adjustment costs, are uncovered from second moments of the observed series. We also fix certain parameters to conventional values. Data from our primary source, the National Bureau of Statistics of China, are augmented with up-to-date series from the IMF (2017a, p. 46), the World Bank database, and PBoC annual reports. Although the model is quarterly, annual figures are targeted due to limited quarterly data availability. Model calibration is broadly in line with the estimates of deep parameters presented in Dai, Minford, and Zhou (2015), Le et al. (2014), and Li and Liu (2017).

4.1 Calibrated Parameters

The risk-aversion/intertemporal substitution parameters are calibrated to a conventional value – $\xi^P, \xi^E = 2$.[13] See table 3. Demand elasticity for differentiated labor input is calibrated to higher values than in Gerali et al. (2010), so that lower wage markup is achieved, $\frac{\epsilon_l}{(\epsilon_l-1)} = 1.2$. We choose the inverse Frisch elasticity of labor supply to be $\phi = 1$, the same as in Gerali et al. (2010).[14] The elasticity of foreign interest rates (r^*) to the ratio of foreign assets to GDP is held to 0.1 percent, so as not to affect short-term dynamics but still ensure that foreign debt does not follow a random walk. The exchange rate elasticity to the spread between domestic and foreign interest rates, i.e., the openness of China's current and capital account, is kept low

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[13]As noted by Thimme (2017), it is notoriously difficult to obtain reliable empirical estimates of the parameter of intertemporal substitution in consumption. Hence, we do not use it to match actual data.

[14]Macro and micro estimates of Frisch elasticity differ, with micro studies typically finding values below one, while values used in macro models are usually greater than one.

Table 3. Calibrated Parameters

Parameter	Description	Value
β_P	Discount Factor of Households	0.997
β_E	Discount Factor of Entrepreneurs	0.983
ϵ^d	Demand Elasticity for Deposits	1.31
κ_d	Deposit Rate Adjustment Cost	1.49
ϵ^{bs}	Demand Elasticity for Loans	2.37
κ_{bE}	Lending Rate Adjustment Cost	15.9
δ^b	Commercial Banks Capital Depreciation Rate	0.08
ν^b	Target Capital Adequacy Ratio	0.1
κ_{Kb}	Elasticity of the Spread on the Interbank Market w.r.t. Banks' Leverage	16.9
κ^τ	Exchange Rate Elasticity to the Spread between Domestic and Foreign Interest Rates	0.001
a^P	Habit Formation Parameter	0.86
ξ^P	Inverse of the Elasticity of Intertemporal Substitution for Households	2
ξ^E	Inverse of the Elasticity of Intertemporal Substitution for Entrepreneurs	2
ϵ_l	Demand Elasticity for Differentiated Labor Input	6.3
κ_w	Wage Adjustment Cost	85.5
i_w	Wage Indexation Parameter	0.83
m^E	Loan-to-Value Constraint Parameter	0.48
α	Output Elasticity of Capital	0.5
δ	Depreciation Rate	0.03
κ_i	Capital Adjustment Cost Parameter	2.4
ϕ	Inverse Frisch Elasticity of Labor Supply	1
ϵ^y	Demand Elasticity for Differentiated Goods	21
κ_p	Price Adjustment Cost	39.7
ι	Price Indexation Parameter	0.41
ϵ^C	Demand Elasticity for Domestic Consumer Goods	5
ϵ^I	Demand Elasticity for Domestic Investment Goods	5
ϵ^F	Foreign Demand for Domestic Goods (Exports)	5
η^c	Home Bias Parameter for Consumption Goods	0.77
η^I	Home Bias Parameter for Investment Goods	0.77
χ_0	Capital Utilization Adjustment Cost (Linear Part)	0.042
χ_1	Capital Utilization Adjustment Cost (Nonlinear Part)	0.0042
ϕ_R	Policy Inertia Parameter in the Taylor Rule	0.82
ϕ_π	Inflation Parameter in the Taylor Rule	1.76
ϕ_y	Output Parameter in the Taylor Rule	0.83
σ_C	Standard Deviation of Consumption Shock	0.0732
σ_I	Standard Deviation of Investment Shock	0.0147
σ_{mk}	Standard Deviation of Financial Intermediation Shock	0.0688
ρ_C	AR(1) Coefficient of Consumption Shock	0.0876
ρ_I	AR(1) Coefficient of Investment Shock	0.0001
ρ_{mk}	AR(1) Coefficient of Financial Intermediation Shock	0.0001

Table 4. Steady-State Values of Endogenous Variables

Parameter	Description	Value
r^d	Real Interest Rates on Retail Deposits (Annual)	1.3%
r^{bE}	Real Interest Rates on Retail Loans (Annual)	4%
r	Policy Interest Rate	2.3%
$1 + x$	Price Markup	1.05
$x\frac{rk}{y}$	Capital Income Share	0.5
k/y	Capital-to-GDP Ratio (Annualized Ratio)	2.8
C/Y	Consumption Share in GDP	0.65
I/Y	Investment Share in GDP	0.32
$\frac{C^F + I^F}{Y}$	Import Share in GDP	0.22
C^{H*}	Export Share in GDP	0.25
$\frac{B}{Y}$	Loans to Nonfinancial Corporations to GDP (Annualized Ratio)	1.3
$\frac{D^{CB}}{Y}$	Central Bank's Bonds in Domestic Currency, Held by Commercial Banks, to GDP (Annualized Ratio)	0.5
$\frac{B}{K}$	Nonfinancial Corporations Leverage	0.66
$\frac{K^b}{B}$	Capital Adequacy Ratio	0.1

at $\kappa^r = 0.001$, reflecting the very gradual pass-through of interest rate differentials to nominal exchange rate movements.

4.2 Matching the Steady State

The household annual discount rate, calibrated to a conventional level of 1.3 percent, implies a quarterly discount factor $\beta_P = 0.997$.[15] The annual discount rate for entrepreneurs is set to 7 percent, implying the quarterly discount factor $\beta_E = 0.983$. The steady-state real annual interest rate on loans $\left(r^{bE}\right)$ is calibrated to 4 percent, i.e., the average PPI-deflated rate on one-year loans over the period 2010–15. The entrepreneur's discount factor and lending rates jointly determine the steady-state rate of return on capital. See table 4.

The model assumes that in the steady state the official policy rate (r_t) is transmitted to the interbank market $\left(R^b\right)$ via arbitrage, where it serves as a basis for pricing deposit and loan rates. The average

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[15]The financial repression of China's financial system makes it impossible to recover the discount rate from historical data.

one-year SHIBOR (Shanghai interbank offered rate) for the period
2010–15 is 4.2 percent. The seven-day repo rate average during 2011–
15 is 4.8 percent. The real interbank interest rate is calculated by
deflating the nominal one with 2 percent steady-state inflation, i.e.,
the average annual CPI inflation for the past 20 years in China. The
spreads of deposit and lending rates with respect to the interbank
market determine the parameters of market power by branches of
retail banks $\left(\epsilon^d, \epsilon^{bs}\right)$.

The national accounts reflect China's sky-high investment-to-
GDP ratio, which averaged 45 percent in the period 2010–16. The
aggregate figures conceal an important distinction between differ-
ent components of total investment. Infrastructure projects consti-
tute a sizable share of fixed-asset investment, averaging 22 percent
between 2010 and 2016.[16] We exclude this type of capital formation,
when we construct the calibration target for the share of investment
to GDP, for two reasons. First, in the model, investment decisions
are made optimally by private agents, while decisions on accelera-
tion/deceleration of infrastructure projects are centralized and with
the aim to support the economy. Second, infrastructure capital stock
would not enter the production function in the same way as pri-
vate capital, nor are they necessarily a market product per se. The
share of non-infrastructure investment in GDP that we target is
32 percent, which corresponds to the average for the period 2003–
16. Given the high investment rate, depreciation is calibrated at a
quarterly rate of $\delta = 0.03$. In a balanced growth context, a high
depreciation rate is necessary to cover both the attrition of existing
capital and labor-augmenting technological progress. The parame-
ters χ_0, χ_1 describe the costs of changing capital utilization rates. In
order to ensure that capital operates at full capacity at steady state,
we equate the linear term with the return on capital $\chi_0 = r^k = 0.042$.
The quadratic cost parameter is set to $\chi_1 = 0.1\chi_0$. Both values are
close to those reported in Gerali et al. (2010).

Output elasticity of capital α targets the capital income share
stated in the income account. Published figures show that gross
operating surplus formed 50 percent and 55 percent of aggregated
gross product in 2012–14. Zhang (2016) cites higher values for labor

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[16]Please refer to online appendix H, for an empirical presentation of the various
components of total investment expenditures.

income as a percentage of GDP, i.e., an average of 60 percent for the period 2010–15. In the model, capital income share is calibrated to $\alpha = 0.5$. Bank loans to entrepreneurs (B) are set at 130 percent of annual GDP in the model. The empirical counterpart of this variable would be the item "Bank Credit to Private Non-financial Sector" in the Bank for International Settlements (BIS) data tables. Central banks' bonds in domestic currency $\left(D^{CB}\right)$, held by the banking sector, are 50 percent of annual GDP in the model, reflecting the data in the "Balance Sheet of Other Depository Corporations."

These calibration targets give rise to high leverage ($B/K = 0.46$) in the nonfinancial corporate sector. The capital adequacy ratio of banks is governed by the parameter $\nu^b = 0.1$, thus matching the average tier 1 capital adequacy ratio of the Chinese banking sector for 2013–15 as reported by the IMF (2017a, p. 46). Commercial banks' capital depreciation rate should stabilize bank capital given the steady-state profits, which implies $\delta^b = 0.08$.

Net exports are calibrated at 3 percent of GDP, matching the average since 2009. Demand elasticity in the Dixit-Stiglitz aggregator (ϵ^y) is calibrated to achieve a markup of 5 percent for final goods prices from intermediate goods prices. The home-bias parameters $\left(\eta^c, \eta^I\right)$ are adjusted to replicate the average share of exports and imports in GDP in the period 2009–15.

4.3   Matching Second Moments

Adjustment costs and habit formation disappear from the deterministic steady state and can be uncovered by targeting second moments of detrended data. The same holds true for the parameters that describe central banks' reaction function and for demand elasticities when steady-state relative prices are calibrated at unity. Furthermore, the type, magnitude, and persistence of the shocks that drive the economic cycle crucially determine the link between parameters and data statistics, as well as the overall fit of the model. Chinese macroeconomic series exhibit less persistence after detrending, as well as lower contemporaneous correlation between GDP and domestic absorption components (consumption and investment). These stylized facts suggest that adjustment costs are likely to be smaller than in a typical calibration of a developed economy, in line with the findings in Dai, Minford, and Zhou (2015) and Le et al. (2014).

Next, we discuss how different parameters affect second moments of selected macroeconomic time series. Then we describe the method we employ to estimate the parameters in question and the results obtained.

4.3.1 Estimation Procedure

The remaining parameters of interest are estimated by the method of moments using observables from the real economy (output, private consumption, investment, price inflation, and real wage dynamics) and four financial measures—the capital adequacy ratio, the three-month SHIBOR interest rate, plus the official interest rates on loans and deposits. The variables are observed at annual frequency in the periods 2000–06 and 2010–16.[17] The pre- and post-crisis years 2007–09 are excluded from the sample, since the series exhibit exceptionally high volatility and very little persistence in this period, partly reflecting high public investment spending and other strong administrative measures and interventions. First of all, the targeted moments include the standard deviations of all variables, except the official interest rates on loans and deposits, and the first-order autocorrelations of the real economy variables, plus the SHIBOR. Further targeted moments are the contemporaneous cross-correlations of GDP with all real economy variables and the SHIBOR, price inflation with wage inflation and the SHIBOR, and SHIBOR and the official interest rates on loans and deposits.

Output, private consumption, and investment are deflated with the appropriate price index, and then HP filtered ($\lambda = 6.25$). This data set provides 22 moments—seven standard deviations, nine cross-correlations, and six autocorrelations. On the other side we have 19 parameters of interest—three Taylor coefficients $(\phi_\pi, \phi_y, \phi_R)$, five nominal/real rigidities parameters $(\kappa_p, \kappa_w, \kappa_i, \iota, i_w)$, two consumption preferences $(\epsilon^C, a^{P,E})$, three financial frictions $(\kappa_{Kb}, \kappa_{bE}, \kappa_d)$—and we specify three shocks—a consumption shock, an investment shock, and a financial

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[17]The quarterly model is appended by auxiliary variables that correspond to the annual figures in data.

intermediation shock—that give rise to an additional six shock parameters $(\sigma_C, \sigma_I, \sigma_{mk}, \rho_C, \rho_I, \rho_{mk})$.[18]

Ideally, each parameter should affect only a subset of the 22 moments of data. The habit persistence parameter (a^P) affects primarily the cross-correlations between consumption and the other time series. The demand elasticity for imports/exports $(\epsilon^{C,I,F})$ has a large effect on the cross-correlations between inflation and the rest of the variables, while it barely changes the cross-correlations with the real wage inflation and the AR(1) coefficients. The adjustment costs for real wages (κ_w) have a large impact on the autocorrelations of order one as well as the cross-correlations of inflation and of real wage growth. Price adjustment costs (κ_p) affect mostly the cross-correlations of price inflation and of real wage inflation. The two indexation coefficients, for prices (ι) and wages (i_w), are relatively weakly identified by the data set. The quadratic adjustment costs for changing interest rates on loans (κ_{bE}, κ_d) affect the correlation of the interbank rate vis-à-vis the official lending and deposit rates, while the leverage adjustment cost (κ_{Kb}) affects the dynamics of capital adequacy ratio. The Taylor coefficients $(\phi_\pi, \phi_y, \phi_R)$, the capital adjustment parameter (κ_i), and the shock parameters $(\sigma_C, \sigma_I, \sigma_{mk}, \rho_C, \rho_I, \rho_{mk})$, however, have sizable impact on all statistics simultaneously. It is impossible to isolate the effect of each of these parameters on the objective function and solve the system by blocks. Hence, we resort to the MATLAB's constrained nonlinear solver fmincon. This procedure finds a minimum of the objective function, given a set of constraints and an initial value for the parameters of interest. There is no guarantee that the minimum found is a global minimum. In fact, the estimates of price/wage adjustment costs (κ_p, κ_w), for capital adjustment costs (κ_i) and for financial frictions $(\kappa_{Kb}, \kappa_{bE}, \kappa_d)$ vary widely with the initial values, suggesting multiple local equilibriums.[19] We tackle this issue by sampling

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[18]The estimation could potentially include a host of various shocks that may account for the cyclical movements of Chinese economy. Our choice of picking these three shocks aims at parsimony, while achieving relatively good data fit. Dai, Minford, and Zhou (2015) also find that consumption and investment shocks account for most of the variance in the observable series.

[19]The estimates of other parameters also depend on initial values, although to a lesser extent. These include parameters ϕ_y, a^P, i_w, ι. The nonconvexity of the objective function arises because of the nonlinear link between deep parameters

Figure 3. Model Fit with Respect to the Chosen Data Moments
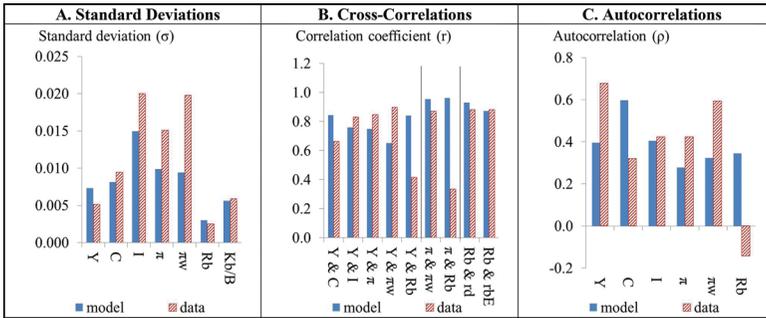
Notes: Y is GDP, C is consumption, I is investment, π is inflation, π^w is real wage inflation, R^b is SHIBOR, r^d is interest rate on deposits, r^{bE} is interest rate on loans, and K^b/B is capital adequacy ratio. In panel B, there are three sets of cross-correlations: (i) cross-correlations of GDP (Y) with other variables, (ii) cross-correlations of inflation (π) with real wage inflation (π^w) and SHIBOR (R^b), and (iii) cross-correlations of SHIBOR (R^b) with official interest rates (r^d) on deposits and loans (r^{bE}).

1,000 initial parameter values from the parameter set and finding the local minimum for each of the initial values. Subsequently, we select the estimates that produce the smallest distance between data and model.

Figure 3 compares the model-implied moments and those in the data. Given the complexity of the modeling framework, the model matches relatively well the cross-correlations between output and real variables, between inflation and wage growth, and among interest rates. It shows higher cross-correlation of interbank rates with output and with inflation, while it falls short in replicating standard deviations of investment, inflation, and wage growth. There are some mild sign differences as well. In the data, consumption is less correlated with output than investment is, but in the model this

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and moments and the possible tradeoffs in matching some dimensions of the data, i.e., high values of the parameter favor a subset of the matched moments, while low values match another subset of moments better. Structural breaks could also contribute to the existence of multiple local minimums, as deep parameters may not be stable. Weak identification may explain the changing estimates of i_w and ι w.r.t. initial values.

is reversed. Model-implied autocorrelation of investment is matched well. Output, inflation, and wage dynamics exhibit higher persistence in data than in the model, while consumption is more persistent in the model. Overall, one can say that the calibrated model is able to replicate the cyclical patterns of the Chinese data.

4.3.2   Parameterization

The Taylor coefficients show considerable interest rate smoothing and a moderate reaction to inflation and to output. The price elasticity of imports and exports is high, suggesting high substitutability of internationally traded goods. Dai, Minford, and Zhou (2015) and Le et al. (2014) argue that substitutability of import/export goods cannot be uncovered from data, since decisions on quantities of imports and exports are made on a centralized level. Despite the fact that price elasticities may not reflect "deep" preference parameters, they provide an important adjustment channel, so we keep the estimated parameters. In accordance with the data as well as Dai, Minford, and Zhou (2015) and Le et al. (2014), capital adjustment costs are relatively low. The estimates reveal moderate wage and price stickiness. Prices are comparatively flexible, while wages are more inelastic and indexed by past dynamics. These findings are in line with those of Dai, Minford, and Zhou (2015) and Le et al. (2014), where wage indexation is stronger than price indexation. The estimate reveals rigidities on both retail lending (κ_{bE}) and wholesale market (κ_{Kb}), while deposit rates are flexible. The estimated shock parameters show sizable roles for consumption and investment disturbances and small persistence for all three shocks.

4.4   Impulse Response Functions

As a first model evaluation, we model two shocks: a positive consumption shock and a negative investment shock. The size of the shocks is chosen so that the limit on loans binds for several periods. For lower magnitude shocks, the constraint does not bind, so impulse responses of our no-window-guidance and with-window-guidance cases coincide.[20]

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[20]Because the model is linearized, certainty equivalence holds. In higher-order approximations, impulse responses will differ even for shocks that fail to reach

The model is solved up to first-order approximation with the help of the Dynare MATLAB toolbox (see Adjemian et al. 2014). The computation of impulse responses with occasionally binding constraints is implemented with the OccBin toolkit (see Guerrieri and Iacoviello 2015). The toolbox initially guesses the periods when the constraint is binding, then computes the optimal piecewise transition paths and verifies/rejects its guess. If the guess is incorrect, it guesses again until convergence is validated. As explained in section 3, lending rates have to fall relative to the no-window-guidance scenario to keep credit above the equilibrium transition path. Favorable financing conditions for firms stoke recovery through improved investment and income, but it remains an open question as to how much financial fragility is generated through impaired bank profits, especially if the poor financial performance of banks drags on.

For reasons of space, the impulse responses are presented in online appendix I. In each graph, the results are presented with or without the additional window guidance policy tool. The presentation in the appendix also contains a detailed explanation of the numerical results. A provisional conclusion from the impulse response analysis is that window guidance may help deliver additional monetary stimulus in challenging macroeconomic environments.

4.5   Window Guidance in the Great Recession

Structural models, DSGE models in particular, are suitable for discussing important economic events, as they explicitly account for various external shocks and macroeconomic channels, potentially relevant for the period in question. In the context of the current paper's topic, the macroeconomic effect of window guidance practices of the PBoC is probably best assessed in the period of the global financial crisis 2008–09, when the lower bound on credit activity had been binding most.

In China the output gap turned deeply negative in the fourth quarter of 2008 and closed by the end of 2010. The same period also

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the lower bound on loans. A precautionary motive emerges: banks may want to step up lending activity to stay away from the contingency of hitting the floor on lending.

Figure 4. IRFs from a Financial Intermediation Shock without (- -) and with (−) Window Guidance
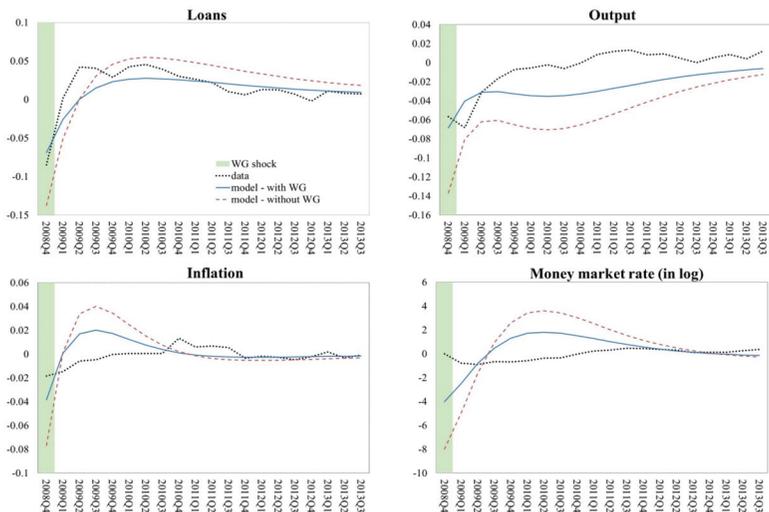
evidenced inflation below trend and low money market interest rates. These stylized facts suggest that a demand shock has played a prominent role in this period, in line with the findings of Le et al. (2014). The current paper augments these findings by considering a negative intermediation shock (i.e., a positive markup shock on lending interest rates) that occurred in 2008:Q4, large enough to trigger the quantitative policy tools of the PBoC. The model is again solved up to first-order approximation with the help of the Dynare MATLAB toolbox (see Adjemian et al. 2014), and the computation of impulse responses with occasionally binding constraints is implemented with the OccBin toolkit (see Guerrieri and Iacoviello 2015).

The results of impulse response analysis are summarized in figure 4. We first analyze the no-window-guidance case, as a baseline on top of which window guidance operates. The increase in spreads induces higher lending rates and a decline in credit activity, while policy interest rates and money market rates decline on impact. The negative trend on investment drives the economy into a deep recession. Consumption also reacts negatively, reflecting lower income, combined with higher interest rates. Inflation initially declines to

equilibrate markets, but then remains above trend, following with a lag the elevated marginal costs associated with the higher cost of capital.

Since the shock is rather transitory, the lower bound on credit activity is binding only on impact. Nevertheless, the entire transition path is affected by the presence of window guidance. Lending rates are lower relative to the no-window-guidance scenario to keep credit above the equilibrium transition path. Favorable financing conditions for firms stoke recovery through improved investment and income. A positive second-round effect through the monetary authority reaction function is realized. With decreased cost of capital, marginal costs are also lower in the window guidance case, leading to lower inflation rates. Weaker inflation pressures feed into lower policy interest rates that additionally stimulate recovery.

The numerical results suggest that the monetary policy reaction should go beyond the simple Taylor rule. The alternative nonlinear Taylor rule with window guidance that differentiates between normal times and severe crisis has appealing properties. Window guidance helps the recovery through both investment and consumption without jeopardizing bank profits.

The tentative conclusion is that the window guidance policy instrument can make a helpful contribution to economic stabilization.

4.6   Welfare Analysis

A possible way to determine the amount of euphoria window guidance brings is welfare analysis. We adopt a practical approach when evaluating the implications of introducing window guidance as an additional monetary policy tool. Following Glocker and Towbin (2012), we append a traditional loss function $\mathcal{L} = E\big(a^\pi \hat{\pi} + a^y \hat{y}^2\big)$ with macroprudential concerns. Similarly to Rubio and Carrasco-Gallego (2014), we proxy financial-sector soundness by the variance of the stock of bank loans. Specifically, we assume that the PBoC's objective is to minimize the function

$$\mathcal{L}^f = E\left(a^\pi \hat{\pi}^2 + a^y \hat{y}^2 + a^b \widehat{b^E}^2\right), \tag{33}$$

where $\widehat{\pi}, \widehat{y}, \widehat{b}^E$ are the percentage deviations of inflation, output, and loans to firms and the parameters a^π, a^y, a^b reflect the relative importance of the three components for the PBoC.

The task at hand is to simulate a series of exogenous shocks to consumption, investment, and financial intermediation. We then obtain the trajectories of key endogenous variables in response to these shocks with and without window guidance, and compare their variances. Window guidance is symmetric: it kicks in when borrowing deviates more than 1.5 percent from its steady-state value.[21]

In order to broaden our understanding of the effectiveness of window guidance practices in China, we extend our welfare analysis by constructing efficient policy frontiers in the spirit of Iacoviello (2005) and Levin, Wieland, and Williams (1999). The points on this frontier (also called Taylor curve) represent the tradeoffs that the authorities confront when they stabilize the economy—reaching lower variability of output may entail higher variance of inflation. The simulations below are based on the behavior of the model economy with the three shocks—consumption, investment, and intermediation—combined.[22] The three policy objectives and their tradeoffs can be represented on three two-dimensional plots—$(\sigma(y), \sigma(\pi))$; $(\sigma(b^e), \sigma(\pi))$; and $(\sigma(b^e), \sigma(y))$.

Next, we explain how the Taylor curves on the $(\sigma(y), \sigma(\pi))$-plane (with and without window guidance) are constructed. The other two graphs—on the $(\sigma(b^e), \sigma(\pi))$-plane and on the $(\sigma(b^e), \sigma(y))$-plane—are generated in the same way. For each set of weights $(a^\pi = \{0.1,\ 0.2,\ 0.3,\ 0.4,\ 0.5,\ 0.6,\ 0.7,\ 0.8,\ 0.9\}, a^y = 1 - a^\pi)$, we

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[21]The model is simulated for 700 periods subject to a random sequence drawn from a normal distribution with appropriate variance. The first 100 periods are discarded to ensure that simulated statistics do not depend on the starting point. Then the entire simulation is repeated 300 times and the simulated time series are stacked together. Our decision to repeat a simulation of 700 periods 300 times is driven by the nature of the OccBin toolbox. The software employs a guess-and-verify approach for choosing between the binding and nonbinding regimes, so the procedure becomes very time consuming in long simulations.

[22]We avoid constructing Taylor curves for each shock separately, since we are interested in the counterfactual behavior of the Chinese economy as a whole, when the possibilities of traditional monetary policy are exhausted. Moreover, looking at efficient policy frontiers for each shock would considerably lengthen the discussion without providing much further insight on the effectiveness of window guidance in China.

Figure 5. Conceivable Efficient Policy Frontiers
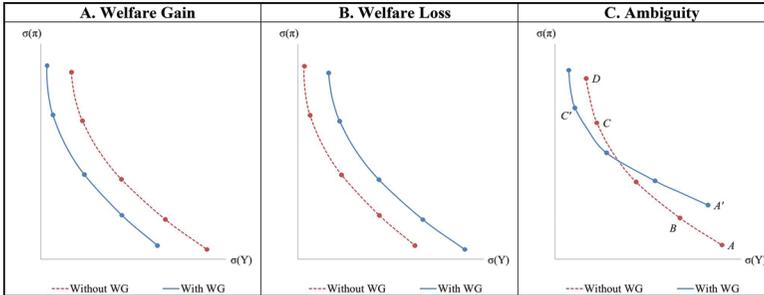
find the optimal response to inflation (ϕ^π) and plot the corresponding points on the $(\sigma(y), \sigma(\pi))$-plane. By adding window guidance at each of these nine points, we can measure the effect of introducing window guidance. Graphically, the position of the window guidance curve with respect to the original policy frontier is governed by the relative tradeoffs that window guidance offers at each of the original points. If window guidance can reduce output volatility by more than the reduction along the original curve, then window guidance is placed to the left of the traditional policy frontier and is welfare improving. Figure 5 displays the appearance of a hypothetical window guidance frontier in the case of welfare gains, welfare losses, and ambiguous results. In the first two panels the result is clear—all five points shift inward in figure 5A and outward in figure 5B. In figure 5C, however, each of the five dots moves up and left, meaning that window guidance decreases output volatility at the cost of more uncertain inflation outcomes. Hence, in point A the tradeoff offered along the no-window-guidance schedule (point B) is superior to A'. On the contrary, in point C window guidance offers a better tradeoff (point C') than movement to point D along the no-window-guidance policy frontier.

Figure 6A demonstrates that window guidance can stabilize fluctuation of output and prices beyond the conduct of standard monetary policy, since the window guidance curve lies to the left of the original frontier. We construct a policy frontier on the $(\sigma(b^e), \sigma(\pi))$-plane by finding the optimal response to inflation (ϕ^π) for each weight pair (a^b, a^π). Again, the curve with window guidance is constructed by adding window guidance policy at each point on the

Figure 6. Model-Based Efficient Policy Frontiers
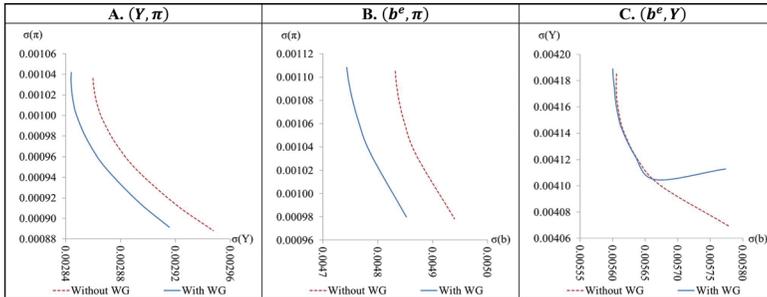
original frontier. Since the new schedule in figure 6B lies to the left of the original one, we conclude that window guidance can potentially improve the economic outcome beyond the one achievable by a standard monetary policy rule. In constructing the policy frontier on the $(\sigma(b^e), \sigma(y))$-plane in figure 6C, we adopt a slightly different approach. Instead of changing the optimal response to inflation (ϕ^π) for each weight pair (a^b, a^y), we vary ϕ^y optimally with the different values of (a^b, a^y). The reason behind this choice is that the tradeoff between the variance of output and bank loans is much more pronounced when ϕ^y is the argument that minimizes the loss function. Again, the curve with window guidance is constructed by adding window guidance policy at each point on the original frontier. The new schedule crosses the original one, indicating that there is not a clear-cut answer as to whether window guidance is improving welfare. When bank loans are more volatile, window guidance is not efficient. A better tradeoff along the original policy frontier is available—$\sigma(b^E)$ is reduced by more, while $\sigma(y)$ increases by less than if window guidance is introduced at the point of high volatility of loans. This result can be rationalized as follows. When loans are more volatile, then window guidance is binding more often and for longer periods. That entails more distortions in interest rates and, consequently, real activity—consumption and investment. Output becomes more volatile, and constraining loan dynamics through the occasionally binding constraint becomes very costly. The alternative, i.e., changing the Taylor coefficient ϕ^y, offers a better tradeoff, since the slope is quite flat at that part of the original policy frontier

(due to the convex shape of the curve). No such result is present on the $(\sigma(b^e), \sigma(\pi))$-plane, since inflation is less affected than output by the distortions that window guidance creates.

The evidence presented above brings a modicum of clarity to the polarized debate on the efficiency of window guidance. Altogether, the impulse response functions and the efficient policy frontiers for a combined demand, investment, and financial intermediation shock demonstrate that the addition of nonlinear window guidance policy may improve policy efficiency and welfare.

The reservation must be made, however, that our modeling framework analyzes business cycle dynamics and stabilization in a first-best environment. The reason for this is that we do not aim to model and evaluate the effect of financial market reforms in China. Unlike our paper, for example, Song, Stroesletten, and Zilibotti (2011) have studied a heterogeneous second-best environment with contractual and financial market imperfections. State-owned firms are less productive but have full access to the credit market. Entrepreneurial private firms are more productive but face credit constraints. In a comparable manner, Liu, Wang, and Xu (2017) have analyzed the relaxation of interest rate controls in China in a second-best environment. The ambiguous and varied quantitative conclusion is that interest rate liberalization improves capital allocation within each sector but exacerbates misallocations across sectors. What is the likely effect of such financial market distortions upon the efficient policy frontiers presented above? Since most of the window guidance loans are absorbed by state-owned firms, the existing misallocation in the capital markets would be reinforced. Recently, Cao et al. (2018) have studied the consequences of month-end quantity lending targets for Chinese bank managers. Using data from two banks, one state-owned and the other partially privatized, they show that in their pursuit of increased lending to meet targets, credit risk has become a secondary consideration. On that account, the use of window guidance leads to concerns about the longer-term sustainability of China's economic boom.

5.   Window Guidance—Panacea or Curse?

Window guidance is an administrative measure for monetary policy implementation. Given that China's banking system is dominated by

large state-owned banks, the PBoC's window guidance has shown itself to be very effective in short-run stabilization. However, over the long run, it generates distortions and inefficiency. Window guidance is much easier to implement in conditions of excess liquidity, a common situation in China, where the banking system often carries excess reserves. In terms of allocation of credit or addressing misallocation of credit among different sectors, window guidance is also a direct measure, and therefore quite effective. Given that it overrides the market mechanism, it could lead to inconsistency and structural imbalance in the long run. Some of the overcapacity problems in the Chinese economy could well be the consequence of the past window guidance policy. The PBoC has used window guidance as a supplementary policy to regular monetary policy and fiscal policy. In a transition economy with substantial distortions, administrative measures such as window guidance can help partly correct distortion effects, but in the long run, structural and institutional reforms are needed to create a smoothly functioning market economy and allow market incentives to work. Thus, window guidance should be used sparingly to correct market failures, as well as in times of crisis to avoid hard landings or dark corners.[23]

China's window guidance policy provides several lessons for policymakers. The Chinese economy has gone through boom-and-bust cycles since the launch of reforms in early 1980s. Whether the issue was overheating, recession, or structural imbalances such as overcapacity in some sectors, window guidance was a go-to tool to affect bank lending.

The first lesson is that excessive encouragement of banking lending may prevent the economy from falling into deep recession, but

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[23]According to Zilibotti (2017), even though the window-guidance-type stimulus package of 2008–09 helped China to take shelter from the Great Recession, it significantly distorted the development trajectory of the Chinese economy. The investment boom strengthened investment-led growth and delayed the transition to an innovation-led growth. The easy credit was not channeled to innovative startup businesses but rather favored large firms in traditional sectors and local governments. The growth-enhancing decline in the share of SOEs was reversed. Furthermore, the credit-induced boom led to excess capacity in many key sectors, which calls for another set of costly state interventions to shut down unproductive plants and support workers with safety nets in the afflicted areas.

Figure 7. Private Non-financial Loans and Financial Crises in Selected Economies
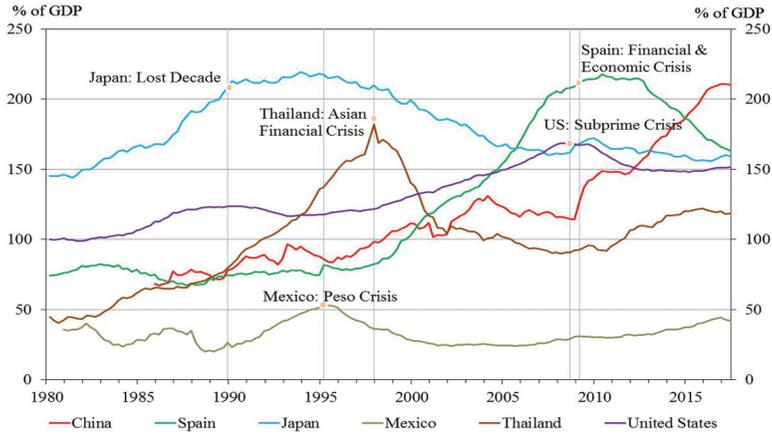
Sources: Bank for International Settlements and authors' calculations.

it can also lead to high levels of debt that may be unsustainable. In 2008–09 at the height of the global financial crisis, the Chinese government implemented a 4-trillion-yuan fiscal stimulus package and encouraged banks to lend another 10 trillion yuan to finance "infrastructure" projects. The drastic increase of bank credit caused the credit-to-GDP ratio to soar, and tolerated exuberant lending practices. Even after the government's efforts to deleverage both the government and private sectors, overall debt levels in China are quite high and still rising.

In international comparison, China's debt has reached an alarming level. By mid-2017, China's private nonfinancial debt exceeded 200 percent of GDP, a level close to the peak levels of Japan and Spain just before their crises (figure 7)—and only slightly lower than in Japan during the onset of the lost decade. Among major economies, only China attempted to sustain a high pace of credit growth after the global financial crisis. The recent surge in China's credit growth since 2012 partly reflects the PBoC's failure to curb lending and remaining reliant on bank credit to support the economic growth through window guidance policy. Overreliance on

window guidance, subsequently, has ratcheted up corporate debt to unsustainable levels.[24]

As we have seen, window guidance can correct misallocation of credit in a distorted economy. But it can also create further distortion. To optimize the bank credit structure, the PBoC introduced a differentiated window guidance policy approach in 2012. This nuanced approach allows the PBoC to rein in bank lending in overcapacity sectors, while encouraging the banks to step up policy lending to the real economy. Credit growth in overcapacity sectors (e.g., cement, coal, steel, glass, real estate, etc.) decreased to single digits in the 2011–15 period (in 2015, the growth rate was 1.5 percent, 2.4 percentage points below the 2014 figure), while the growth in total loans exceeded 10 percent in the same period. In the first half of 2016, loans to these sectors showed negative growth.[25] This development suggests that more selective use of window guidance may help improve bank credit structure and that steering window guidance in a targeted and effective manner may help with overcapacity problems. However, it is not easy a priori for the PBoC to say how much it needs to tighten credit or deleverage in the overcapacity sector, or how much it should encourage banks to lend to policy sectors such as the high-tech sector or small and medium-sized enterprises. Window guidance ultimately is a crude measure and may lead to dynamic inefficiency. Some sectors appearing to suffer from overcapacity during a downturn may face capacity constraints when the economy recovers.

Furthermore, with the ongoing process of financial liberalization, the effectiveness of window guidance gradually wears off. China's financial system is still dominated by banks, but its stock and bond markets have grown very fast, not to mention the shadow banking sector. Banks are also increasingly subject to market discipline and profit pressure. All these developments dilute the effectiveness

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[24]The Bank for International Settlements (2016) raised the red flag of debt overhang when it reported a "credit gap" of 30 percent for China. Drehmann and Tsatsaronis (2014) assert that the credit gap is a reliable and robust early-warning indicator of impending banking crises.

[25]The information on growth rates of lending to overcapacity sectors was taken from Chinese-language news reporting on credit growth. For instance, see http://cn.reuters.com/article/pboc-fin-cost-idCNKCS0UT0OY and http://www.gov.cn/xinwen/2016-07/15/content_5091793.htm.

of window guidance measures that are focused solely at traditional banks (Fukumoto et al. 2010). Thus, while window guidance may help the PBoC in fulfilling its multiple policy objectives, its use (if at all) must be highly restrained and applied only in exceptional circumstances. The overuse of window guidance leads to such problems as overshooting monetary targets and misallocation of credit. It is very difficult to implement the "quantity-based" policy within appropriate targets, particularly in the long term. It leaves the PBoC with a tradeoff between short-term stabilization and deep structural reform.

6.   Conclusions

The DSGE model presented here provided insights into the pros and cons of the nonstandard monetary policy tool, window guidance, in China. Policymakers should find our modeling exercise worthwhile, and it serves as a serious starting point in the current discussion on overhauling Chinese monetary policy.

Over the past decades, a defining feature of the PBoC's policy is its focusing on the quantity, not the price, of money. This feature has slowly changed, bringing China closer to the norm in advanced economies, an essential transition for an increasingly complex economy. It is confirmed by the IMF. In its annual Article IV review of China's economy (IMF 2017a), the IMF passed a tentative verdict (p. 29): "The conduct of monetary policy increasingly resembles a standard interest-rate-based framework." The IMF also pointed out that this new approach would be strengthened by formally acknowledging this new price-based framework and dropping quantitative targets. In a response, the Chinese authorities stated that "(it) is premature to drop monetary aggregate targets ... (and) to refer explicitly to the 7-day repo as the policy rate" (p. 29). The gradual monetary policy shift is work in progress, however, the precise outcome of which is uncertain. It is therefore safe to assume that window guidance remains a policy instrument as evidenced from PBoC monetary policy reports. Here, we applied a DSGE modeling approach enriched by a nonstandard window guidance toolkit to shed light on the efficacy of window guidance. While the DSGE framework suggests that window guidance can help provide additional monetary

policy stimulus, our welfare analysis shows that the window guidance toolkit could have a negative welfare effect in certain cases.

Finally, we are aware that a number of potential extensions could affect the findings reported in this paper. An interesting extension to this analysis of window guidance would be to incorporate recurring, endogenous financial booms and busts. The financial cycle develops over time and eventually collapses in a costly bust. The optimal monetary policy then reflects the tradeoff between the short-run macroeconomic stabilization and the longer-run benefits of stabilizing the financial cycle. One might expect that occasional nonstandard window guidance policy is then justified because the policy also smooths the financial cycle. In doing so, the central bank reduces the probability and severity of a financial bust. In sum, occasional window guidance policies might support a shift away from narrow price stability orientation to a more inclusive joint price and financial stability orientation.

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The Impact of the Designation of Global Systemically Important Banks on Their Business Model[*]

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To the best of our knowledge, this paper is among the first to provide empirical evidence on how the recent international regulation designed for global systemically important banks (G-SIBs) drove changes in these institutions' activity. Our econometric approach quantifies the impact of the designation of G-SIBs on their activity, controlling for both structural differences and industry trends. We find that G-SIBs have reduced the expansion of their balance sheet, which further improved their leverage ratio. A downward pressure is noticed on their return on equity, but no adverse consequences are observed on lending. We find no effect on G-SIBs' funding cost advantage, which suggests that "too-big-to-fail" distortions still persist.

JEL Codes: G01, G21, G28, G32.

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1.   Introduction

At the Pittsburgh Summit in 2009, G-20 leaders called on international regulators to propose solutions to the "too-big-to-fail" (TBTF) problem (Financial Stability Board 2010). Whereas this category of banks had already been identified in 1984[1] and the adverse incentives related to their status had largely been analyzed by academics (Flannery and Sorescu 1996; Freixas, Rochet, and Parigi 2004; Brandao-Marques, Correa, and Sapriza 2013; Gropp, Gruendl, and Guettler 2013), no concrete measure had been taken until the crisis had burst in order to end the TBTF distortions. The 2008 financial crisis clearly revealed that size is only one determinant of systemic risk; the complexity of a bank's business model, its interconnections with other financial entities, and internationally driven activities are other key dimensions of systemic risk.

Thus, the quantification of banks' systemic footprint and the identification of "the financial institutions whose distress or disorderly failure could cause significant disruption to the wider financial system and to the economic activity" (Financial Stability Board 2011) became a priority for international regulators and a key element of the post-Lehman reform agenda. Several measures of the systemic footprint of large banks have been developed in the academic literature, mainly based on market data, and they are still subject to ongoing discussions and refinements: the marginal expected shortfall and the systemic expected shortfall of Acharya et al. (2017), the SRISK of Acharya, Engle, and Richardson (2012) and Engle, Jondeau, and Rockinger (2015), and the CoVaR of Adrian and Brunnermeier (2016).[2] In parallel, using mainly accounting and prudential information, international regulators developed specific frameworks to make large financial institutions more resilient and to bring an end to the "too-big-to-fail" paradigm (Financial Stability Board 2010, 2013a).

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[1]In 1984, the U.S. federal government made the decision to intervene in order to avoid the failure of any of the nation's 11 largest banks. This led to the identification of a new category of banks, whose disorderly failure, due to their size, could cause significant disruption in the functioning of financial markets and the economy as a whole.

[2]Benoit et al. (2017) provides a comparative analysis of these systemic risk indicators.

To that end, the concept of a "global systemically important bank" (G-SIB) has been introduced to characterize banks to be submitted to more stringent regulatory, supervisory, and resolution regimes. The publication of the first list of G-SIBs by the Financial Stability Board (FSB) occurred in November 2011. This approach further facilitated a focused implementation of additional capital requirements (additional capital buffers, higher loss-absorbency requirements imposed under the total loss-absorbing capacity, or TLAC, framework), macroprudential measures, and additional recovery and resolution regulation (FSB 2013a, 2014a, 2015a, 2016a). The rollout of the framework has taken place progressively and will continue in the coming years.[3]

In this context, this paper seeks to evaluate whether the regulatory reforms for systemic banks have contributed to the G-20 objectives to strengthen the resilience of financial institutions and enhance global financial stability. More precisely, we will evaluate whether and how much banks designated as G-SIBs have experienced changes in line with the intended objectives, and if some unintended consequences also occurred.

Research efforts have been driven so far to investigate the effects of G-SIB regulation, but usually from a different point of view: the impact of G-SIB designation on banks' debt implicit public guarantees and the efficiency of resolution regimes and practices (Schich and Toader 2017), or the shifts in stock market evaluations driven by the recent regulatory frameworks imposed on G-SIBs (Moenninghoff, Ongena, and Wieandt 2015), or the calibration of optimal capital requirements (Passmore and von Hafften 2017). Birn, Dietsch, and Durant (2017) investigate with a nonlinear optimization model how Basel III capital and liquidity requirements combine and result in a changing balance sheet.[4] They suggest that G-SIBs, contrary to their peers, have decreased total balance sheet and simultaneously increased more than other banks the share of highly liquid instruments required to fulfill the liquidity coverage ratio (LCR). To the

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[3]Additional prudential requirements were phased in from January 1, 2016 to January 1, 2019. TLAC requirements have to be fulfilled by 2022.

[4]The empirical part of this study is based on bank-level data from the Basel Committee on Banking Supervision's (BCBS's) quantitative impact studies for 156 banks between 2011 and 2014.

best of our knowledge, almost no empirical analysis on the structural changes in G-SIBs' business models has been published so far,[5] thus our paper intends to fill this gap in the literature.

In this study, we empirically assess whether the post-crisis regulations specifically applied to G-SIBs, starting with their first designation by the FSB in 2011, have driven changes in their business models, broadly speaking. We first investigate whether the size and structure of the balance sheet has evolved in response to the new regulatory reforms, and we focus on the effects on the traditional activity of lending. Then, we evaluate changes in the risk-taking behavior and the cost of funding, to ultimately assess regulatory driven variations in overall profitability. In order to deal with such questions, we use granular balance sheet and income statement data from a sample of 97 large banks over a 12-year period between 2005 and 2016. Using this database, we apply an econometric approach inspired by the "difference-in-difference" methodology. We show that some key objectives of the BCBS have been achieved, namely we identify a major reduction of the balance sheet expansion of G-SIBs and a return to the mean in terms of financial leverage. However, it appears that the funding advantage derived by G-SIBs from the implicit public guarantees persists, which indicates that the "too-big-to-fail" status has not totally been put to an end.

The remaining of this paper proceeds as follows. Section 2 presents an overview of the post-crisis reforms dedicated to G-SIBs. In sections 3 and 4 we describe the data set and the methodology that allows us to analyze empirically our topic of interest. In section 5, we present the econometric results focusing on different aspects of banks' business model (balance sheet patterns, risk-taking, cost of funding, and profitability). Section 6 elaborates on the robustness of these results and section 7 concludes.

2.   Overview of Post-Crisis Reforms for G-SIBs

The G-20 post-crisis agenda dealt with the systemic and moral hazard risks associated with systemically important financial

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[5]See BCBS (2019) for a recent analysis of the trends of the indicators used in the BCBS methodology.

institutions (SIFIs)[6] with the aim to build a more resilient financial system. Almost 10 years after the G-20 leaders called on the FSB to propose possible measures to address the too-big-to-fail distortions generated by SIFIs, the need for concrete evidence on the contribution of the G-20 reforms in building a more resilient financial system is mandatory for the legitimacy and the credibility of FSB's post-crisis reform agenda.

Following the G-20 mandate given to the FSB in 2009, the concept of a G-SIB has been introduced to characterize the banks to be subject to new additional regulations. In November 2011, the BCBS published a methodology designed to identify these systemically important institutions focusing on five main features: size, interconnectedness, substitutability, global activity, and complexity (FSB 2011; BCBS 2011). Based on a score analysis, a first list of 29 G-SIBs (17 from Europe, 8 from the United States, and 4 from Asia) was published by the FSB in November 2011. Ever since, this list is updated and published annually each November on the FSB website.[7] This identification methodology went through several changes since its creation, particularly in November 2012 when it was revised to allocate G-SIBs into five *"buckets"* of ascending levels of systemic importance (FSB 2013a, 2014a, 2015a).[8] The latest version of the BCBS methodology was disclosed in July 2013 (BCBS 2013a).[9] Appendix B provides a broad description of this methodology developed by the BCBS for the identification of G-SIBs.

The designation of G-SIBs and their allocation into buckets were primarily conceived to enforce gradual additional capital requirements. Initially, only risk-based capital buffers were required, staging from 1 percent to 3.5 percent. More recently, in 2017, a corresponding additional buffer for the leverage ratio requirement of G-SIBs

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[6]FSB (2011).

[7]http://www.fsb.org/work-of-the-fsb/policy-development/systematically-important-financial-institutions-sifis/global-systemically-important-financial-institutions-g-sifis/. For annual updates used for this paper, please see FSB (2012, 2013b, 2014b, 2015b, and 2016b).

[8]Benoit, Hurlin, and Pérignon (2019) question the adequacy of the current BCBS's methodology. They propose a correction of the score methodology and an alternative list of systemically important institutions to be further used to set capital surcharges or alternative tax on systemic risk.

[9]Available online at https://www.bis.org/publ/bcbs255.htm.

was also introduced. However, such additional capital buffers are only one aspect of the direct consequences of being designated as a G-SIB. Indeed, G-SIBs are also subject to a minimum TLAC requirement ensuring that in case of resolution the bank holds enough instruments to absorb losses and to be recapitalized without public funds intervention (cf. FSB 2014a). Other consequences of the G-SIB designation also have to be taken into account: for instance, cross-border supervisory colleges are put in place for almost all G-SIBs in order to enhance international supervisory cooperation, and G-SIBs are subject to further resolution planning expectations from authorities. G-SIBs are also requested to take part into additional reporting and statistical data collections, such as the FSB Datagaps initiative that imposes a weekly submission of their main exposures and a monthly submission of their top financing sources. Finally, the annual publication of the list of G-SIBs by the FSB is supposed to draw investors' attention on this particular set of banks, so a specific "market discipline" is supposed to affect them. Hence, for the remainder of this paper, it is crucial to have in mind that what we call *the impact of the G-SIB designation* actually covers this complete set of consequences that applies to G-SIBs, and not only the sole capital buffer.

The constraints resulting from being a G-SIB were staged through time, with a leeway for G-SIBs to anticipate or delay the change in balance sheet until the effective implementation date. Additionally, the phasing-in of Basel III may have affected G-SIBs differently from other banks due to their structure of activity.[10] It is thus not possible to precisely define a clear cutoff date where the G-SIB constraint would apply.

3.   Data Set Description

We exploit balance sheet and income statement data for 97 large banks from 22 countries over the period from 2005 to 2016 (12 years). We focus on a sample of large banks with total assets exceeding 200

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[10]For example, Birn, Dietsch, and Durant (2017) demonstrate that G-SIBs have suffered more than other banks from the treatment of derivatives and short-term loans that was made more stringent for the net stable funding ratio (NSFR).

Figure 1. Shares of Total Assets by National Banking System (left) and by Type of Bank (right)
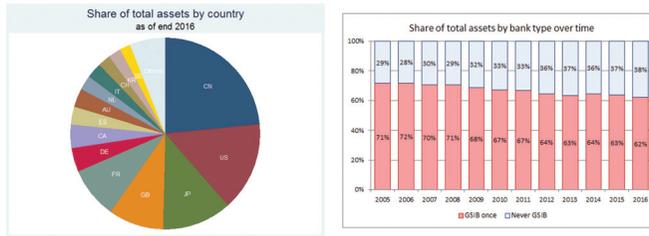
billion euros[11] as of end-2016, at the highest level of consolidation (subsidiaries are excluded). A detailed list of banks considered in the study is provided in appendix A. The distribution of national banking systems into the aggregated total assets is shown in the left panel of figure 1 (for color versions of the figures, see http://www.ijcb.org). The right panel of figure 1 shows that the share of total assets held by banks that have been designated as G-SIB at least once by the FSB between 2011 and 2016[12] is decreasing over time within our sample.

For each bank, we collected a set of variables at yearly frequency[13] using the S&P Global Market Intelligence database.[14] Table 1 provides a description of the variables that we use as successive dependent variables in the regressions.[15]

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[11]This cutoff is inspired by the €200 billion threshold in terms of Basel III leverage ratio exposure which is used by the BCBS to identify its sample. There are usually around 75 banks in this BCBS sample. The difference with our sample of 97 banks mostly comes from the different measures used (total assets versus leverage exposure) for several banks whose size is close to the €200 billion threshold. We chose total assets, as the leverage ratio exposure measure was not fully available over the period.

[12]They are listed in appendix A.

[13]Most series were not available at higher frequency (half-yearly or quarterly) for many banks. Moving to such higher frequency would therefore drastically reduce the number of banks in the sample.

[14]This was previously known as the "SNL Financial" database.

[15]Note that in order to avoid potential disturbance of our results by extreme outliers, some variables are winsorized at the 1st and 99th percentiles. This means that, for a given variable, any value larger than the 99th percentile will actually be capped at this level. Similarly, any value lower than the 1st percentile will be raised up to this level. Also note that, in order to ensure the stationarity of our series, which is required from an econometric technical perspective, all variables are expressed either as scaled by an aggregate (e.g., total assets), as ratios, or as growth rates.

Table 1. List of Dependent Variables

Variable Code	Variable Description	Obs.	Mean	Std. Dev.	Min.	Max.
Balance Sheet and Prudential Ratios						
TA gr	Total Assets (TA) Growth Rate	1,023	8.94%	13.34%	−21.01%	65.03%
TA/GDP	Total Assets over GDP	1,083	38.28%	41.61%	1.07%	206.96%
T1 gr	Tier 1 Capital (T1) Growth Rate	886	13.94%	21.75%	−25.4%	119.75%
T1/TA	Tier 1 Capital over Total Assets ("Leverage Ratio")	990	5.09%	1.81%	1.23%	10.22%
T1/RWA	Tier 1 Capital over RWA (Solvency Ratio)	972	11.72%	4.51%	4.9%	37.87%
CASH CB/TA	Cash and Balances with Central Banks over TA	681	5.97%	5.19%	0.11%	22.12%
CUST LOANS/TA	Net Customer Loans over TA	681	51.61%	14.95%	2.11%	82.05%
SUB DEBT/TL	Total Subordinated Debt over Total Liabilities	679	1.84%	1.13%	0%	6%
Profitability, Risk-Taking, and Yield Ratios						
NET PROF/OP INC	Net Profit over Op. Inc.	663	23.99%	44.36%	−513.49%	424.54%
ROA	Return on Average Assets	1,037	0.66%	0.53%	−0.87%	2.24%
ROE	Return on Average Equity	1,017	10.5%	9.08%	−24.6%	30.33%
NPL/LOANS	Share of NPL over Total Loans	1,003	2.73%	2.96%	0%	15.94%
RWA Density	Total RWA over Total Assets	1,000	47.4%	17.88%	6.77%	87.9%
LOAN YIELD	Total Loans Yield	686	5.22%	3.15%	0.58%	18.5%
DEP COST	Total Deposits Interest Cost	686	2%	1.66%	0.05%	8.4%
NIM	Net Interest Margin	686	2.16%	1.33%	0.09%	6.76%

In a first set of dependent variables, we focus on some key indicators of balance sheet and prudential ratios. Our first variables of interest are the yearly growth rates of total assets and tier 1 capital, as well as the size of banks relative to their national economy measured by gross domestic product (GDP). We also include two capital adequacy ratios: a nonweighted ratio dividing tier 1 capital (T1) by total assets (TA), which is a proxy of the leverage ratio (hereafter referred to as "leverage ratio"[16]) and a weighted solvency ratio dividing T1 capital by total risk-weighted assets (RWA). Finally, we have three indicators for the composition of the balance sheet: the share of cash (and balances with central banks) within total assets, the share of loans to nonfinancial customers within total assets, and the share of subordinated debt within total liabilities.

In a second set of dependent variables, we focus on profitability measures, risk-taking indicators, and yield rates. We include in this set of variables the ratio of net profit over the operating income, the return on assets (ROA), and the return on equity (ROE). In order to capture the risk-taking behavior of banks, we use the RWA density (i.e., total RWA over total assets), which corresponds to the average risk weight of the balance sheet, and we also compute the nonperforming loans (NPL) ratio as a measure of asset quality. We also investigate the loan yield, the average cost of deposits, and the net interest margin.

Table 2 displays some summary statistics for these dependent variables and details the means for G-SIBs and non–G-SIBs over the two periods (2005–11 and 2012–16). Figures 2 and 3 illustrate the evolution over time of the average of these variables of interest for G-SIBs versus non–G-SIBs. These figures and table 2 provide preliminary indications about some general trends that will further be confirmed econometrically in section 5. For instance, we notice a drastic reduction of the growth rate of total assets and of the return on equity for G-SIBs, compared with non–G-SIBs, during the second period. They also highlight a structurally lower leverage ratio for G-SIBs, but the gap compared with non–G-SIBs tended to shrink over time.

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[16]It differs from the regulatory definition of the Basel III leverage ratio, which was not fully available over the period.

Table 2. Means by Subgroup and Subperiod

Variables	All Banks			G-SIB (At Least Once)			Never G-SIB			
	Mean 2005–11 (A)	Mean 2012–16 (B)	T-test (B) – (A) t-stat	Mean 2005–11 (C)	Mean 2012–16 (D)	Mean 2005–11 (E)	Mean 2012–16 (F)	T-test (E) – (C) t-stat	T-test (F) – (D) t-stat
				Balance Sheet and Prudential Ratios						
TA gr	11.8% $Obs=542$	5.71% $Obs=481$	−7.489***	10.32% $Obs=193$	0.48% $Obs=167$	12.62% $Obs=349$	8.49% $Obs=314$	1.78**	7.977***
TA/GDP	38.97% $Obs=600$	37.43% $Obs=483$	−0.607	58.14% $Obs=215$	52.07% $Obs=168$	28.27% $Obs=385$	29.62% $Obs=315$	−8.258***	−6.574***
T1 gr	17.87% $Obs=465$	9.59% $Obs=421$	−5.761***	14.98% $Obs=170$	5.68% $Obs=137$	19.54% $Obs=295$	11.48% $Obs=284$	1.86**	3.646***
T1/TA	4.72% $Obs=556$	5.56% $Obs=434$	7.393***	4.33% $Obs=201$	5.31% $Obs=143$	4.94% $Obs=355$	5.68% $Obs=291$	3.851***	2.097**
T1/RWA	10.15% $Obs=548$	13.74% $Obs=424$	13.356***	10.15% $Obs=201$	14.1% $Obs=143$	10.15% $Obs=347$	13.55% $Obs=281$	−0.018	−1.159
CASH CB/TA	5.4% $Obs=356$	6.6% $Obs=325$	4.687***	4.2% $Obs=129$	7.33% $Obs=116$	6.08% $Obs=227$	6.2% $Obs=209$	3.092***	−2.13**
LOANS CUST/TA	51.84% $Obs=356$	51.37% $Obs=325$	−0.417	43.6% $Obs=129$	43.4% $Obs=116$	56.52% $Obs=227$	55.79% $Obs=209$	8.209***	8.233***
SUB DEBT/TL	1.94% $Obs=372$	1.73% $Obs=307$	−6.059***	1.93% $Obs=142$	1.73% $Obs=116$	1.94% $Obs=230$	1.73% $Obs=191$	0.044	0.007

(*continued*)

Table 2. (Continued)

Variables	All Banks			G-SIB (At Least Once)		Never G-SIB		T-test (E) − (C) t-stat	T-test (F) − (D) t-stat
	Mean 2005–11 (A)	Mean 2012–16 (B)	T-test (B) − (A) t-stat	Mean 2005–11 (C)	Mean 2012–16 (D)	Mean 2005–11 (E)	Mean 2012–16 (F)		
Profitability, Risk-Taking, and Yield Ratios									
NET PROF/ OP INC	21.09% *Obs = 367*	27.59% *Obs = 296*	2.178**	17.07% *Obs = 134*	24.72% *Obs = 94*	23.4% *Obs = 233*	28.93% *Obs = 202*	1.17	0.932
ROA	0.69% *Obs = 556*	0.63% *Obs = 481*	−1.635	0.59% *Obs = 202*	0.46% *Obs = 167*	0.74% *Obs = 354*	0.72% *Obs = 314*	3.201***	5.588***
ROE	11.52% *Obs = 536*	9.37% *Obs = 481*	−3.8***	9.9% *Obs = 189*	6.08% *Obs = 167*	12.4% *Obs = 347*	11.12% *Obs = 314*	2.816***	6.948***
RWA Density	49.09% *Obs = 551*	45.33% *Obs = 449*	−3.326***	44.07% *Obs = 201*	41.45% *Obs = 159*	51.97% *Obs = 347*	47.45% *Obs = 290*	5.237***	3.38***
NPL/LOANS	2.65% *Obs = 540*	2.83% *Obs = 463*	0.941	3.25% *Obs = 199*	3.12% *Obs = 161*	2.3% *Obs = 341*	2.67% *Obs = 302*	−3.922***	−1.431***
LOAN YIELD	5.57% *Obs = 362*	4.83% *Obs = 324*	−3.316***	4.7% *Obs = 113*	3.5% *Obs = 93*	5.96% *Obs = 249*	5.36% *Obs = 231*	4.036***	4.534***
DEP COST	2.25% *Obs = 362*	1.72% *Obs = 324*	−5.812***	1.76% *Obs = 113*	0.92% *Obs = 93*	2.47% *Obs = 249*	2.04% *Obs = 231*	4.065***	5.538***
NIM	2.25% *Obs = 362*	2.05% *Obs = 324*	−2.381***	1.88% *Obs = 113*	1.51% *Obs = 93*	2.42% *Obs = 249*	2.26% *Obs = 231*	3.674***	4.749***

Note: Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 2. Evolution of the Average Balance Sheet and Prudential Ratios for G-SIBs (red/lighter bars) versus Non–G-SIBs (blue/darker bars)
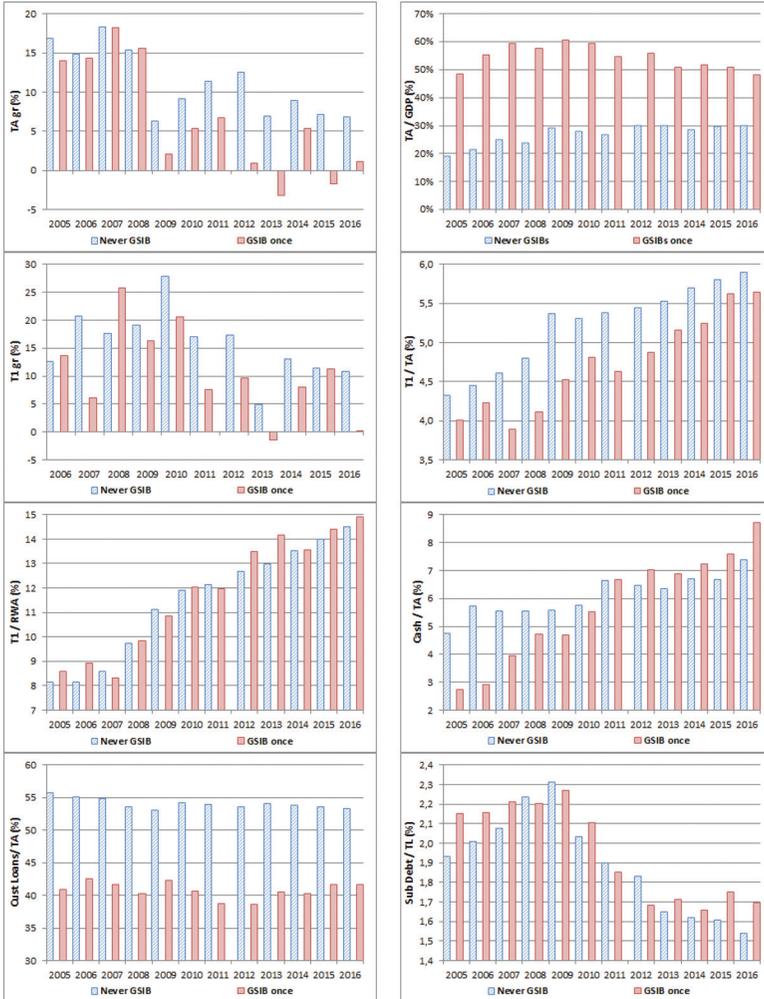
**Figure 3. Evolution of the Average Profitability,
Risk-Taking, and Yield Ratios for G-SIBs (red/lighter
bars) versus Non–G-SIBs (blue/darker bars)**
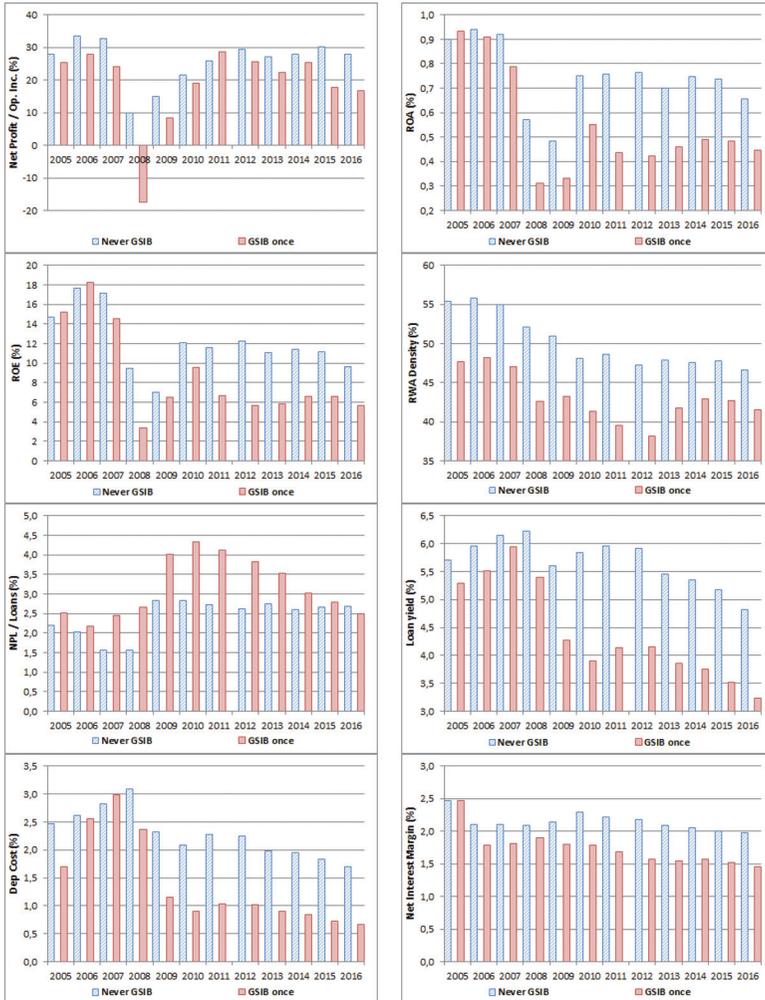
4.   Econometric Methodology

4.1   Specification

This paper seeks to evaluate the changes that affected G-SIBs following the announcement and/or implementation of the prudential

rules dedicated to this specific category of banks. With such objective in mind, we rely on an approach inspired by the difference-in-difference methodology.[17] In a standard difference-in-difference model, the group of G-SIBs would correspond to the *treated* group while the group of other banks (here "non–G-SIBs") would constitute the *control* group. We compare the post-crisis reform-driven evolutions of business models' characteristics for these two groups of banks.

As the list of G-SIBs is relatively stable (with only a few entries and exits each year, if any),[18] we will consider as a G-SIB every bank that has been designated at least once by the FSB between 2011 and 2016. Hence we construct the $GSIB_{i,k}$ binary variable that takes value 1 for all periods t if the G-SIB i located in country k appeared on the FSB list at least once between 2011 and 2016, and 0 otherwise. Regarding the time dimension, even if it is not possible to precisely define a clear cutoff date where the G-SIB constraint would apply (due to the phased-in approach of the regulation, as discussed in section 2), we should recall that the first list of banks designated as G-SIBs was disclosed by the FSB in November 2011. Hence, we construct a binary variable $Post2011_t$ that equals 1 if $t > 2011$ and 0 otherwise. Note that, contrary to "event studies" papers, we do not rely on this precise cutoff date, as we do not claim that G-SIBs reforms had an effect on a very precise and short timing, but instead had a gradual effect over time. Section 6 provides some robustness checks testing alternative definitions of the $GSIB_{i,k}$ and $Post2011_t$ variables. Contrary to "placebo tests" usually performed in event studies, the fact that results remain stable for alternative cutoff date shows that the "arbitrary" decisions made for these two binary variables here are not driving the results.

In addition to these two main explanatory variables, a set of bank-specific time-varying control variables and some country-specific time-varying factors are considered. At the end, we select a given dependent variable Y (among those listed in table 1) for all

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[17]We use a similar approach to the one developed by Grill, Lang, and Smith (2018), Hills et al. (2017), and especially Schich and Toader (2017), applied to different regulatory contexts.

[18]These rare changes of the list of G-SIBs might be used for other analyses, such as case studies, but this is not the purpose of this paper and this is left for future research.

banks i, incorporated in country k at time t, and we regress it on the two binary variables described above, $GSIB_{i,k}$ and $Post2011_t$, and on the cross-variable *interaction term* of these two variables: $(GSIB_{i,k} \times Post2011_t)$, as well as on control variables. We estimate the following model[19]:

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t)$$
$$+ \varphi B_{i,k,t} + \chi C_{k,t} + PTH_t + u_{i,k,t}, \tag{1}$$

with $B_{i,k,t}$ being the set of bank-specific control variables, $C_{k,t}$ the set of country-specific macroeconomic control variables, PTH_t a conditional time-dummy variable capturing potential violations of the "parallel trend hypothesis,"[20] and $u_{i,k,t}$ being an error term. Since we cannot be sure that observations are iid among banks, standard errors will be clustered at individual level in all our regressions.

The set of country-specific macroeconomic control variables $C_{k,t}$, described in table 3, will be included in all following regressions to take into account potential structural discrepancies between economies in terms of growth, wealth, unemployment, inflation, public debt, aggregate credit growth, and sovereign yield. These variables can also capture specific conditions of the macroeconomic environment in some countries, such as the sovereign debt crisis in Europe.[21] The annual growth rate of exchange rate against the euro is also included since our data set in entirely denominated in euros, for consistency reasons. The set of bank-specific control variables $B_{i,k,t}$ included in the regressions can vary from one dependent variable to another and will be described below each regression table in the next section.

The econometric identification strategy described in equation (1) allows us to assess the impact of the G-SIB designation on their

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[19]Section 6 also provides some robustness checks of this model, testing alternative specifications.

[20]See the explanation below in section 4.2.

[21]As an additional robustness check, we also include the 10-year government CDS spreads in order to capture the impact of the sovereign debt crisis that affected some countries. These results are presented in column "Gov. CDS Spread" of table 8.

Table 3. Set of Country-Specific Macroeconomic Control Variables $C_{k,t}$

Variable Code	Variable Description	Obs.	Mean	Std. Dev.	Min.	Max.
GDP gr	Real GDP Growth (%)	1,164	3.03%	3.72%	−7.93%	15.24%
GDPperCap	GDP per Capita (USD/Year)	1,164	35,943	19,160	714	102,723
UR	Unemployment Rate (%)	1,164	6.12%	3.18%	1.9%	26.09%
INPL	Inflation (%)	1,164	2.13%	1.96%	−1.35%	15.52%
PUBD/GDP	Public Debt/GDP (%)	1,164	67.17%	48.30%	4.95%	222.23%
DOMCRED gr	Domestic Credit Growth (%)	1,164	7.97%	8.23%	−15.07%	40.63%
SOVYIELD	10-Year Sovereign Debt Yield (%)	1,164	3.38%	2.47%	−0.14%	16.49%
FXRATE gr	Annual Growth Rate of Exchange Rate against Euro (%)	1,164	−0.60%	9.53%	−25.27%	59.6%

Figure 4. Illustration of the Econometric Methodology in the Univariate Case
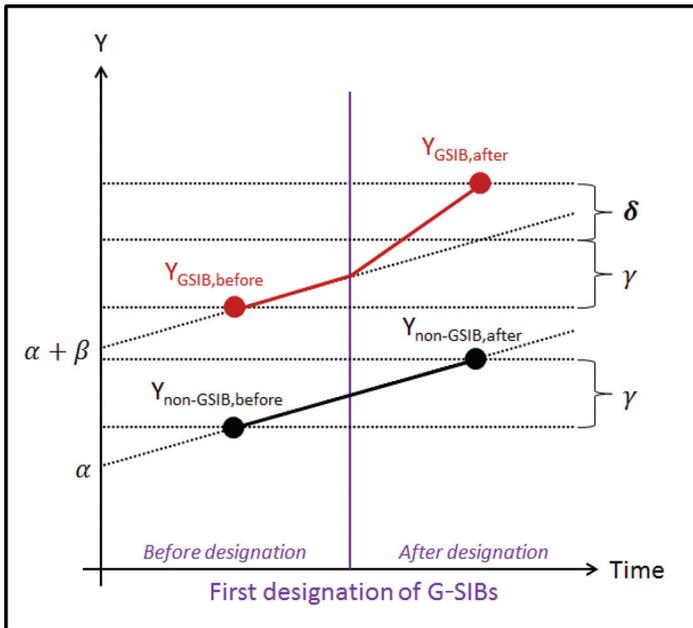
structural patterns. It is applied successively to each of our dependent variables listed in table 1. Within this framework, our main parameter of interest will be δ, the coefficient of the interaction term. It captures the causal impact of the designation by the FSB on the Y variable for G-SIBs, controlling for both the effect of structural differences between G-SIBs and non–G-SIBs (captured by the coefficient β of the binary variable $GSIB_{i,k}$), and the time structural changes, or "industry trends" (captured by the coefficient γ of the variable $Post2011_t$). The graphic illustration in figure 4 gives a visual illustration of this approach in a simple univariate case.

However, it is recognized that this econometric identification has some limitations. The model is able to take into account general evolutions of the environment, both macroeconomic conditions and implementation of new regulations affecting the whole banking system. This is the purpose of using two subgroups and two subperiods that should be affected in a similar way by these general evolutions,

while only G-SIBs are affected by the designation. On the other hand, it will not be able to disentangle the effects of each individual consequence of the designation of a bank as a G-SIB by the FSB. As described in section 2, such designation entails several regulatory implications, such as capital buffers and TLAC requirements. Therefore, one should keep in mind that the estimator δ captures the *overall* effect of all diverse consequences posterior to the G-SIB designation, and not the impact of the sole additional capital requirement.

4.2 Parallel Trend Hypothesis

In an "ideal world" where the difference-in-difference methodology would purely apply, we should use as a control group the exact same set of treated banks, the *only* difference being that banks in the control group would not have been designated as G-SIBs. Such configuration is obviously impossible in the real world. Indeed, non–G-SIB are from the beginning smaller or less systemic than G-SIBs. Furthermore, some non–G-SIBs may also be subject to additional requirements, especially when they are designated as domestic systemically important banks (D-SIBs), even if this framework decided at the jurisdiction level is usually more recent and less homogeneous than the one of G-SIBs.

Thus, as a *second-best* option in this paper, we use all other large international banks not designated as G-SIBs as a kind of control group to capture the "industry trends" (i.e., the γ coefficient). The underlying assumption in this methodology is that both groups of banks (G-SIBs and non–G-SIBs) follow parallel trends before the designation, and that they would have continue to do so if the designation would not have occurred.[22] If the latter is clearly not testable, at least we can empirically check the former.

We can graphically assess on figures 2 and 3 whether the averaged characteristics of the two subgroups tended to evolve similarly before

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[22]We also checked the parallel trends across different geographical regions (Europe, North America, China, and the rest of the world). We find no major differences in the evolutions of these variables for these four regions before 2011. However, the level of some indicators can differ for China. Therefore, we run an additional robustness check in section 6 (table 8) excluding Chinese banks from the sample. Results remain broadly unchanged.

the first designation of G-SIBs in November 2011. In order to assess more formally this "parallel trend hypothesis" (PTH) we perform a test, in line with what Danisewicz, Reinhardt, and Sowerbutts (2017) proposed. For each year preceding the first designation of G-SIBs we compute the annual growth rate of the dependent variables and then compare these growth rates between the two subgroups. Applying mean-difference t-tests, we determine whether these variables show significantly different annual evolutions between G-SIBs and non–G-SIBs. That is to say, if we notice a difference in the growth rates of G-SIBs versus non–G-SIBs, even at 10 percent significance level, then the parallel trend hypothesis will be deemed not fully met for this particular year. Table 4 summarizes the results of these tests of the parallel trend hypothesis for all our dependent variables listed in table 1.

Looking at the overall result of table 4, we see that the PTH seems met for most of the variables over the years between 2006 and 2011. The few violations of the PTH mostly tend to appear in years 2007, 2008, and 2009, which might be related to a different impact of the crisis on the two subgroups. When such violation of the PTH appears for a given year for a dependent variable, then we will include the time-dummy variable PTH_t in the regression. It will take value 1 for all i if the parallel trend hypothesis seems violated at time t for the dependent variable $Y_{i,k,t}$, even at a 10 percent significance level, and value 0 otherwise. Hence, it will try to capture the underlying source of divergence between the two subgroups that occurred during that particular year. When the PTH_t variable is introduced, it will be indicated at the bottom of each regression table in section 5.

4.3   Propensity Score Matching

In order to reduce heterogeneity between the G-SIB and non–G-SIB subgroups, an alternative approach can be used to construct the control group. We tested a propensity score matching (PSM) methodology and followed Stuart (2010). First, using a logit model, we computed the propensity scores of all banks (i.e., the probability of being designated as a G-SIB, given some covariates), using balance sheet, income statement, and profitability characteristics as

Table 4. Test of the Parallel Trend Hypothesis

Variable	2006			2007			2008		
	ΔGR	p-val.	Sig.	ΔGR	p-val.	Sig.	ΔGR	p-val.	Sig.
TA gr	2.80	0.43		16.0	0.22		−1.3	0.27	
TA/GDP	0.02	0.37		0.00	0.98		0.09	0.09	*
T1 gr				−13.0	0.19		−3.6	0.63	
T1/TA	0.01	0.75		−0.1	0.01	**	−0.0	0.54	
T1/RWA	0.02	0.58		−0.1	0.00	***	0.13	0.00	***
CASH CB/TA	−0.0	0.79		0.44	0.20		−0.2	0.34	
LOANS CUST/TA	0.02	0.23		−0.0	0.81		−0.0	0.15	
SUB DEBT/TL	−0.0	0.35		−0.0	0.40		−0.2	0.28	

Variable	2009			2010			2011		
	ΔGR	p-val.	Sig.	ΔGR	p-val.	Sig.	ΔGR	p-val.	Sig.
TA gr	−1.1	0.61		1.31	0.45		0.68	0.03	
TA/GDP	−0.0	0.94		0.01	0.37		0.00	0.91	
T1 gr	2.57	0.02	**	1.36	0.61		−0.3	0.33	
T1/TA	0.06	0.26		0.03	0.31		−0.0	0.06	*
T1/RWA	−0.0	0.41		0.03	0.17		−0.0	0.50	
CASH CB/TA	0.64	0.07	*	0.07	0.57		−0.9	0.06	*
LOANS CUST/TA	0.10	0.00	***	−0.0	0.22		−0.0	0.18	
SUB DEBT/TL	0.21	0.00	***	0.02	0.72		0.00	0.95	

Table 4. (Continued)

Variable	2006 ΔGR	p-val.	Sig.	2007 ΔGR	p-val.	Sig.	2008 ΔGR	p-val.	Sig.
NET PROF/OP INC	−0.1	0.22		0.03	0.85		3.80	0.21	
ROA	2.88	0.32		0.22	0.47		0.30	0.56	
ROE	3.78	0.29		−0.0	0.66		0.14	0.79	
RWA Density	−0.0	0.74		0.01	0.57		−0.2	0.14	
NPL/LOANS	0.08	0.31		0.04	0.84		0.12	0.58	
LOAN YIELD	0.08	0.03	**	−0.0	0.36		−0.1	0.07	*
DEP COST	0.15	0.19		−0.0	0.88		−0.2	0.00	***
NIM	0.04	0.52		0.04	0.59		0.16	0.17	

Variable	2009 ΔGR	p-val.	Sig.	2010 ΔGR	p-val.	Sig.	2011 ΔGR	p-val.	Sig.
NET PROF/OP INC	−2.9	0.28		−3.6	0.23		1.10	0.11	
ROA	−2.0	0.37		−1.1	0.00	***	0.22	0.71	
ROE	−1.8	0.35		−1.0	0.00	***	0.24	0.65	
RWA Density	0.07	0.00	***	−0.0	0.46		−0.0	0.09	*
NPL/LOANS	−0.0	0.78		0.64	0.27		0.03	0.43	
LOAN YIELD	−0.0	0.81		−0.0	0.09	*	−0.0	0.36	
DEP COST	−0.2	0.00	***	−0.0	0.18		−0.1	0.21	
NIM	0.07	0.24		−0.0	0.27		−0.0	0.07	*

Notes: ΔGR indicates the difference between the year-on-year growth rates of the two subgroups of banks (G-SIBs and non–G-SIBs). We also report the p-value of the mean-difference t-test between these two growth rates. When we notice a significant difference, even at the 10 percent significance level, then the parallel trend hypothesis will be deemed not fully met for this particular year. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

explanatory variables. Then, each G-SIB was matched to the non–G-SIB with the closest propensity score (without replacement). All remaining non–G-SIBs were simply ignored. Finally, we rerun our regressions using this alternative control group. Results are displayed in table 8, column "PS Matching." Since they are very similar to our main approach described in the two previous subsections, both in terms of significance and magnitude, we decided to retain as the main methodology our initial strategy and consider the PSM as a robustness check analysis since it is based on a smaller sample.

5.   Assessing Changes in Banks' Business Model

This section presents the regression results regarding the different aspects of the banks' business models. We first focus on some key balance sheet and prudential ratios (including balance sheet growth and structure, as well as capital adequacy). Then we turn to an analysis of profitability, risk-taking behavior, and yields.

5.1   Balance Sheet and Prudential Ratios

5.1.1   Growth of the Balance Sheet

Looking at the regression results in table 5, we notice a very significant negative sign for the interaction variable (δ coefficient) for the growth rate of total assets. It decreases by 5.8 percentage points (pp) on average for G-SIBs starting with 2012, everything else equal.

RESULT 1. *Everything else equal, G-SIBs have strongly curbed the expansion of their balance sheet since their first designation by the FSB.*

Note that, as shown in table 2, growth rates of total assets remain—at least slightly—positive on average for the two types of banks over the two subperiods. However, this relative slowdown of the expansion of G-SIBs' balance sheet, which we can attribute to the designation, is strongly consistent with the steady decline over time of the share of assets held by G-SIBs versus non–G-SIBs illustrated in the right panel of figure 1. When total asset is scaled by GDP, we also find strong evidence of the relative decrease of the weight of G-SIBs into their national economies.

Table 5. Balance Sheet and Prudential Ratios: Regression Results

				Dependent Variable				
	TA gr	TA/GDP	T1 gr	T1/TA	T1/RWA	CASH CB/TA	LOANS CUST/TA	SUB DEBT/TA
(β) GSIB	0.177	37.981**	0.100	−0.907**	−0.748	−0.300	−4.475	0.294
	(1.605)	(16.107)	(1.780)	(0.375)	(0.922)	(0.844)	(4.137)	(0.347)
(γ) Post2011	−1.651**	2.301	−3.730**	0.509***	1.974***	2.312***	3.555***	−0.234
	(0.834)	(1.499)	(1.737)	(0.107)	(0.451)	(0.804)	(1.160)	(0.157)
(δ) GSIB × Post2011	−5.763***	−14.704**	−2.512	0.589***	−0.133	2.340***	−1.120	0.301*
	(1.392)	(7.234)	(2.039)	(0.200)	(0.569)	(0.809)	(1.545)	(0.169)
Size	0.019		−0.418	0.337**	−0.675*	0.232	−5.499***	−0.221*
	(0.636)		(0.765)	(0.167)	(0.350)	(0.387)	(1.070)	(0.115)
LOANS/TA			−0.074**	0.004	−0.058**			
			(0.029)	(0.008)	(0.025)			
DEP/TL			0.006	0.013*	0.013			
			(0.034)	(0.007)	(0.018)			
ROA			4.794***	0.459***	0.282			
			(1.579)	(0.117)	(0.224)			
Intercept	5.428	6.287	34.671**	−2.008	26.618***	2.900	151.677***	6.951***
	(12.297)	(5.752)	(16.821)	(3.407)	(6.627)	(7.983)	(21.167)	(2.148)
Obs.	1,023	1,083	883	946	930	681	681	679
Adj.-R^2	0.333	0.023	0.266	0.227	0.383	0.547	0.103	0.122
Macro Control Var.	YES	YES	YES	YES	YES	YES	YES	YES
PTH Dummy = 1 for Nonparallel Trends in Year(s)		2008	2009	2007 2011	2007 2008	2009 2011	2009	2009

Bank-Specific Control Variables included for Some Variables of This Set

Size: Balance Sheet Size (Log of Total Assets)
LOANS/TA: Loans to Total Assets
DEP/TL: Deposits to Total Liabilities
ROA: Return on Assets

Notes: Figures are in percentage points. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

This result 1 is then fairly consistent with the design of the BCBS's methodology used to identify G-SIBs, as it tends to indicate that G-SIBs try to reduce their systemic footprints by actively reducing the expansion of their balance sheet, as the size indicator is of paramount importance in the identification of G-SIBs performed by the BCBS (cf. appendix B for more details). It is then not surprising that this indicator seems strategically managed in order to avoid, or at least minimize, the additional regulatory constraints that follow the designation of a bank as a G-SIB. Note that conversely some banks might also be tempted to increase their systemic footprint so as to be designated as G-SIB and benefit from an increased implicit bailout guarantee. However, such behavior would tend to bias our δ estimate toward zero, hence it does not contradict result 1.

We also tested whether such downward pressure was noticed for other indicators used in the BCBS's methodology. Out of the 12 indicators used by the BCBS in its G-SIB identification methodology, we could replicate 6 of them with enough accuracy using the S&P Global Market Intelligence database. Apart from the growth rate of total assets, although we find a negative coefficient for most of them, the strategic reduction of the systemic footprint does not appear significant for the other systemic indicators of the BCBS methodology, as they can be proxied from public data.[23]

5.1.2   Prudential Ratios

Our focus is now drawn toward solvency patterns.[24] Both structural and time differences can be noticed. We find a significant structural gap in terms of leverage ratio (T1/TA) between G-SIBs and non–G-SIBs (coefficient β). This implies that G-SIBs are generally more leveraged than non–G-SIBs, with a leverage ratio 0.91 percentage point lower than the one of non–G-SIBs, everything else equal. Such

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[23]This complete analysis of the proxy indicators used in the BCBS's methodology can be obtained from the authors upon request.

[24]For the growth rate of tier 1 capital, and for the two capital adequacy ratios (leverage ratio and tier 1 solvency ratio), we include as bank-specific control variables two ratios describing the level of retail activities in banks' balance sheets: the share of loans within total assets and the share of deposits within total liabilities. We also include the return on average asset to take into account differences in assets profitability, which is likely to impact banks' ability to raise capital.

structural gap between G-SIBs and non–G-SIBs does not appear significant for the risk-weighted capital ratio (T1/RWA). For these two capital ratios, the coefficient γ is positive and strongly significant, so all banks display higher solvency levels in the second period. This is consistent with the adoption of the Basel III regulatory framework that imposed all banks to boost their solvency ratios.

The main interest variable, $GSIB \times Post2011$, brings additional interesting evidence, although counterintuitive at a first view: the coefficient δ is significant only for the leverage ratio and not for the risk-weighted solvency ratio. Since the designation of a bank as a G-SIB automatically results in an additional capital buffer on top of the minimum risk-weighted solvency requirements, one may have expected a positive and significant coefficient here. In fact, such mechanical explanation does not take into account the general race for higher solvency ratios. Many banks, either G-SIBs or not, have increased their solvency ratio more than requested by the Basel III standards, as a response to market and supervisory pressure (such as "pillar 2" additional requirements, for instance). Such general hoarding of new capital is reflected in our results by the coefficient δ which is not significant for the growth rate of tier 1 capital (T1 gr): G-SIBs did not increase their tier 1 more than their peers following their designation. This may also come from the fact that some banks among the non–G-SIBs might be subject to equivalent additional capital requirements, such as a D-SIB buffer.[25] These two elements could partly explain why the G-SIB designation has no significant effect on the G-SIBs' risk-weighted capital adequacy ratio in our results.

On the contrary, we notice a significant and substantial effect on the leverage ratio, which shows an additional increase by 0.59 pp for G-SIBs on top of the general improvement of 0.51 pp that affected all banks in the second period. As G-SIBs used to be more leveraged than other banks before 2011, this further improvement of the leverage ratio helped them bridge this leverage gap, at least partly. It is noticeable that such an evolution occurred years before the discussion about a possibly higher leverage ratio requirement for G-SIBs began.

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[25]If they are listed as "domestic systemically important banks" by their national supervisory authority; please see BCBS (2012).

RESULT 2. *The G-SIBs designation seems to have triggered an additional increase of the leverage ratio for the subgroup of G-SIBs since 2012, tending to bridge the structural leverage gap noticed between G-SIBs and non–G-SIBs. Surprisingly, the designation does not seem to have an impact on the levels of the risk-weighted capital ratio in the second period.*

5.1.3 Balance Sheet Structure

Beyond the pressure to raise capital, the G-SIB reform agenda might also lead banking institutions to modify their balance sheet. In order to reach the new capital requirements, an alternative to capital increase would be to change the composition of the balance sheet or to improve the quality of asset portfolio. One can also expect that banks will be incentivised to increase the share of stable loss-absorbing liabilities. To assess the evolutions of banks' balance sheets, we use a detailed breakdown of both assets and liabilities.[26] All variables of this breakdown of banks' balance sheet have been tested to provide an in-depth assessment of potential structural changes attributable to the G-SIB designation. For the sake of simplicity and brevity, only results with the most important policy implications are reported in this paper. However, results for all other variables for both asset and liability structure are gathered into a supplementary document available upon request to the authors.

   With respect to asset portfolio, two main changes have to be highlighted. First, we find a significant positive impact (+2.3 pp) of the G-SIB reform agenda on cash and central bank holdings for the subsample of G-SIBs compared with other banks. This result

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[26]Over the full database that comprises a maximum of 1,164 observations (97 banks time 12 years), we get 681 observations for assets structure and 679 observations for liabilities. On average, total assets can be broken down into cash and balances with central banks (6.0 percent of assets over the full panel), loans to banks (6.9 percent), loans to nonfinancial customers (51.6 percent), trading account (7.2 percent), available for sales securities (7.6 percent), held to maturity securities (2.9 percent), derivatives (6.6 percent), other financial assets (1.2 percent), intangible assets (0.7 percent), and other assets (9.3 percent). Total liabilities can be split into deposits from banks (11.6 percent of liabilities over the full sample), customer deposits (53.1 percent), subordinated debt (1.8 percent), senior debt obligations (17.5 percent), derivatives (7.0 percent), other financial liabilities (2.1 percent), and other liabilities (6.9 percent).

brings empirical proof of the efforts made by G-SIBs to catch up with a higher share of liquid assets of good quality from a relatively lower level recorded over the period 2005–11. This effect is likely to have been partially driven by expansive monetary policies around the world (quantitative easing programs and low interest rates) and the implementation of a new liquidity framework within the post-crisis reform agenda. Indeed, cash and balances with central banks are high-quality liquid assets taken for 100 percent as a buffer in the context of the liquidity coverage ratio (LCR). Even though the LCR is not a G-SIB-specific regulation, the fact that G-SIBs tended to lag behind in terms of cash holdings put a stronger pressure on these institutions.[27] Moreover, as one can see in figure 2, G-SIBs started to increase the share of cash since the crisis; this can easily be explained through market pressure to increase the holdings of high-quality liquid assets (the so-called flight to liquidity and quality). Still, taking into account the crisis effect in the regressions, using a set of macroeconomic control variables, we find that the G-SIB designation pushed further this reallocation of assets toward larger cash holdings.

Secondly, the share of loans to nonfinancial customers in the balance sheet was not affected by the overall regulatory framework designated for G-SIBs. It appears that over the second period all banks have raised their holdings of loans on average (as indicated by the coefficient γ of +3.6 pp). The estimated coefficient δ of the interaction variable is negative although not statistically significant. Such finding is in line with Admati and Hellwig (2014) sustaining that, according to the Modigliani-Miller view, higher capital requirements should have a limited impact on the bank's lending policy. It therefore provides empirical evidence against some industry's concerns that higher regulatory requirements would lead to a drop in credit supply.

RESULT 3. *Everything else equal, the most important change in broad asset structure driven by the G-SIB designation has been a 2.3 pp increase in the share of cash and central bank reserves that tended to*

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[27]Our findings are in line with the conclusions of Birn, Dietsch, and Durant (2017) highlighting that between 2011 and 2014, G-SIBs effectively increased liquid assets more than other banks.

affect the structural gap in the share of cash recorded before 2011 compared with non–G-SIBs. Beyond that, the rest of the balance sheet does not seem to have been affected by the G-SIB designation, especially the ability of G-SIBs to provide loans and finance the real economy remained unchanged.

Turning now to the analysis of the structure of liabilities, the estimated coefficients δ suggest that the G-SIB designation and its regulatory consequences did not drive major shifts in the liabilities composition of G-SIBs, except a slightly significant increase of the share of subordinated debt (+0.3 pp after 2011 compared with non–G-SIBs). This finding may be linked to the introduction of the TLAC requirement, as some of the underlying debt instruments can be eligible to fulfill the required loss-absorbing capacity of the bank.

RESULT 4. *Everything else equal, apart from a small increase of subordinated debt, the G-SIB designation does not seem to have changed the liability structure of G-SIBs' balance sheet.*

5.2 Profitability, Risk-Taking, and Yield Ratios

We now focus on other aspects of banks' business model and analyze measures of profitability, risk-taking behavior, and yields. The challenges posed by new regulations and the macroeconomic environment are likely to affect the results of financial institutions. Banks designated as G-SIBs since 2011 are subject to more stringent regulatory requirements, which is generally considered costly by regulated banks (Institute of International Finance 2010). At the opposite, several empirical studies highlight that an improvement of the quality of capital reduces banks' risk-taking and leaves profitability unchanged in the long run (King 2010; Kashyap, Stein, and Hanson 2010). The aim of the analysis in this subsection is to examine the extent to which the regulatory driven changes have affected the risk-taking behavior, the cost of funding, and ultimately the profitability of banks designated as G-SIBs since 2011.

5.2.1 Profitability

Our investigation on the income statement composition provided clear evidence of the existence of a major structural difference in

the revenue mix of the two groups: G-SIBs report a much lower income generated by interest-bearing activities compared with other banks (non–G-SIBs) while the revenues from trading securities are considerably higher for the former subgroup. With regard to time variations, net gains on securities have increased for all banks during the second subperiod to the detriment of net interest revenues, which is consistent with the macroeconomic conditions characterized by low interest rates and the flattening of the yield curve. On the other hand, the model fails to find evidence that the designation of G-SIBs has significantly affected whatsoever their income statement composition, and especially their net profit.

RESULT 5. *The FSB designation of G-SIBs seems not to have had any statistically significant impact on their net profit (scaled by operating income).*

We observe from descriptive statistics (see table 2 and figure 3) that G-SIBs and non–G-SIBs have rather comparable profitability levels in terms of net profit, ROA, and ROE at the beginning of the study period, i.e., 2005–07. Then G-SIBs tend to be more heavily affected during the 2008–09 crisis. Finally, in the aftermath of the crisis, profitability is recovering for all banks relative to the crisis level, but G-SIBs' profitability remains at a lower level compared with their peers.

The results of the regressions fail to confirm the existence of a structural difference (β coefficient) between the two subgroups of banks over the full period (2005–16), all things being equal. The second subperiod (2012–16) is characterized by a significantly higher profitability than the first one (i.e., 2005–11), which is rather consistent given the fact that the first subperiod includes the financial crisis. Such overall improvement of profitability can be seen for the three profitability indicators. As a consequence, the net profit (scaled by operating income) appears 21.6 pp larger in the second subperiod for the complete set of banks (γ coefficient).

Our empirical results in table 6 suggest that becoming a G-SIB had a significant negative impact on the ROE (–3.1 pp), which more than offset the upward profitability trend (+1.9 pp) noticed over the period for the whole sample of institutions. Econometrically, we do not find any impact of the designation on the return on assets

Table 6. Profitability, Risk-Taking, and Yield: Regression Results

	Dependent Variable							
	NET PROF/ OP INC	ROA	ROE	RWA Density	NPL/ LOANS	LOAN YIELD	DEP COST	NIM
(β) GSIB	24.457	−0.024	1.782	−3.784	0.737	−0.899*	−0.418**	−0.529*
	(15.034)	(0.093)	(1.566)	(3.615)	(0.692)	(0.497)	(0.193)	(0.295)
(γ) Post2011	21.553***	0.157***	1.853**	−2.714**	0.154	−0.087	−0.122	−0.064
	(8.073)	(0.042)	(0.790)	(1.256)	(0.242)	(0.110)	(0.120)	(0.082)
(δ) GSIB × Post2011	−4.610	−0.074	−3.064***	4.609***	−0.675*	0.096	0.086	−0.051
	(7.309)	(0.053)	(1.056)	(1.432)	(0.348)	(0.134)	(0.138)	(0.087)
Size	−12.531*	0.046	−0.246	3.011***	−0.612**	−0.179	0.044	−0.072
	(7.580)	(0.037)	(0.652)	(1.152)	(0.290)	(0.114)	(0.081)	(0.067)
LOANS/TA	0.291	0.001	0.039	0.294***	−0.009	−0.017*	0.005	0.001
	(0.215)	(0.002)	(0.032)	(0.083)	(0.014)	(0.009)	(0.004)	(0.006)
DEP/TL	−0.155	0.004***	0.065*	0.001	−0.017	−0.014**	−0.020***	0.005
	(0.289)	(0.001)	(0.036)	(0.059)	(0.013)	(0.007)	(0.004)	(0.004)
RWA Density	−0.013							
	(0.207)							
Intercept	223.261	−0.872	2.801	−4.787	13.600***	10.289***	1.491	3.277**
	(150.737)	(0.741)	(13.333)	(22.710)	(5.254)	(2.278)	(1.783)	(1.374)
Obs.	637	1,026	1,007	994	998	686	686	686
Adj.-R^2	0.100	0.404	0.364	0.364	0.204	0.676	0.729	0.317
Macro Control Var.	YES	YES	YES	YES	YES	YES	YES	YES
PGH Dummy = 1 for Nonparallel Trends in Year(s)		2010	2010	2009 2011		2006 2008 2010	2008 2009	2011

Bank-Specific Control Variables included for Some Variables of This Set

Size: Balance Sheet Size (Log of Total Assets)
LOANS/TA: Loans to Total Assets
DEP/TL: Deposits to Total Liabilities
RWA Density: Total RWA over Total Assets

Notes: Figures are in percentage points. Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

of G-SIBs, as the fall in their ROA is triggered by the crisis and not the designation. Therefore, taking the ROA as exogenous, and everything else equal, we interpret the negative impact of the designation on the return on equity (ROE) as a "mechanical" effect of the general improvement of G-SIBs' leverage ratio (LR), as it can easily be seen looking at the accounting equation (2) below.

$$ROE = \frac{R}{TE} = \frac{R}{TA} \times \frac{TA}{TE}$$

$$= ROA \times \frac{1}{LR} \qquad \Rightarrow \qquad ROA \times \frac{1}{\underset{\nearrow}{LR}} = R\overset{\searrow}{O}E \qquad (2)$$

RESULT 6. *There is no empirical evidence of any G-SIB specificity in the level and change in the profitability of assets (ROA). On the contrary, G-SIBs' return on equity (ROE) appears negatively affected through a deleveraging effect induced by the G-SIB regulation.*

5.2.2   Risk-Taking Behavior

One can notice a sizable relative increase of the RWA density for G-SIBs in the second subperiod (+4.6 pp) while non–G-SIBs record a slight reduction of their RWA density. This situation could be interpreted as a willingness from banks to pursue riskier activities, and the moral hazard behavior springs to mind, but it may not be the main reason. Birn, Dietsch, and Durant (2017) tend to underline that off-balance-sheet (OBS) activity increased only for G-SIBs starting in 2011.[28] Such increase of OBS items would then translate into an increase of RWAs but not of total assets (by construction), which would ultimately result in an increase of the RWA density of G-SIBs. Meanwhile, such off-balance-sheet activities (for example, guarantees and undrawn credit lines) are not riskier than balance sheet activities, if correctly measured.

Secondly, the increase in the amount of RWAs for G-SIBs could be partly explained by the implementation of Basel III standards for all banks through the period, combined with G-SIBs' higher

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[28]This is an *indirect* observation based on the difference between the total leverage exposure measure, which comprises OBS items, and total assets, which does not.

exposure to market activities and particularly to counterparty credit risk and market risk. Indeed, the revision of market risk framework (under Basel 2.5 and Basel III) drove important increases in risk-weighted assets measures (counterparty risk capital charges, higher asset value correlation parameter for exposures to certain financial institutions, higher risk weights for securitized assets or derivatives).[29] Hence, this change of weights would have affected differently the two groups of banks and would have also triggered an increase of the average risk weight of G-SIBs' balance sheet, irrespective of any change in activity.

Finally, we cannot fully exclude the remaining explanation that some G-SIBs might have started to gradually shift their assets toward more heavily weighted (i.e., riskier) assets. However, if such voluntary risk-shifting is occurring for some banks in search for higher returns, it has not yet materialized in the intended improved profitability of G-SIBs' assets, neither in an increase of nonperforming loans (NPL). On the contrary, the share of NPL even seems to have been slightly reduced for G-SIBs following the designation.

Whatever the explanation for the underlying phenomenon of the increased RWA density of G-SIBs, this fact also brings insights for why we do not notice any significant impact of the designation on G-SIBs' risk-based solvency ratio (see section 5.1). In addition to the global race toward solvency ratios higher than minimum requirements for all banks, the higher increase of RWA density for G-SIBs also played a role, as it caught up their effort to increase tier 1, as shown in equation (3) below.

$$\frac{T1}{RWA} = \frac{T1}{TA} \times \frac{TA}{RWA}$$

$$= LR \times \frac{1}{RWA\,dens} \Rightarrow \overset{\nearrow}{LR} \times \frac{1}{\overset{\nearrow}{RWA}\,dens} = \left(\frac{\overrightarrow{T1}}{RWA} \right) \quad (3)$$

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[29]See BCBS (2013b), which shows that group 1 banks' RWA increased in the aggregate by approximately 16.1 percent after applying the Basel 2.5 and Basel III frameworks.

Result 7. *The G-SIB regulation seems to have triggered an increase of their RWA density, but this does not seem to reflect a shift in the risk-taking behavior of these banks.*

5.2.3   Yields

The question that can be raised further in the analysis concerns the extent to which banks subject to higher regulatory requirements responded to the reduction in ROE. Using equation (1), we analyze the effects of G-SIB reform agenda on the cost of funding (especially for deposits), the yield of loans, and interest margins.

Over the available sample for the complete 2005–16 period (686 observations), the average yield on loans equals 5.2 percent while the average cost of deposits is 2.0 percent and the global net interest margin is 2.2 percent. The results of regressions, and particularly the estimated coefficient β, suggest that G-SIBs, compared with their peers, benefit from a structural lower cost of deposits in the range of 0.4 pp. Such funding advantage can be related to both the existence of implicit public support (cf. Schich and Toader 2017) and the greater diversification of G-SIBs (in terms of activity and geographic locations) that could lower their idiosyncratic risk in the view of investors.

Our findings suggest that, for G-SIBs, this lower cost of liabilities is transmitted to loans pricing to the extent that their average loan yield is structurally 0.9 pp lower than for non–G-SIBs. Furthermore, these structural features are stable over time for all banks, G-SIBs or not. The lack of significance for the coefficient γ of the "Post2011" time-dummy variable can be explained by the introduction of macroeconomic control variables, and particularly the 10-year sovereign debt yield that captures the impact of the evolution of the general interest rates environment. As for the interaction variable, we do not find any direct and significant impact of the G-SIB designation on these dependent variables.

Result 8. *The G-SIB designation did not have any impact on loans yields, cost of deposits, nor net interest margin. This lack of significant impact suggests that stricter regulation had no unintended effects so far on banks' and customers' funding cost. However, since the cost of funding appears to be structurally lower for G-SIBs, the*

absence of impact of the G-SIB regulation on this variable also cor-roborates the fact that the designation of G-SIBs did not put an end to the implicit public support.

6.   Robustness Checks

6.1   Alternative Subperiods

In section 4, we described that we chose to split our panel into the two subperiods 2005–11 and 2012–16, so we included the $Post2011_t$ time-dummy variable in the regressions. As explained above, this cutoff date between 2011 and 2012 seems the more "natural," since the first list of G-SIBs was published in November 2011. However, on the one hand, someone could argue that a longer time is needed for real effects of this designation to materialize in the balance sheet/income statement of G-SIBs. This would lead to postponement of the cutoff date, for instance considering that the second subperiod only started in 2013 or 2014, instead of 2012. On the other hand, one could say that most effects may have been anticipated, either by banks themselves, or by the market.[30] This would argue for setting an earlier cutoff date—for instance, in 2011 or 2010. Therefore, we reran all the regressions displayed in section 5, each time using an alternative starting date of the second subperiod, ranging from 2010 to 2014, with 2012 being the baseline starting date used in all previous sections of the paper.

Table 7 shows the coefficient δ of the interaction variable for all dependent variables listed in table 1 and discussed in section 5 and for all alternative starting dates of the second subperiod between 2010 and 2014. As one can notice in this table, coefficients generally remain of the same magnitude, as well as their significance level. This indicates that the choice we made to consider 2012 as the start of the second subperiod—although still "arbitrary"—is not driving the results, and that similar conclusions would have been drawn if we had decided to set an earlier or later cutoff date.

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[30]As mentioned by Moenninghoff, Ongena, and Wieandt (2015), the *Financial Times* published two lists of systemic banks in 2009 and 2010, before the first official publication of the FSB list in November 2011.

Table 7. Alternative Subperiods and Definition of G-SIB Subsample

δ Coefficient for Dependent Variable:	Second Subperiod Starting in:					G-SIB Binary Variable Used		
	2010	2011	2012	2013	2014	G-SIB Once	G-SIB 2011	G-SIB Always
TA gr	−5.079***	−5.532***	−5.763***	−3.401*	−2.154*	−5.763***	−6.31***	−5.434***
	(1.65)	(1.385)	(1.392)	(1.325)	(1.306)	(1.392)	(1.497)	(1.653)
TA/GDP	−14.374*	−14.687*	−14.704**	−14.849**	−13.837**	−14.704**	−17.472**	−13.46
	(8.544)	(7.9)	(7.234)	(6.737)	(6.081)	(7.234)	(8.38)	(8.693)
T1/TA	0.45**	0.483**	0.589***	0.65***	0.646***	0.589***	0.541**	0.49**
	(0.215)	(0.204)	(0.2)	(0.199)	(0.191)	(0.2)	(0.213)	(0.222)
T1/RWA	−0.332	−0.203	−0.133	−0.426	−0.63	−0.133	0.103	−0.248
	(0.505)	(0.523)	(0.569)	(0.601)	(0.626)	(0.569)	(0.584)	(0.542)
T1 gr	−4.99	−4.641**	−2.512	−1.514	−0.828	−2.512	−3.211	−2.024
	(3.079)	(2.332)	(2.039)	(1.721)	(1.78)	(2.039)	(2.057)	(2.023)
CASH CB/TA	2.7***	2.518***	2.34***	2.249***	2.196***	2.34***	2.319***	2.266***
	(1.028)	(0.905)	(0.809)	(0.732)	(0.702)	(0.809)	(0.803)	(0.833)
CUST LOANS/TA	−1.659	−1.592	−1.12	−0.244	−0.181	−1.12	−1.099	−0.327
	(2.031)	(1.746)	(1.545)	(1.365)	(1.295)	(1.545)	(1.538)	(1.605)
SUB DEBT/TL	0.33*	0.324*	0.301*	0.323*	0.271*	0.301*	0.281	0.35*
	(0.177)	(0.178)	(0.169)	(0.161)	(0.158)	(0.169)	(0.178)	(0.18)
NET PROF/OP INC	6.064	1.798	−4.61	−6.663	−9.781*	−4.61	0.333	−7.774
	(10.907)	(11.4)	(7.309)	(5.449)	(5.822)	(7.309)	(10.098)	(9.043)
ROA	−0.063	−0.101*	−0.074	−0.031	−0.039	−0.074	−0.092*	−0.08
	(0.065)	(0.061)	(0.053)	(0.054)	(0.052)	(0.053)	(0.05)	(0.05)
ROE	−2.302*	−3.284***	−3.064***	−2.052*	−1.841**	−3.064***	−3.084***	−2.306**
	(1.399)	(1.268)	(1.056)	(0.971)	(0.92)	(1.056)	(1.079)	(1.072)
NPL/LOANS	−0.393	−0.553	−0.675*	−0.743**	−0.699**	−0.675*	−0.509	−0.071
	(0.379)	(0.341)	(0.348)	(0.343)	(0.31)	(0.348)	(0.367)	(0.372)
RWA Density	4.108**	3.914***	4.609***	5.429***	5.608***	4.609***	3.468**	3.733*
	(1.619)	(1.514)	(1.432)	(1.409)	(1.408)	(1.432)	(1.598)	(1.616)
LOAN YIELD	−0.145	−0.039	0.096	0.31**	0.337**	0.096	0.015	0.051
	(0.156)	(0.13)	(0.134)	(0.158)	(0.165)	(0.134)	(0.154)	(0.159)
DEP COST	−0.018	0.012	0.086	0.225	0.198	0.086	−0.002	0.002
	(0.138)	(0.134)	(0.138)	(0.142)	(0.126)	(0.138)	(0.139)	(0.14)
NIM	−0.056	−0.058	−0.051	0.003	0.045	−0.051	−0.083	−0.064
	(0.111)	(0.1)	(0.087)	(0.082)	(0.082)	(0.087)	(0.095)	(0.099)

Note: Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

6.2   Alternative Definition of "G-SIB" Subsample

Similarly, section 4 explains that the $GSIB_{i,k}$ dummy variable indicates all banks that have been identified as G-SIB at least once by the FSB between 2011 and 2016. In table 7, this baseline definition of the G-SIB subsample is referred to as "G-SIB Once." Alternative definition of this "G-SIB" subsample could have been used instead. Therefore, we reran all regressions presented in section 5 using two alternative G-SIB binary variables. With the first alternative we simply focus on the initial list of G-SIBs published by the FSB in November 2011 and simply ignore the few changes of this list that intervened in the following years. We refer to this first alternative dummy variable as "G-SIB 2011" in the regression table 7. The second alternative consists in restraining the binary variable to banks that have constantly been listed as G-SIBs between 2011 and 2016, and therefore use a stable list of permanent G-SIBs. We refer to this second alternative dummy variable as "G-SIB Always" in table 7.[31] We notice that most results remain the same whatever definition for the G-SIB subsample is used.

6.3   Taking into Account the Financial Crisis

The baseline equation (1) used in the paper includes a set of macroeconomic control variables, notably the unemployment rate and the GDP growth that should—at least partially—capture the effect of a macroeconomic downturn. However, in order to specifically isolate the impact of the 2008–09 financial crisis, on top of the macroeconomic control variables, we can add a "crisis" time-specific dummy variable taking value 1 only for years 2008 and 2009, like in equation (4) below. The results of this specification are available in column "Crisis Dummy" of table 8 and do not show major differences compared with the baseline results.

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[31]The "G-SIB Always" variable identifies 26 banks. "G-SIB 2011" adds the following three banks compared with "G-SIB Always": Lloyds Banking Group, Commerzbank, and Dexia. "G-SIB Once" adds the following five banks compared with "G-SIB 2011": Industrial and Commercial Bank of China, China Construction Bank Corporation, Agricultural Bank of China Limited, BBVA, and Standard Chartered.

Table 8. Alternative Econometric Specifications

δ Coefficient for Dependent Variable:	Baseline Eq. (1)	Crisis Dummy Eq. (4)	Buffer Rates Eq. (5)	First Bucket Eq. (1)	Country FE Eq. (6)	Country FE * 2 Eq. (7)	Regional FE Eq. (6)	Without China Eq. (1)	Gov. CDS Spread Eq. (1)	Europe Eq. (1)	No State Support (EU) Eq. (1)	PS Matching Eq. (1)
TA gr	−5.763*** (1.392)	−5.818*** (1.386)	−2.783*** (0.9)	−5.49*** (1.543)	−5.963*** (1.514)	−4.701*** (1.472)	−5.818*** (1.386)	−6.828*** (1.595)	−6.664*** (1.64)	−5.577*** (1.998)	−4.999** (2.327)	−5.134*** (1.507)
TA/GDP	−14.704** (7.234)	−14.791** (7.162)	−6.603 (4.108)	−15.115 (9.803)	−13.152** (6.699)	−9.623** (4.189)	−14.791** (7.162)	−16.994** (8.37)	−7.662* (4.323)	−20.788* (11.12)	−18.835 (13.046)	−13.471* (6.932)
T1/TA	0.589*** (0.2)	0.592*** (0.199)	0.415*** (0.124)	0.369 (0.226)	0.642*** (0.197)	0.399** (0.171)	0.592*** (0.199)	0.491*** (0.181)	0.414** (0.189)	0.362* (0.213)	0.446** (0.243)	6.408** (0.201)
T1/RWA	−0.133 (0.569)	−0.187 (0.573)	−0.247 (0.292)	−0.081 (0.662)	0.018 (0.631)	−0.378 (0.532)	−0.187 (0.573)	−0.263 (0.595)	−0.695 (0.029)	−1.71* (0.739)	−1.947** (0.867)	0.697 (0.517)
T1 gr	−2.512 (2.039)	−2.819 (2.108)	−0.847 (1.033)	−2.386 (2.337)	0.275 (1.913)	−1.435 (1.991)	−2.819 (2.108)	−4.989*** (1.852)	−2.746 (2.278)	−0.948 (3.118)	−1.197 (3.253)	−2.036 (2.211)
CASH CB/TA	2.34*** (0.809)	2.24*** (0.806)	1.218** (0.494)	2.501*** (0.864)	2.422*** (0.763)	2.094*** (0.655)	2.24*** (0.806)	2.587*** (0.895)	2.268*** (0.864)	2.474*** (1.261)	2.444* (1.484)	2.048*** (0.649)
CUST LOANS/TA	−1.12 (1.545)	−1.091 (1.53)	−0.396 (0.969)	−1.441 (1.631)	−1.257 (1.473)	−0.903 (1.424)	−1.091 (1.53)	−2.742* (1.555)	−0.584 (1.572)	−3.404* (2.064)	−2.617 (2.43)	0.685 (1.488)
SUB DEBT/TL	0.301* (0.169)	0.298* (0.169)	0.185* (0.105)	0.261 (0.178)	0.183 (0.205)	0.157 (0.169)	0.298* (0.169)	0.191 (0.192)	0.151 (0.158)	0.206 (0.213)	0.104 (0.237)	−0.009 (0.208)
NET PROF/OP INC	−4.61 (7.309)	−2.099 (7.28)	−11.315* (6.345)	−0.829 (8.536)	−0.606 (8.622)	−2.993 (8.359)	−2.099 (7.28)	−8.96 (8.915)	−8.759 (7.123)	−10.248 (9.529)	−0.443 (8.663)	−4.155 (5.702)
ROA	−0.074 (0.053)	−0.052 (0.049)	−0.054* (0.03)	−0.052 (0.061)	−0.093 (0.064)	−0.039 (0.057)	−0.052 (0.049)	−0.151** (0.052)	−0.04 (0.056)	−0.207*** (0.064)	−0.165** (0.065)	−0.107* (0.06)
ROE	−3.064*** (1.056)	−2.714*** (1.001)	−1.706*** (0.654)	−2.366*** (1.157)	−3.109*** (1.157)	−2.365*** (1.076)	−2.714*** (1.001)	−4.435*** (1.153)	−2.845* (1.133)	−5.543*** (1.466)	−4.233*** (1.554)	−3.23*** (1.17)
NPL/LOANS	−0.675* (0.348)	−0.676* (0.352)	−0.062 (0.197)	−0.835** (0.417)	−0.384 (0.432)	−0.716* (0.412)	−0.676* (0.352)	−0.395 (0.394)	−0.671* (0.399)	−1.791* (0.751)	−1.092 (0.722)	−0.677 (0.432)
RWA Density	4.609*** (1.432)	4.816*** (1.415)	3.443*** (0.876)	3.457*** (1.549)	3.809** (1.512)	3.246** (1.302)	4.816*** (1.415)	4.494*** (1.469)	4.156*** (1.515)	8.382*** (2.147)	8.877*** (2.521)	2.937*** (1.332)
LOAN YIELD	0.096 (0.134)	0.057 (0.129)	−0.017 (0.091)	0.136 (0.146)	−0.1 (0.18)	−0.051 (0.145)	0.057 (0.129)	0.17 (0.146)	0.154 (0.133)	0.381 (0.27)	0.499 (0.308)	0.079 (0.151)
DEP COST	0.086 (0.138)	0.086 (0.138)	−0.015 (0.103)	0.129 (0.141)	−0.134 (0.167)	0.074 (0.123)	0.086 (0.138)	0.134 (0.148)	0.069 (0.129)	−0.026 (0.3)	−0.019 (0.366)	0.26 (0.171)
NIM	−0.051 (0.087)	−0.067 (0.088)	−0.02 (0.058)	−0.072 (0.095)	−0.052 (0.089)	−0.095 (0.086)	−0.067 (0.088)	−0.08 (0.089)	−0.02 (0.093)	0.158 (0.115)	0.413*** (0.154)	−0.88 (0.103)

Notes: Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard deviations are in parentheses.

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t)$$
$$+ \varphi B_{i,k,t} + \chi C_{k,t} + \lambda Crisis_t + PTH_t + u_{i,k,t} \qquad (4)$$

6.4 Including G-SIB Buffers

In this paper we use a binary variable to distinguish G-SIBs from non–G-SIBs. Such approach is justified in order to apply the difference-in-difference methodology and to get directly interpretable magnitude of the coefficients. However such a choice neglects the fact that there are several G-SIB "buckets" (groups). Therefore, as a robustness check, we replace the dummy variable $GSIB_{i,k}$ in the interaction term with the level of G-SIB buffer applied to each bank. This gives us an alternative econometric specification to equation (1).

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(Buffer_{i,k,t} \times Post2011_t)$$
$$+ \varphi B_{i,k,t} + \chi C_{k,t} + PTH_t + u_{i,k,t} \qquad (5)$$

This alternative specification hence takes into account the various levels of the G-SIB buffers (from 1 percent to 2.5 percent). Overall results are displayed in the "Buffer Rates" column of table 8. If the sign and significance level of coefficients can still be interpreted as in equation (1), on the other hand the magnitude of coefficients are no longer comparable to the one estimated using equation (1). As one can notice, the main findings of the paper are still valid using this specification.

Furthermore, one could expect that being identified as a G-SIB in the first bucket (i.e., with the smallest systemic footprint) may not have the same consequences as being listed in the higher G-SIB buckets. Then, as a robustness check, we exclude the largest G-SIBs in order to focus only on G-SIBs in the first bucket (i.e., with systemic scores between 130 and 230 bp in the 2016 FSB's designation). Results are presented in the "First Bucket" column of table 8. Once again, the main findings of the paper are confirmed, though the effect on the leverage ratio disappears, as it seems mostly driven by the largest G-SIBs.

6.5   Geographic Dimensions

The baseline regression (1) of the paper includes a set of eight country-specific macroeconomic control variables that evolve over time. More simply, we could have used some country fixed effects (FE), as in equation (6) below, to capture time-invariant country-specific characteristics. Results of this alternative specification are shown in the "Country FE" column of table 8.

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t)$$
$$+ \varphi B_{i,k,t} + \chi FE_k + PTH_t + u_{i,k,t} \tag{6}$$

On top of that, we can take into account that the 2008–09 financial crisis may have affected differently all countries represented in the panel, these country fixed effects may be differentiated between the pre- and post-crisis periods as in equation (7) below. These alternative results are displayed in the "Country FE * 2" column of table 8.

$$Y_{i,k,t} = \alpha + \beta GSIB_{i,k} + \gamma Post2011_t + \delta(GSIB_{i,k} \times Post2011_t)$$
$$+ \varphi B_{i,k,t} + \chi_1 FE_{k,(2005-2007)} + \chi_2 FE_{k,(2008-2016)}$$
$$+ PTH_t + u_{i,k,t} \tag{7}$$

Using equation (6), we can also use fixed effects by region, instead of by country, in order to take into account potential differences among regulatory frameworks in the United States, Europe, Asia, and the rest of the world. These results are shown in the "Regional FE" column of table 8.

Finally, we also rerun equation (1) excluding banks from China, as it is the largest country in the data set in terms of total assets as of end-2016. Results are presented in the "Without China" column of table 8. Once again, looking at these alternative specifications, we can broadly draw the same conclusions as those exposed in section 5.

6.6   The Influence of the State

The final alternative robustness check analysis will complement the set of macroeconomic country-specific control variables with market

data (retrieved from the Bloomberg database): we include the year-end spread level of the 10-year maturity sovereign CDS. Such additional variable will better capture the situation of countries that had to face a sovereign debt crisis, which could have had some repercussions on its national banking system. The results of this robustness check are shown in the "Gov. CDS Spread" column of table 8.

States can also influence banks through public support interventions, especially following the financial crisis. An alternative explanation for the reduction in asset growth observed in the paper could be that some banks received public financial assistance during the crisis and were subsequently forced to reduce their activity. In order to rule out this alternative hypothesis, we rerun our regressions, focusing only on European banks, excluding banks that received public assistance, as listed by the European Commission.[32] These two alternative specifications are shown in the "Europe" and "No State Support (EU)" columns of table 8, and, as one can notice, the δ coefficient for the growth rate of assets remains highly significant and of the same order of magnitude as in the baseline. Hence we can claim that this effect is not particularly driven by state supports.

7.   Concluding Remarks

This empirical analysis of 97 banks over 12 years is designed to identify the changes in G-SIBs' business model characteristics after their first designation by the FSB in 2011, controlling for the changes also experienced by other banks (industry trends). First, it allows to identify initial structural differences between G-SIBs and other banks. In that respect, we show that G-SIBs are structurally more leveraged. We also find empirical evidence that G-SIBs benefit from a lower cost of deposits that is likely to indicate lower perceived idiosyncratic risk due to higher diversification and implicit public support.

Secondly, we also identify some changes that affected G-SIBs after their first designation by the FSB in 2011. Using our econometric identification methodology based on a difference-in-difference approach, we identify some key effects of the designation on G-SIBs'

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[32]European Commission (2018).

activity. Using these quantitative results, this paper provides a first assessment of the effectiveness of the G-SIBs reforms undertaken after the 2008 crisis and determines whether the highlighted changes are in line with the objectives of the international regulators.

In terms of policy implications, this paper shows that some intended objectives have been achieved: the expansion of the balance sheet of G-SIBs has been drastically slowed down by the regulation. The financial leverage of the G-SIBs, structurally greater than that of the other banks before the designation, has also been reduced. Such increase of G-SIBs' capital base has strengthened their resilience, which has improved further global financial stability and social welfare. However, this "deleveraging" of the G-SIBs led to another logical consequence, although not specifically sought by the regulation: the reduction of their return on equity, due to a mechanical accounting effect.

Moreover, we show in this paper that potential negative unintended consequences of these regulations, which were pointed out either by theoretical considerations or by the fears expressed by the industry, actually did not materialize. Indeed, for the time being, we have not measured any reduction in the supply of loans to the economy, or excessive risk-taking by banks in search for higher yields, that could be attributed to these regulations.

On the other hand, as the structural funding advantage derived by G-SIBs from the implicit public guarantees appears to persist in the data, it seems that the objective of ending the status of "too big to fail" is yet to be achieved.

Appendix A. Banks included in the Panel

Table A.1. List of Banks Included in the Panel

N	Institution Name	Country	Total Assets (€bn)	Identified as G-SIB by the FSB						
				At Least Once	In 2011	In 2012	In 2013	In 2014	In 2015	In 2016
1	Dexia SA	BE	213	1	1	0	0	0	0	0
2	UBS Group AG	CH	872	1	1	1	1	1	1	1
3	Credit Suisse Group AG	CH	765	1	1	1	1	1	1	1
4	Industrial and Comm. Bank of China	CN	3,293	1	0	0	1	1	1	1
5	China Construction Bank Corp.	CN	2,860	1	0	0	0	0	1	1
6	Agricutural Bank of China Limited	CN	2,670	1	0	0	0	1	1	1
7	Bank of China Limited	CN	2,476	1	1	1	1	1	1	1
8	Deutsche Bank AG	DE	1,591	1	1	1	1	1	1	1
9	Commerzbank AG	DE	480	1	1	1	0	0	0	0
10	Banco Santander, SA	ES	1,339	1	1	1	1	1	1	1
11	Banco Bilbao Vizcaya Argentaria, SA	ES	732	1	0	1	1	0	0	0
12	BNP Paribus SA	FR	2,077	1	1	1	1	1	1	1
13	Credit Agricole Group	FR	1,723	1	1	1	1	1	1	1
14	Societe Generale SA	FR	1,382	1	1	1	1	1	1	1
15	Groupe BPCE	FR	1,235	1	1	1	1	1	1	1
16	HSBC Holdings Plc	GB	2,252	1	1	1	1	1	1	1
17	Barclays Plc	GB	1,421	1	1	1	1	1	1	1
18	Lloyds Banking Group Plc	GB	958	1	1	0	0	0	0	0
19	Royal Bank of Scotland Group Plc	GB	935	1	1	1	1	1	1	1
20	Standard Chartered Plc	GB	613	1	0	1	1	1	1	1
21	Morgan Stanley and Co. International	GB	401	1	1	1	1	1	1	1
22	UniCredit SpA	IT	860	1	1	1	1	1	1	1
23	Mitsubishi UFJ Financial Group, Inc.	JP	2,330	1	1	1	1	1	1	1
24	Mizuho Financial Group, Inc.	JP	1,511	1	1	1	1	1	1	1
25	Sumitomo Mitsui Financial Group	JP	1,457	1	1	1	1	1	1	1
26	ING Groep N.V.	NL	845	1	1	1	1	1	1	1
27	Nordea Bank AB (publ)	SE	616	1	1	1	1	1	1	1
28	JPMorgan Chase and Co.	US	2,362	1	1	1	1	1	1	1
29	Bank of America Corporation	US	2,074	1	1	1	1	1	1	1
30	Wells Fargo and Company	US	1,830	1	1	1	1	1	1	1
31	Citigroup Inc.	US	1,699	1	1	1	1	1	1	1
32	Goldman Sachs Group, Inc.	US	816	1	1	1	1	1	1	1
33	Bank of New York Mellon Corporation	US	316	1	1	1	1	1	1	1
34	State Street Corporation	US	230	1	1	1	1	1	1	1
	Total for G-SIBs		47,236	34	29	28	29	30	30	30

Table A.1. (Continued)

N	Institution Name	Country	Total Assets (€bn)	At Least Once	Identified as G-SIB by the FSB					
					In 2011	In 2012	In 2013	In 2014	In 2015	In 2016
35	Commonwealth Bank of Australia	AU	626	0	0	0	0	0	0	0
36	Australia and NZ Banking Group	AU	623	0	0	0	0	0	0	0
37	Westpac Banking Corporation	AU	571	0	0	0	0	0	0	0
38	National Australia Bank Limited	AU	529	0	0	0	0	0	0	0
39	KBC Group NV	BE	275	0	0	0	0	0	0	0
40	Banco do Brasil S.A.	BR	404	0	0	0	0	0	0	0
41	Itau Unibanco Holding S.A.	BR	394	0	0	0	0	0	0	0
42	Caixa Economica Federal	BR	369	0	0	0	0	0	0	0
43	Banco Bradesco S.A.	BR	347	0	0	0	0	0	0	0
44	Royal Bank of Canada	CA	805	0	0	0	0	0	0	0
45	Toronto-Dominion Bank	CA	803	0	0	0	0	0	0	0
46	Bank of Nova Scotia	CA	611	0	0	0	0	0	0	0
47	Bank of Montreal	CA	469	0	0	0	0	0	0	0
48	Canadian Imperial Bank of Commerce	CA	342	0	0	0	0	0	0	0
49	Bank of Communications Co., Ltd.	CN	1,147	0	0	0	0	0	0	0
50	Industrial Bank Co., Ltd.	CN	830	0	0	0	0	0	0	0
51	China Merchants Bank Co., Ltd.	CN	811	0	0	0	0	0	0	0
52	China Minsheng Banking Corp., Ltd.	CN	804	0	0	0	0	0	0	0
53	Shanghai Pudong Development Bank	CN	799	0	0	0	0	0	0	0
54	China Everbright Bank Company	CN	549	0	0	0	0	0	0	0
55	Ping An Bank Co., Ltd.	CN	403	0	0	0	0	0	0	0
56	Hua Xia Bank Co., Limited	CN	321	0	0	0	0	0	0	0
57	Bank of Beijing Co., Ltd.	CN	289	0	0	0	0	0	0	0
58	China Guangfa Bank Co., Ltd.	CN	279	0	0	0	0	0	0	0
59	Bank of Shanghai Co., Ltd.	CN	240	0	0	0	0	0	0	0
60	DZ BANK AG	DE	509	0	0	0	0	0	0	0
61	Landesbank Baden-Wurttemberg	DE	244	0	0	0	0	0	0	0
62	Bayerische Landesbank	DE	212	0	0	0	0	0	0	0
63	Danske Bank A/S	DK	469	0	0	0	0	0	0	0
64	Banco de Sabadell, SA	ES	213	0	0	0	0	0	0	0
65	La Banque Postale, SA	FR	230	0	0	0	0	0	0	0
66	Nomura International Plc	GB	336	0	0	0	0	0	0	0
67	Nationwide Building Society	GB	262	0	0	0	0	0	0	0
68	State Bank of India	IN	408	0	0	0	0	0	0	0
69	Intesa Sanpaolo SpA	IT	725	0	0	0	0	0	0	0
70	Cassa depositi e prestiti SpA	IT	410	0	0	0	0	0	0	0

Table A.1. (Continued)

N	Institution Name	Country	Total Assets (€bn)	Identified as G-SIB by the FSB						
				At Least Once	In 2011	In 2012	In 2013	In 2014	In 2015	In 2016
71	Japan Post Bank Co., Ltd.	JP	1,617	0	0	0	0	0	0	0
72	Norinchukin Bank	JP	790	0	0	0	0	0	0	0
73	Sumitomo Mitsui Trust Holdings, Inc.	JP	455	0	0	0	0	0	0	0
74	Resona Holdings, Inc.	JP	384	0	0	0	0	0	0	0
75	Shinkin Central Bank	JP	274	0	0	0	0	0	0	0
76	Japan Housing Finance Agency	JP	214	0	0	0	0	0	0	0
77	Shinhan Financial Group Co., Ltd.	KR	312	0	0	0	0	0	0	0
78	KB Financial Group Inc.	KR	296	0	0	0	0	0	0	0
79	NongHyup Financial Group Inc.	KR	289	0	0	0	0	0	0	0
80	Hana Financial Group Inc.	KR	274	0	0	0	0	0	0	0
81	Woori Bank	KR	245	0	0	0	0	0	0	0
82	Korea Development Bank	KR	215	0	0	0	0	0	0	0
83	Cooperatieve Rabobank U.A.	NL	663	0	0	0	0	0	0	0
84	ABN AMRO Group NV	NL	394	0	0	0	0	0	0	0
85	DNB ASA	NO	292	0	0	0	0	0	0	0
86	PAO Sberbank of Russia	RU	394	0	0	0	0	0	0	0
87	Svenska Handelsbanken AB (publ.)	SE	274	0	0	0	0	0	0	0
88	Skandinaviska Enskilda Banken	SE	274	0	0	0	0	0	0	0
89	Swedbank AB (publ.)	SE	225	0	0	0	0	0	0	0
90	DBS Group Holdings Limited	SG	316	0	0	0	0	0	0	0
91	Oversea-Chinese Banking Corp.	SG	269	0	0	0	0	0	0	0
92	United Overseas Bank Limited	SG	223	0	0	0	0	0	0	0
93	Cathay Financial Holding Co., Ltd.	TW	239	0	0	0	0	0	0	0
94	Federal Home Loan Banks	US	1,002	0	0	0	0	0	0	0
95	U.S. Bancorp	US	423	0	0	0	0	0	0	0
96	PNC Financial Services Group, Inc.	US	347	0	0	0	0	0	0	0
97	Capital One Financial Corporation	US	339	0	0	0	0	0	0	0
	Total for Non–G-SIBs		28,696	0	0	0	0	0	0	0

Note: Banks are ranked by (i) G-SIBs versus non–G-SIBs, (ii) country, and (iii) decreasing total assets as of end-2016.

Appendix B. Description of the Methodology Used by the BCBS to Identify G-SIBs

According to the BCBS methodology, banks' systemic footprint is assessed using a set of 12 indicators grouped into five categories. For each indicator, a "market share" is computed at bank level (i.e., the value of the indicator for bank i is divided by the sum of this indicator's values for all banks in the sample used by the BCBS). Within each of the five categories, the "market shares" of the underlying indicators are then equally weighted to compute a score in basis points. Finally, these five categories' subscores are averaged (20 percent each) to get the final systemic score. Figure B.1 provides an illustration of this methodology.

Once the systemic score is computed, banks are ordered and allocated into buckets according to their systemic score value. Only banks with systemic scores above 130 basis points are labeled as G-SIBs. For these banks, the allocation into buckets is made as follows. If its systemic score is between 130 and 230 basis points, the bank will be allocated to the first bucket and face an additional CET1 capital requirement (or "buffer") of 1 percent of its total risk-weighted assets. Next, buckets are then imposing more and more stringent buffers: 1.5 percent for banks with systemic scores between 230 and 330 bp, 2 percent between 330 and 430 bp, and 2.5 percent between 430 and 530 bp. Currently, the fifth and last bucket would

Figure B.1. Illustration of Current BCBS Methodology to Identify G-SIBs
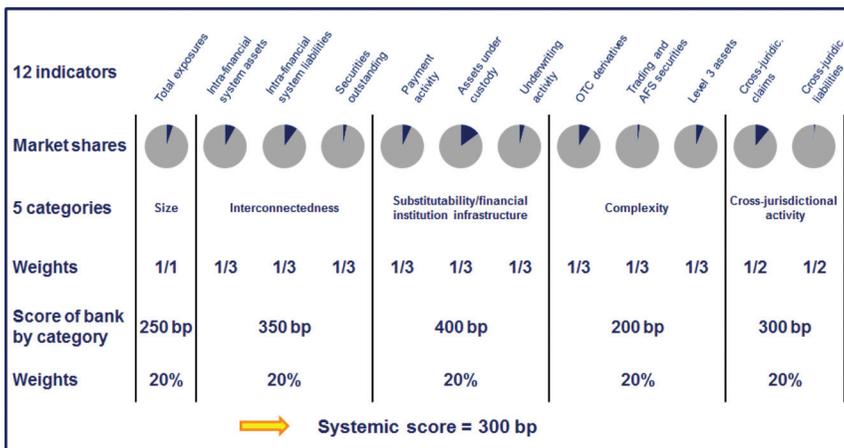
trigger a 3.5 percent buffer if the systemic score were to reach the 530 bp threshold. For the time being, this last bucket is only "dissuasive" and has never been applied to any G-SIB.

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Measuring the Liquidity Profile of Mutual Funds[*]

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We measure the liquidity profile of open-end mutual funds using the sensitivity of their daily returns to aggregate liquidity. We study how this sensitivity changes around real-activity macroeconomic announcements that reveal large surprises about the state of the economy and after three relevant market events: Bill Gross's departure from PIMCO, Third Avenue Focused Credit Fund's suspension of redemptions, and the effect of Lehman Brothers' collapse on Neuberger Berman. Results show that, following negative news, the sensitivity to aggregate liquidity increases for less-liquid mutual funds, like those that invest in the stocks of small companies and in high-yield corporate bonds. The effect is more pronounced during stress periods, suggesting that a deterioration in the funds' liquidity could amplify vulnerabilities in situations of already weak macroeconomic conditions.

JEL Codes: G11, G20, G23.

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1.   Introduction

We measure the liquidity profile of open-end mutual funds using the sensitivity of their daily portfolio returns to an aggregate liquidity factor, and we offer a methodology to monitor liquidity at a higher frequency than possible with regulatory data. Our way of measuring fund liquidity builds on the asset pricing literature that studies asset returns in terms of systematic risk factors (as in, for instance, Fama and French 1993). Instead of characterizing a mutual fund portfolio using the assets it holds, we rely on a set of factor sensitivities that capture the nondiversifiable risk to which the assets in the portfolio are exposed. We interpret an increase in the liquidity-factor loading as a deterioration in the fund's liquidity profile, with fund returns becoming more closely related to aggregate liquidity conditions.

As applications of our methodology, we study how the liquidity profile of open-end mutual funds changes around scheduled macroeconomic announcements that reveal unexpected news about the economy. In addition, we study fund liquidity around three significant market events: William H. (Bill) Gross's departure from Pacific Investment Co. (PIMCO); the suspension of redemptions from Third Avenue's Focused Credit Fund; and the effect of Lehman Brothers' collapse on Neuberger Berman, an affiliated asset manager that survived the parent company's bankruptcy.

Our analysis and results are of particular interest to policymakers and academics alike in light of the increased regulatory scrutiny on mutual fund liquidity and potential systemic risks arising from the asset-management industry. Liquidity transformation and first-mover advantage have in fact been highlighted as potential vulnerabilities for open-end mutual funds (see Chen, Goldstein, and Jiang 2010; Financial Stability Board and International Organization of Securities Commissions 2015).[1] Liquidity transformation refers to the fact that some pooled investment vehicles, while holding less-liquid assets, allow daily redemptions. A first-mover advantage may arise if the costs of meeting investor redemptions are largely borne by

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[1]The joint report of the Financial Stability Board and the International Organization of Securities Commissions is available at http://www.fsb.org/wp-content/uploads/2nd-Con-Doc-on-NBNI-G-SIFI-methodologies.pdf.

the remaining investors in the fund. During a stress event, these features might raise potential financial stability concerns in that funds might sell liquid assets first, worsening their liquidity profile, further impairing performance, putting downward pressure on prices, and potentially leading to more fund outflows.

In order to monitor the liquidity profile of mutual funds ahead of stress events, the U.S. Securities and Exchange Commission (SEC) proposed in 2016 that mutual funds classify their individual holdings into four liquidity categories, based on the number of days needed to convert each holding into cash without a significant price effect. This liquidity-bucketing provision received substantial comments from the public, and the SEC decided to postpone the provision by six months, with the regulations going into effect in the second half of 2019.[2] Importantly, even in the absence of more detailed regulatory disclosures, our methodology can help monitor the liquidity of individual funds at a relatively high frequency. This feature is especially valuable given that stress events—including the three we consider in an application of our methodology—unfold quickly and are difficult to monitor with the low-frequency regulatory disclosures that are currently available.

Different drivers can affect the liquidity profile of a mutual fund over time, as measured by the sensitivity of its daily portfolio returns to an aggregate liquidity factor. Unexpected investor flows can alter the composition of a fund's portfolio—the balance of liquid and illiquid assets held—and hence its liquidity profile. Similarly, such a composition can also be altered by a change in the manager's investment strategy. Finally, a shift in the underlying liquidity of the assets held by the fund could affect its liquidity profile without affecting its portfolio composition. While understanding the source of this shift goes beyond the scope of this paper, the literature suggests that the latter channel is the least likely explanation because stock-specific liquidity is driven by slow-moving company characteristics (Frieder and Subrahmanyam 2005; Grullon, Kanatas, and Weston 2004). In addition, we distinguish between active and passive funds, finding evidence that changes in the liquidity profile of mutual funds are not

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[2]For additional details, see https://www.treasury.gov/press-center/press-releases/Documents/A-Financial-System-That-Creates-Economic-Opportunities-Asset_Management-Insurance.pdf.

driven by changes in the liquidity of the underlying assets.[3] In this paper, we therefore interpret our results as changes in the liquidity profile of mutual funds around events that could potentially alter it because of investors' flows or managerial investment decisions.

In a first application of our methodology, we concentrate on significant macro news that could induce portfolio managers to adjust a fund's holdings in light of unexpected news, and could also generate unexpected fund flows driven by investors' decisions to change their exposure to the assets held by the fund. Of note, the literature supports the view that unexpected macro news generates flows into and out of mutual funds. For example, Jank (2012) provides evidence that the correlation between stock returns and inflows into equity funds is due to a reaction to macroeconomic news. Similarly, Chalmers, Kaul, and Phillips (2013) find that mutual fund investors rebalance their portfolios out of equity funds when they anticipate deteriorating economic conditions, and vice versa.[4] In a second application of our methodology, we monitor the liquidity profile of selected mutual funds around three consequential market events that had the potential to generate significant investor flows. Importantly, the events we consider, either scheduled announcements with large unexpected news or significant market developments, are unlikely to be endogenous with the changes in liquidity profiles that we observe. Market developments on these days are, by construction, unexpected

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[3]In an unreported exercise, we explore the different responses of active and passive funds to macroeconomic announcements. We find that index (passive) funds, which are by design constrained to hold their benchmarks, maintain the same exposure to the liquidity factor following unexpected news. In contrast, active funds experience a deterioration in the liquidity profile following negative news. This result corroborates the idea that the liquidity profile of non-index mutual funds more likely changes due to investors' flows or managerial investment decisions, rather than because of changes in the liquidity of the assets in their portfolios.

[4]Using available daily flow data over the 2014–15 period for a subset of funds (equity, high-yield, and investment-grade funds), we verify that the average daily outflow in the four weeks following announcements with unexpected negative news equals 0.3 percent of daily assets under management (AUM), corresponding to an AUM drop of about 6 percent in a four-week window. In the four weeks leading up to the announcements, however, the average flow is not statistically different from zero. Therefore, during these specific days, mutual funds are likely to experience relatively large flows that, by construction, are unexpected to managers.

to managers and investors. In the first exercise, our sample spans the 2004–16 period and includes U.S. equity, government, high-yield, and investment-grade corporate bond funds. Liquidity loadings are estimated in a panel setting, where we regress daily changes in funds' net asset values (NAV) on market liquidity while controlling for other relevant market factors and fund-specific characteristics. We compare changes in the liquidity-factor loadings between the four weeks before and the four weeks after the announcements. The set of real-activity macroeconomic announcements we study is selected on the basis of how large their realizations are compared with the corresponding Bloomberg expectations, as measured by the Scotti (2016) surprise index. We restrict our attention to events with the largest positive or negative surprise within a given quarter. We find an increase in the sensitivity of less-liquid mutual funds—in particular, those investing in the stocks of small companies and in high-yield corporate bonds—following the release of unexpected negative macroeconomic news. We interpret this result as a deterioration in the liquidity profile of those funds. The effect is more pronounced during stress periods, suggesting that a deterioration in the funds' liquidity could amplify vulnerabilities in situations of already weak macroeconomic conditions.

In the second application of our methodology, we monitor the liquidity of selected funds around three relevant market events: Bill Gross's departure from PIMCO; the suspension of redemptions from Third Avenue's Focused Credit Fund; and the effect of Lehman Brothers' bankruptcy on Neuberger Berman, an asset manager owned by the ailing investment bank. We find that PIMCO fixed-income funds became less liquid after Gross's resignation and that high-yield funds were also less liquid following the suspension of redemptions from Third Avenue's fund. In contrast, Lehman Brothers' default is associated with an improvement in the liquidity profile of Neuberger Berman funds.

Our paper is related to two main branches of the literature: one on mutual fund flows and their interaction with portfolio liquidity, and one on the pricing of systematic liquidity risk. Papers belonging to the first group include, among others, Chen, Goldstein, and Jiang (2010); Chernenko and Sunderam (2016); Feroli et al. (2014); Goldstein, Jiang, and Ng (2017); Hanouna et al. (2015); and Zeng (2017). Goldstein, Jiang, and Ng (2017) find that the sensitivity

of outflows to bad performance in corporate bond funds is much stronger at times of aggregate illiquidity and among funds that hold more illiquid assets; Hanouna et al. (2015) find that U.S. equity funds with lower portfolio liquidity experience a greater decrease in liquidity due to large redemptions. Chernenko and Sunderam (2016) study mutual fund cash holdings and flows using semiannual holdings obtained from regulatory filings. They find that mutual funds manage a significant share of flows by changing their cash holdings rather than by buying and selling the underlying assets, especially in the case of funds that invest in illiquid assets and during periods of poor market liquidity. As the authors note, however, their results largely reflect endogenous relations because the variables they analyze are jointly determined. We contribute to this literature by studying the liquidity profile of mutual funds in a daily setting, following unexpected macro news and market events. By construction, such events are unanticipated to managers and investors and hence can help address the endogeneity issue.

Relevant papers in the literature on systematic liquidity-risk pricing are, among others, the seminal work on equities by Pastor and Stambaugh (2003) and the study of bond liquidity by Acharya, Amihud, and Bharath (2013), who find that, in times of weak macro conditions, the prices of investment-grade bonds rise and the prices of junk bonds fall following a deterioration in overall liquidity. The question we are interested in is related to, but different from, the liquidity-based market timing studied by Cao, Simin, and Wang (2013). They investigate changes in the exposure to the market factor, rather than the liquidity factor, conditional on monthly deviations of market liquidity from its 60-month moving average. Their results are also not driven by liquidity risk, which is the focus of our analysis.

The remainder of the paper is organized as follows. Section 2 presents the data used in the analysis, section 3 describes the panel regression framework, section 4 discusses the results, and section 5 concludes.

2.   Data

We study open-end U.S. mutual funds over the period 2004:Q3 to 2016:Q4, excluding money market funds, index funds,

exchange-traded funds (ETFs), and sector funds (e.g., healthcare, financials) but including inactive funds to avoid survivorship bias. We obtain fund characteristics, such as age, category, and assets under management (AUM), from Morningstar Direct. On the basis of Morningstar's classification, we consider the following fund categories: large- and medium-cap equity, small-cap equity, government bonds, investment-grade corporate bonds, and high-yield corporate bonds.[5] The data are at the share-class level, but our focus is on fund-level variables. When aggregating share-level data, we sum or value-weight the variables as appropriate, with weights based on the AUM for each share class (we value-weight ratios like the turnover ratio and sum variables measured in dollars, like AUM). Daily NAV data at the share-class level are from the Center for Research in Security Prices (CRSP) and are matched to the Morningstar Direct data with CUSIP numbers.

Table 1 reports selected summary statistics for the sample we study. The number of funds generally increased between 2004 and 2009 and declined afterward. Exceptions are the high-yield and investment-grade corporate bond funds, which increased through 2016, although they started from a lower number in 2004. As of December 2016, the average large- and medium-cap equity fund managed $2 billion. Fixed-income funds were smaller than domestic equity funds, with the average size around $1.5 billion at the end of 2016. The average AUM is typically larger than the 75th percentile, indicating the presence of a small number of very large funds in each category. Between 2004 and 2016, the average AUM roughly doubled for almost all funds' categories. Average fund age increased over time, highlighting the presence of well-established funds, and it was between 8 and 20 years over our sample.

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[5]The classification is based on Morningstar Direct's Global Broad Category (GBC), Global Category (GC), Institutional Category (IC), and Category (C) variables. A fund is classified as "Large and Medium Cap Equity" if GC is equal to "US Equity Large Cap." or "US Equity Medium Cap.", and as "U.S. Small Cap" if GC is "US Equity Small Cap." It is classified as "Government Bond" if (i) C contains "Gov" or "Inflation-Protected" and GBC is equal to "Fixed Income" or (ii) C is equal to "Fixed Income" and the fund's name contains "Gov" or "Treas" or IC contains "Gov" or "Treas." A fund is classified as "High-Yield Corporate Bond" if IC is equal to "High Yield Bond" and C to "Corporate Bond." A fund is classified as "Investment Grade Corporate Bond" if C is "Corporate Bond" and IC contains "Grade" or "A-Rated" or "BBB-Rated."

Table 1. Fund Summary Statistics

		Number of Funds	Fund AUM (mm$)			Fund Age (Years)		
			Average	25th Perc.	75th Perc.	Average	25th Perc.	75th Perc.
U.S. Large–Mid Cap	2004	1,854	1,224	42	707	12	4	13
	2009	1,909	1,128	33	707	13	5	16
	2016	1,559	2,072	72	1,517	17	8	22
U.S. Small Cap	2004	535	449	47	484	8	4	11
	2009	591	429	28	390	11	5	14
	2016	548	693	44	662	14	6	20
Government Bonds	2004	179	837	90	621	13	7	19
	2009	194	1,173	107	797	16	9	23
	2016	166	1,289	135	1,036	20	12	29
IG Corp. Bonds	2004	30	793	73	807	13	3	22
	2009	38	1,164	94	754	15	5	23
	2016	49	1,726	89	1,208	17	7	24
HY Corp. Bonds	2004	124	944	88	1,043	12	5	18
	2009	153	1,010	104	827	14	5	17
	2016	183	1,383	77	1,123	15	5	19

Source: Authors' calculations based on Morningstar Direct.
Notes: The table shows the number of funds at the beginning, middle, and end of the sample. For the same years, the table also shows the average and selected percentiles of assets under management (AUM, in $ million) and fund age in years.

We proxy for aggregate market liquidity with different measures depending on whether we consider equity or fixed-income funds. In the first case, we build a daily measure based on the Pastor and Stambaugh (2003) value-weighted traded factor obtained from the Wharton Research Data Services (WRDS).[6] As is typical in the asset pricing literature, the replicating portfolio includes common stocks in CRSP that trade on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and Nasdaq. We require that the stocks have at least 60 monthly observations between 1980 and 2016. For each stock, we calculate the liquidity beta with factor regressions of excess returns on the monthly Pastor and Stambaugh (2003) factor in addition to the Fama-French market, small-minus-big (SMB), high-minus-low (HML), and momentum (UMD) factors (from WRDS). Stocks in the top (bottom) 10 percent of the liquidity beta distribution are included in the long (short) leg of a replicating portfolio that we use to measure daily liquidity conditions in the equity market. This factor-mimicking approach is similar to the one used by Vassalou (2003) to proxy for future gross domestic product (GDP) news. The original Pastor and Stambaugh (2003) factor and the monthly-compounded daily replicating factor have a correlation of 85 percent.

In the case of fixed-income funds, we proxy for aggregate liquidity with the noise measure introduced by Hu, Pan, and Wang (2013). We use the negative of the measure so that higher values imply better liquidity conditions. This variable is based on differences between observed Treasury prices and model prices that use an interpolated Treasury curve. The methodology builds on the intuition that the Treasury yield curve is smooth when financial intermediaries can deploy enough capital to take advantage of arbitrage opportunities and reduce price deviations relative to the benchmark. When financial intermediaries do not have enough capital to engage in arbitrage,

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[6]The liquidity measure of Pastor and Stambaugh (2003) is based on price reversals conditional on order flow. They use liquidity innovations in a series of asset pricing tests, and also study a factor mimicking portfolio that buys and sells stocks depending on their sensitivity to liquidity innovations. In light of "tantalizing" if not conclusive evidence, Pastor and Stambaugh (2003, p. 682) conclude that, with a narrow focus on explaining the cross-section of stock returns, the traded factor might be a better proxy for liquidity than innovations to the liquidity measure.

and they are most likely unable to provide normal levels of liquidity, the observed Treasury yield curve is more noisy (less smooth). More specifically, Hu, Pan, ad Wang (2013) use end-of-day Treasury prices from 1987 through 2011 and back out the zero-coupon yield curve from coupon-bearing Treasury securities. Then the yield curve is used to price all available bonds on a given day. The noise measure is the root mean squared deviation of the model-implied and observed yields (for details, see Hu, Pan, and Wang 2013). In unreported results, we also repeat the analysis with high-yield, investment-grade, and 10-year Treasury bid-ask spreads obtained from the Federal Reserve Bank of New York.

Our set of explanatory variables includes changes in the level and slope of the term structure, estimated with the Nelson-Siegel model (Nelson and Siegel 1987) on raw data from the U.S. Treasury's Monthly Statement of Public Debt. We also consider daily spreads for the Markit CDX Investment Grade (CDX_{IG}) and CDX High Yield (CDX_{HY}) credit default swap indexes. These spreads measure the cost of insuring against the default risk of a diversified portfolio of investment-grade and high-yield U.S. companies. Finally, we include various fund-level characteristics: size, measured with assets under management (AUM); age in years (AGE); turnover (TURN); and manager tenure (TEN). Turnover indicates the fraction of fund assets that managers sell in a given year. Tenure is the number of years that a fund is managed by the same portfolio manager.

We present selected summary statistics for the explanatory variables used in our analysis in table 2. The standard deviation of the asset pricing factors is high, relative to the mean, because the sample includes the 2008 financial crisis. As expected, the CDX_{HY} spread is notably higher than the CDX_{IG} spread. Turnover is dispersed, indicating that a few funds, typically fixed-income funds, trade a large fraction of their assets. On average, the tenure of fund managers (TEN) is about 10 years.

In the first application of our methodology, we identify scheduled macroeconomic announcements that yield positive or negative surprises with changes in the Scotti (2016) index of real-activity macroeconomic surprises for the United States. The index summarizes surprises, measured as actual announcement minus the Bloomberg median expectation for the scheduled announcements of GDP, industrial production, nonfarm payroll, personal income, the Institute for

Table 2. Descriptive Statistics

	Avg.	St. Dev.	10th Perc.	25th Perc.	50th Perc.	75th Perc.	90th Perc.
PS	−0.008	0.849	−0.962	−0.449	0.023	0.453	0.919
NOISE	−0.031	0.031	−0.054	−0.031	−0.020	−0.016	−0.014
MKT	0.029	1.229	−1.240	−0.470	0.080	0.580	1.220
SMB	0.001	0.577	−0.680	−0.340	0.010	0.330	0.660
HML	0.002	0.655	−0.580	−0.260	−0.010	0.250	0.580
UMD	0.010	0.992	−0.940	−0.360	0.060	0.440	0.920
LEVEL	3.554	0.575	2.941	3.007	3.450	4.116	4.402
SLOPE	0.847	0.086	0.748	0.764	0.857	0.933	0.954
CDX_{IG}	0.864	0.413	0.415	0.578	0.815	1.028	1.345
CDX_{HY}	5.012	2.484	3.102	3.443	4.256	5.735	7.240
AUM (mm$)	1,313	6,259	14	53	207	776	2,324
AGE (Years)	12.5	10.9	2.0	5.0	10.0	17.0	24.0
TURN	96	403	11	23	51	99	184
TEN (Years)	10	5	3	6	9	13	17

Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

Notes: The table shows summary statistics for the main variables used in the regression analysis. PS is the daily portfolio that mimics the Pastor and Stambaugh (2003) traded liquidity factor. NOISE is the negative of the noise measure of Hu, Pan, and Wang (2013). MKT, SMB, HML, and UMD are the coefficients on the Fama–French and momentum factors. LEVEL and SLOPE are the level and slope of the yield curve, respectively. CDX_{IG} and CDX_{HY} are the investment-grade and high-yield CDX spreads, respectively. AUM is fund size, AGE is fund age, TURN is fund turnover, and TEN is fund manager's tenure. Units are in percentages unless indicated otherwise.

Figure 1. An Illustration of Our Event Study
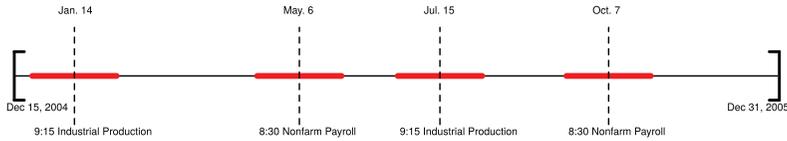
Notes: The figure shows the four announcements with large positive surprises that we study in 2005. The vertical lines indicate the dates of the announcements, with the actual announcements and release times shown under the vertical lines. The thick red segments show the eight-week periods surrounding the announcements over which we calculate the factor-model coefficients. Each eight-week period is equally divided into four weeks before the announcement and four weeks after.

Supply Management (ISM) manufacturing survey, and retail sales. The data are standardized for comparability: a positive (negative) reading of the surprise index suggests that economic releases have, on balance, been higher (lower) than consensus, meaning that investors were pessimistic (optimistic) about the economy. The Scotti (2016) surprise index is a summary statistic that allows us to look at multiple announcements at the same time.

Within each quarter, we consider the macroeconomic announcement for which the release deviates the most from expectations, and we require that a release is at least eight weeks later than the previous quarter's highest-deviation release to ensure that there is no overlap between the pre- and post-announcement windows of two consecutive releases. We consider releases with positive and negative surprises separately. As an illustration of our event-study window, figure 1 shows the announcements that generate the largest positive surprises within each quarter of 2005, together with the corresponding pre-announcement and post-announcement periods. For instance, on January 14, the Scotti (2016) index had the largest increase of the first quarter of 2005 following the scheduled release of industrial production, which read a 0.8 percent increase versus a consensus expectation of 0.4 percent. Similarly, on May 6, July 15, and October 7 of the same year, nonfarm payroll and industrial production caused the largest unexpected positive news, with the data coming in higher than expectations. The non-overlapping periods in

which the analysis is conducted are shown by the eight-week interval around the various releases (thick red lines in the figure).[7]

Our final data set spans from 2004 through the end of 2016 and contains 10,790,971 daily observations across 5,851 unique funds. The data cover 41 (46) days with announcements that yielded the most negative (positive) surprise within each quarter, and the four weeks before and after each announcement day.

In the second application of our methodology, we monitor the liquidity profile of selected mutual funds around three significant market events. First, we consider the sudden resignation of Bill Gross from PIMCO on September 26, 2014, and its effect on PIMCO fixed-income mutual funds (totaling 36 funds). Second, we focus on the liquidity profile of broad-market high-yield bond mutual funds when redemptions from Third Avenue's Focused Credit Fund were suspended on December 9, 2015 (226 funds). Finally, we study the funds managed by Neuberger Berman (30 funds), an asset manager affiliated with Lehman Brothers Holdings, around the bankruptcy of the parent company in September 2008.

3.   Methodology

We study changes in the sensitivity of mutual funds to aggregate market liquidity, first around scheduled macroeconomic announcements and second around the announcement of significant market events. Using fixed-effects panel regressions, we estimate changes in the liquidity factor loadings by interacting the liquidity factor with a dummy variable. The dummy variable is equal to zero in the pre-announcement period and equal to one after the announcement. Both the pre- and post-announcement periods are four weeks long, and the announcement date is included in the second four weeks because the announcements we consider take place during the business day, while the NAV and factors are measured at the end of the day.

We estimate the following fund fixed-effect panel regression, with standard errors double clustered (Cameron, Gelbach, and Miller 2011) by date and fund:

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[7]For color versions of the figures, see the online version at http://www.ijcb.org.

$$RET_{i,t} = \alpha + \alpha_\Delta D_{post,t} + \beta LIQ_t + \beta_\Delta LIQ_{post,t} + \gamma_Z Z_t$$
$$+ \gamma_X X_{i,q-1} + \nu_y + \eta_i + \varepsilon_{i,t}, \tag{1}$$

where i indicates the fund; t the day; q the quarter corresponding to day t; RET the daily return on a given fund, calculated as daily NAV log-changes, in excess of the risk-free rate; and LIQ is the aggregate market liquidity measure, proxied by the Pastor and Stambaugh (2003) liquidity measure for equity and the Hu, Pan, and Wang (2013) noise measure for fixed-income funds. $D_{post,t}$ is a dummy equal to one in the four post-announcement weeks. β is the marginal effect of the liquidity factor in the four weeks before the announcement, and $\beta + \beta_\Delta$ is the marginal effect in the four weeks after the announcement ($LIQ_{post,t} = LIQ_t \times D_{post,t}$). Double clustering the standard errors by date and fund means that the t-statistics we report are adjusted for both time series and cross-sectional correlation. As a result, statistical significance is not unduly inflated by the large number of funds we include in our study.

For equity funds, the matrix Z of control variables includes the Fama-French (MKT, SMB, and HML) and momentum factors. For fixed-income funds, Z includes changes in the level and slope of the yield curve, as well as the Markit CDX index.[8] Fund-level controls (X) include AUM, fund age, turnover ratio, and average tenure of the fund managers in years, all measured as of the end of the previous quarter. ν_y and η_i are the year and fund-level fixed effects, respectively.

Funds with a higher β are more sensitive to liquidity risk. The coefficient β_Δ captures changes in liquidity-risk sensitivity—i.e., changes in the liquidity profile—following the announcements. As illustrated in figure 2, a nonzero β_Δ implies a change in the slope of the relation between fund return and the market liquidity factor. Importantly, the fund-specific slope can change even if aggregate liquidity conditions remain the same (moving from the solid blue circle to the red triangle). At the same time, changes in aggregate liquidity conditions do not necessarily imply a change in the fund's liquidity profile (remaining on the same line but moving from the

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[8]We also estimate a model where we allow the marginal effect of the variables in Z to change in the post-announcement period. Results reported in section 4.4 show that our main findings are unaltered.

Figure 2. The Relation between Expected Returns and Liquidity
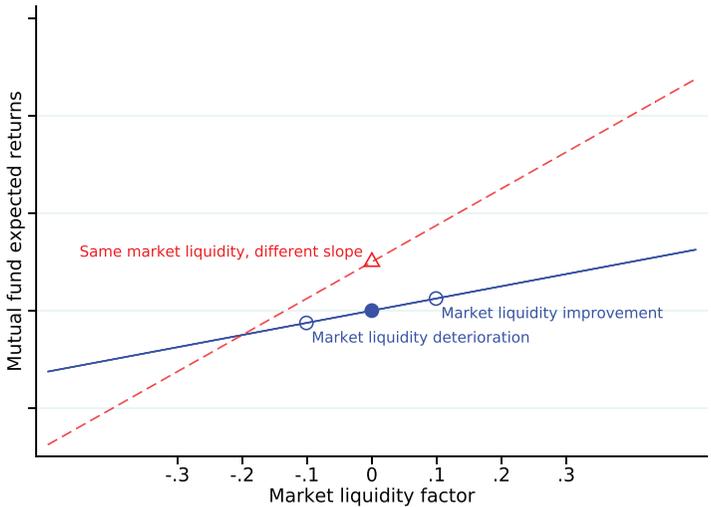
Notes: The figure illustrates the relation between fund expected returns (y-axis) and changes in the liquidity factor (x-axis). If the sensitivity of the fund to aggregate market liquidity remains the same after a macroeconomic announcement, changes in aggregate market liquidity only imply movements along the blue solid line, from the solid marker to the hollow ones. The red dashed line is an example of the relation between fund expected returns and market liquidity after a shift in the sensitivity to market liquidity occurs. Moving from the blue solid circle to the red hollow triangle represents a change in the liquidity profile with constant underlying market liquidity.

solid blue circle to the hollow blue circles). What we capture with β_Δ is a change in the slope, indicating a shift in the sensitivity of fund returns to market liquidity.

3.1   Macro Announcements and Fund Liquidity

In the first application of our methodology, we identify, within each quarter, the announcement with the most positive surprise and the announcement with the most negative surprise. A negative (positive) surprise means that the economy is doing worse (better) than expected by market participants. We run the panel regressions separately on the sets of positive and negative surprises.

We calculate the regression coefficients in (1) for five categories of funds. Funds are classified on the basis of the assets they invest in: large- and mid-cap equity, small-cap equity, government bonds, investment-grade corporate bonds, and high-yield corporate bonds. Our focus is on changes in the co-movement between fund returns and the liquidity factor. As a result, our coefficient of interest is β_Δ: a positive (negative) and statistically significant β_Δ indicates that funds are more (less) exposed to market liquidity in the weeks following the announcement. A positive β_Δ points to a deterioration in the fund's liquidity profile, because fund returns co-move more with liquidity conditions. We expect β_Δ to be larger for funds that invest in less-liquid assets, especially following negative releases that indicate worsening economic conditions.

In addition, given the vast theoretical and empirical literature documenting the different reaction of asset prices to macroeconomic surprises during expansion and recession periods, we study how business conditions affect our results. Specifically, we recalculate the coefficients in equation (1) after partitioning the sample based on whether the Aruoba-Diebold-Scotti Business Conditions Index (Aruoba, Diebold, and Scotti 2009; henceforth, ADS index) is above or below its median value. The index tracks the state of the U.S. economy by combining quarterly, monthly, and weekly real-activity data with a dynamic factor model. A higher value of the index is associated with favorable business conditions.[9] We also consider a sample that only includes the 2008 global financial crisis and its immediate aftermath.

Finally, we investigate whether the impact of these surprises is affected by fund size, initial cash holdings, and the extent to which these funds are held mainly by institutional or retail investors. These characteristics could potentially affect liquidity changes at mutual funds. For example, smaller funds may have different investment styles and less-sophisticated liquidity-management arrangements than larger funds. Similarly, funds with large cash holdings could have more flexible liquidity-management strategies and, for example, might be more inclined to use cash holdings to meet redemptions rather than selling all holdings proportionally. Last

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[9]The variables included in this index correspond to those used in the Scotti (2016) surprise index.

but not least, the change in the liquidity profile of mutual funds could reflect differences in the level of investors' expertise—that is, whether funds are held mainly by institutional or retail investors may play a role. For instance, flows from institutional investors tend to be more sensitive to fundamental signals like poor risk-adjusted performance, while retail flows tend to be more sensitive to uninformative indicators like past total returns (Evans and Fahlenbrach 2012).

3.2   Stress Events and Fund Liquidity

In a second application of our methodology, we consider three events that likely had a significant effect on the liquidity profile of selected mutual funds: Bill Gross's departure from PIMCO on September 26, 2014; Third Avenue's Focused Credit Fund's suspension of redemptions on December 9, 2015; and the effect of the September 2008 Lehman Brothers collapse on Neuberger Berman. We calculate the coefficients in equation (1) around each of these three market events separately. As before, the dummy variable is equal to zero in the pre-event period and equal to one after the event has taken place. Both the pre- and post-event periods are four weeks long, and the event date is included in the post-event sample.

4.   Results

4.1   Macro Announcements

For each of the five fund categories, we run regression (1) and present the results for equity funds in table 3 and for fixed-income funds in table 4. In each table, we show the coefficients computed on negative- and positive-surprise announcements in the left and right panels, respectively. To ease the interpretation of the estimated coefficients, we standardize the liquidity variables in all specifications.

4.1.1   Equity Funds

The results for equity funds are shown in table 3. The coefficient of interest, β_Δ, is positive and statistically significant for small-cap equity funds following negative surprises. The effect is economically significant: a one-standard-deviation increase in aggregate liquidity

Table 3. Regression Results—Equity Funds

	Negative News			Positive News			
	U.S. Large–Mid Cap	U.S. Small Cap	U.S. Small Cap	U.S. Large–Mid Cap	U.S. Large–Mid Cap	U.S. Small Cap	U.S. Small Cap
β	2.91***	1.92***	1.98***	3.39***	3.40***	3.21***	3.23***
	(8.60)	(3.05)	(3.16)	(8.44)	(8.34)	(4.85)	(4.95)
β_Δ	0.76	1.85**	1.95**	−0.76	−0.73	0.16	0.42
	(1.57)	(2.13)	(2.26)	(−1.42)	(−1.33)	(0.20)	(0.52)
MKT	97.74***	98.77***	98.80***	96.68***	96.74***	97.67***	97.70***
	(210.57)	(141.89)	(139.92)	(179.08)	(173.15)	(118.35)	(114.95)
SMB	5.87***	70.67***	70.40***	6.64***	6.70***	72.18***	71.94***
	(8.26)	(68.10)	(67.07)	(6.94)	(6.79)	(58.62)	(57.29)
HML	−2.89***	10.34***	10.14***	−1.39*	−1.24	10.78***	10.87***
	(−4.52)	(8.55)	(8.36)	(−1.69)	(−1.43)	(9.41)	(9.28)
UMD	0.99**	−1.15*	−1.22*	1.31***	1.43***	−0.49	−0.51
	(2.51)	(−1.83)	(−1.94)	(3.06)	(3.18)	(−0.76)	(−0.76)
AUM	−0.37***		−0.43***		−0.15		−0.11
	(−3.17)		(−2.89)		(−1.13)		(−0.63)
AGE	−0.21		−0.11		−0.52		−1.05**
	(−0.64)		(−0.26)		(−1.53)		(−2.33)
TURN	−0.13		−0.07		−0.19**		0.02
	(−1.51)		(−0.52)		(−2.11)		(0.11)
EXPER	−0.29***		−0.23		−0.19*		−0.37**
	(−2.91)		(−1.25)		(−1.88)		(−1.99)
α	−0.01	0.00	0.00	0.00	0.00	0.01	0.01
	(−1.47)	(0.27)	(0.23)	(0.66)	(0.63)	(1.22)	(1.24)
Obs.	2,673,552	841,077	792,365	2,842,710	2,598,905	893,946	828,996
Adj. R2	0.898	0.902	0.904	0.898	0.900	0.903	0.905

Source: Authors' calculations based on CRSP, WRDS, and Morningstar Direct.

Notes: The table shows the coefficients from regression (1) for large- and medium-cap equity and small-cap equity funds. For each quarter between 2004 and 2016, we identify the macro announcement that reveals the most unexpected information by using the Scotti (2016) index. We consider the four weeks before the announcement and the four weeks following (and including) the announcement. β is the coefficient on the daily return of a long/short portfolio that replicates the Pastor and Stambaugh (2003) traded liquidity factor. β_Δ is the change in β over the post-announcement period. MKT, SMB, HML, and UMD are the coefficients on the Fama-French and momentum factors. AUM is the logarithm of fund size, AGE is the logarithm of fund age plus one, TURN is fund turnover, and TEN is the logarithm of the fund manager's tenure, in years plus one. α is the constant and α_Δ is the coefficient on a dummy equal to one in the four weeks after an announcement. We report standardized coefficients for β and β_Δ (in percentage). Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown.

implies, after negative news, an increase in the expected return of small-cap funds of about 2 basis points, which is above the 55th percentile of the daily return distribution, corresponding to an annual return of about 5 percent. While 5 percent might not necessarily mean a systemic event, it is an average effect estimated over a long period of time; thus, it does not reflect interactions with other vulnerabilities that are likely to emerge at times of market distress. In addition, the linearity of the model implies that a two- or three-standard-deviation decrease in aggregate liquidity would cause drops in annual returns in the 10 to 15 percent range, which are fairly large. In contrast, the liquidity profile of large- and mid-cap equity funds is not sensitive to negative surprises, likely because the liquidity of large-company stocks is enough to fully accommodate trading from portfolio adjustments.

The findings suggest that the liquidity profiles of small-cap equity funds deteriorate after scheduled macroeconomic announcements that reveal unexpected negative information about the state of the economy. Several factors can drive such changes in the liquidity profile. Managers can alter the composition of their portfolios in response to investor flows (for instance, by meeting redemptions with liquid assets and selling illiquid securities with a delay) or because of their investment strategy (for instance, adjusting their holdings of less-liquid and higher-yielding assets after macroeconomic news). In light of the correlation between fund flows and macroeconomic news highlighted by Chalmers, Kaul, and Phillips (2013) and Jank (2012), a relation between fund liquidity and news-induced flows would be in line with the results in Hanouna et al. (2015), who show that outflows reduce the liquidity of equity funds.

In principle, however, the composition of a fund's portfolio could also stay constant but the liquidity of the assets themselves could change. This possibility is unlikely, because stock-specific liquidity is driven by slow-moving company characteristics (Frieder and Subrahmanyam 2005; Grullon, Kanatas, and Weston 2004). We corroborate this view in unreported results where we distinguish between active and passive funds, finding that only the liquidity profile of active funds changes after macroeconomic announcements. The holdings of index funds are stable over time because they replicate benchmarks and managers have limited leeway, with the consequence that the liquidity profile would change only to the extent that the liquidity

of the assets would change. As a result, we interpret the changes in the liquidity profile of mutual funds, around events that could potentially alter it, as driven by investor flows or investment strategy modifications, rather than by changes in the underlying liquidity of assets.

Turning to the other coefficients in regression (1), the loadings on the standardized liquidity factor (LIQ) are, as expected, positive and statistically significant for all domestic equity funds, but they are lower for small-cap funds. The positive sign implies that funds' returns increase with market liquidity. Equity funds load heavily on the market factor (MKT), because they are exposed to broad stock market risk by construction. As expected, the coefficient on the Fama-French factor that is long small companies and short large companies (SMB) is largest for small-cap equity funds, because SMB expresses the risk profile of small-cap companies by definition. The coefficient on HML is negative for large- and mid-cap funds and positive for small-cap funds. The reason is that HML is long companies with a high book-to-market—that is, companies whose market value is low relative to the replacement cost of assets. These companies are typically small rather than large (see table 1 in Fama and French 1993), with the consequence that the returns of large (small) companies are negatively (positively) related to HML. Within each fund category, the loadings on MKT, SMB, and HML are fairly similar across the samples with positive or negative surprises.

4.1.2   Fixed-Income Funds

The results for fixed-income funds are shown in table 4. Here, we proxy for liquidity with the negative of the Hu, Pan, and Wang (2013) noise measure. The coefficient of interest, β_Δ, is positive and statistically significant for investment-grade and high-yield funds following negative surprises (left part of the table). A one-standard-deviation increase in the noise measure raises daily returns by about 4 (9) basis points for investment-grade (high-yield) corporate bond funds, which is around the 55th (65th) percentile of the category-specific distribution of daily fund returns. Similarly to equity funds, the results for fixed-income funds indicate that less-liquid funds become more sensitive to aggregate market liquidity in the aftermath

Table 4. Regression Results—Fixed-Income Funds

	Negative News						Positive News					
	Treasury	Treasury	IG Corp. Bond	IG Corp. Bond	HY Corp. Bond	HY Corp. Bond	Treasury	Treasury	IG Corp. Bond	IG Corp. Bond	HY Corp. Bond	HY Corp. Bond
β	0.59	0.59	−3.61*	−3.56*	−12.81***	−12.96***	−1.07	−1.05	−3.53*	−3.39	−6.70***	−6.50***
	(0.37)	(0.37)	(−1.86)	(−1.83)	(−4.21)	(−4.29)	(−0.59)	(−0.58)	(−1.76)	(−1.68)	(−2.69)	(−2.58)
β_Δ	1.08	1.02	3.70**	3.70**	9.28***	9.45***	−0.57	−0.46	0.41	0.50	2.17	2.32
	(0.87)	(0.82)	(2.39)	(2.37)	(4.00)	(4.05)	(−0.36)	(−0.29)	(0.24)	(0.28)	(0.94)	(0.99)
CDX	0.04	0.04	−0.08	−0.08	−0.05***	−0.05***	−0.02	−0.02	−0.14**	−0.13*	−0.06***	−0.06***
	(0.90)	(0.89)	(−1.31)	(−1.31)	(−5.16)	(−5.17)	(−0.46)	(−0.44)	(−2.12)	(−1.99)	(−4.83)	(−4.67)
ΔLEVEL	5.47***	5.51***	7.45***	7.43***	−0.88	−0.88	5.59***	5.69***	7.51***	7.60***	−1.84***	−1.63***
	(8.16)	(8.11)	(7.84)	(7.77)	(−1.59)	(−1.57)	(8.87)	(8.84)	(8.63)	(8.60)	(−3.35)	(−2.96)
ΔSLOPE	−8.12***	−8.12***	−10.72***	−10.68***	6.21***	6.43***	−7.85***	−7.94***	−10.39***	−10.33***	5.79***	5.67***
	(−4.39)	(−4.36)	(−4.24)	(−4.21)	(3.52)	(3.57)	(−4.42)	(−4.41)	(−4.33)	(−4.27)	(3.25)	(3.12)
AUM		−0.04		−0.03		0.36**		−0.06		−0.05***		0.17
		(−0.64)		(−0.73)		(2.04)		(−0.77)		(−3.87)		(1.00)
AGE		−1.47*		−0.70***		−1.68***		−0.18		−0.56***		−0.77
		(−1.86)		(−4.95)		(−3.21)		(−0.27)		(−3.16)		(−1.64)
TURN		0.02		0.31***		0.33**		0.04		0.22*		0.35***
		(0.44)		(4.40)		(2.52)		(0.97)		(1.89)		(4.17)
EXPER		−0.16**		−0.21***		−0.44***		−0.15***		0.00		−0.42***
		(−2.60)		(−4.65)		(−4.67)		(−2.70)		(0.04)		(−3.25)
α	−0.01	−0.01	−0.01	−0.01	−0.02*	−0.02*	−0.02**	−0.02**	−0.03*	−0.03*	−0.02*	−0.02
	(−1.25)	(−1.30)	(−0.81)	(−0.88)	(−1.76)	(−1.81)	(−2.06)	(−2.02)	(−2.32)	(−2.24)	(−1.68)	(−1.61)
Obs.	284,559	267,957	57,504	55,817	226,628	214,417	303,778	282,849	61,540	58,965	242,146	225,578
Adj. $R2$	0.0542	0.0548	0.0926	0.0922	0.0856	0.0869	0.0582	0.0598	0.0912	0.0935	0.0769	0.0778

Source: Authors' calculations based on CRSP, WRDS, and Morningstar Direct.

Notes: The table reports the estimated coefficients of regression (1) for U.S. fixed-income funds. For each quarter between 2004 and 2016, we identify the macro announcement that reveals the most unexpected information by using the Scotti (2016) index. We consider the four weeks before the announcement and the four weeks following (and including) the announcement. β is the coefficient on market liquidity proxied by the negative of the noise measure of Hu, Pan, and Wang (2013). β_Δ is the change in β over the post-announcement period. ΔLEVEL and ΔSLOPE are the changes in the level and slope of the yield curve, respectively. We control for investment-grade and high-yield CDX spreads. All other variables are introduced in table 3. For ease of interpretation, we report standardized coefficients for β and β_Δ (in regression). Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown.

of announcements with large negative surprises. As such, the more-liquid government funds do not exhibit significant changes in sensitivity to underlying market liquidity conditions following negative news about the economy.

The relatively low liquidity of corporate bonds could generate price autocorrelation because prices reflect stale information. Such autocorrelation would dampen the measured sensitivity of asset returns to the liquidity factor (Getmansky, Lo, and Makarov 2004). In addition, Zhou (2015) shows that sophisticated traders might be correctly forecasting macroeconomic news announcements ahead of the release time, and their views might be impounded into bonds ahead of time. In both cases, the liquidity coefficients we calculate would be biased downward, making our results conservative.

The coefficient on the aggregate liquidity factor (β) is negative and mostly statistically significant for investment-grade and high-yield funds. This result is in sharp contrast with our findings for equity funds, but it is a consequence of outlier observations during the 2008 financial crisis. The result disappears when removing the observations corresponding to the December 2007 to June 2009 recession.

Changes in the yield curve level are generally statistically significant across fixed-income fund types. These coefficients are positive for government and investment-grade corporate bond funds, while they are negative for high-yield corporate bond funds. Changes in the slope are also statistically significant for the different types of funds: they are negative for government and investment-grade funds and positive for high-yield funds. These results reflect the equity-like nature of high-yield bonds.

4.1.3   The Role of Business Conditions

A number of theoretical and empirical studies document that the reaction of asset prices to macroeconomic news depends on whether the economy is experiencing a recession or a period of robust growth (see Andersen et al. 2007; Boyd, Hu, and Jagannathan 2005; and Veronesi 1999, among others). Similarly, the effect of macroeconomic surprises on fund liquidity could depend on the state of the economy. For instance, managers may be more worried about future outflows after negative surprises in an already weak economy. As a result, they

may make more noticeable adjustments to fund liquidity during a recession. Similarly, investors might pull out of their investments more heavily following bad news in a weak macroeconomic environment. Hence, we investigate whether post-announcement changes in liquidity coefficients (β_Δ) depend on the broader economic backdrop.

To this end, we first repeat the analysis discussed in sections 4.1.1 and 4.1.2 after partitioning the sample based on whether the ADS index is above (ADS_{high}) or below (ADS_{low}) its median value. Second, we consider a sample that only includes the 2008 global financial crisis and its immediate aftermath.

The post-announcement liquidity coefficients, β_Δ, are reported in table 5, where the sample used to estimate the coefficients is shown in the column headers. The results reveal larger changes in the liquidity factor loading when business conditions are weak for all but Treasury funds following bad news. Higher sensitivity is intuitive given that portfolio reallocation and outflows are more likely when the economy is performing poorly. Both reallocation to less-liquid assets and larger outflows met by selling more-liquid assets would result in a positive β_Δ. The size of the coefficients is also noticeably higher, especially in the crisis period, than during economic expansions. Finally, in the sample that focuses on positive announcements, only in one case (large- and mid-cap equity in expansions) is the coefficient weakly statistically significant. As in tables 3 and 4, the coefficients for small-cap equity and high-yield funds are larger than, respectively, large- and mid-cap equities and investment-grade funds.

4.1.4   The Role of Size, Cash Holdings, and the Investor Base

We now turn to how the change in a fund's liquidity profile following macroeconomic surprises is affected by fund size, initial cash holdings, and the ratio of retail versus institutional investors in the fund. Each of these characteristics could potentially affect the results. For example, smaller funds may have different investment styles and less-sophisticated liquidity-management arrangements than larger funds. Similarly, funds with large cash holdings could have more flexible liquidity-management strategies and might be more inclined to use cash holdings to meet redemptions rather than sell all holdings proportionally. Finally, the change in the liquidity profile of mutual

Table 5. The Role of Business Conditions

	Negative News				Positive News			
	Full Sample	ADS$_{low}$	ADS$_{high}$	Crisis Period (2008–10)	Full Sample	ADS$_{low}$	ADS$_{high}$	Crisis Period (2008–10)
U.S. Large–Mid Cap	0.81	1.16*	0.46	2.33***	−0.73	−0.55	−0.97*	−1.79
	(1.63)	(1.72)	(0.72)	(2.78)	(−1.33)	(−0.71)	(−1.70)	(−1.64)
U.S. Small Cap	1.95**	2.76**	0.48	3.17*	0.42	0.99	−0.28	0.63
	(2.26)	(2.31)	(0.51)	(1.83)	(0.52)	(0.87)	(−0.34)	(0.39)
Treasury	1.02	1.11	−2.54	0.77	−0.46	−0.40	3.76	−1.59
	(0.82)	(0.84)	(−0.48)	(0.36)	(−0.29)	(−0.23)	(0.62)	(−0.55)
Investment-Grade Corp. Bond	3.70**	4.24**	−4.99	6.36**	0.50	0.06	3.25	0.51
	(2.37)	(2.55)	(−0.68)	(2.20)	(0.28)	(0.03)	(0.40)	(0.15)
High-Yield Corp. Bond	9.45***	10.95***	−1.30	17.95***	2.32	0.03	−7.29	6.37
	(4.05)	(4.34)	(−0.17)	(4.07)	(0.99)	(0.01)	(−0.86)	(1.43)

Source: Authors' calculations based on CRSP, WRDS, and Morningstar Direct.

Notes: The table shows the estimated coefficients from regression (1) for the indicated U.S. equity and fixed-income fund categories. We include all of the control variables introduced in tables 3 and 4 but, for the sake of brevity, only the standardized coefficients (in percentage) measuring the post-announcement change in the liquidity factor loadings β_Δ are reported. We partition the sample based on the median Aruoba-Diebold-Scotti Business Conditions (ADS) index (Aruoba, Diebold, and Scotti 2009). ADS$_{low}$ and ADS$_{high}$ refer to the samples where the ADS index is below and above the median value, respectively. Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown.

funds can vary due to a difference in the investors' sophistication level; therefore, the extent to which funds are held mainly by institutional or retail investors may play a role. In particular, fund flows originating from institutional investors react to fundamental signals about the performance of a fund, while those emanating from retail investors respond to less-informative signals, like past returns (Evans and Fahlenbrach 2012). Fund liquidity is likely managed differently to cope with these more idiosyncratic retail flows.

We first partition our sample into low- and high-AUM funds based on the sample median AUM in the previous year. Second, we split the sample into low- and high-cash buffers based on the average cash holdings relative to AUM in the previous four quarters. Third, we classify funds into institutional and retail based on whether the majority of investors are institutional or retail.[10] We estimate the post-announcement liquidity coefficients in equation (1) separately for funds that belong to each of the following six categories: AUM_{low}, AUM_{high}, $CASH_{low}$, $CASH_{high}$, INST, and RETAIL.

Table 6 shows the results of these three exercises in panels A, B, and C, respectively. While we find that the β_Δ coefficient is still significant for small-cap equity funds, as well as investment-grade and high-yield corporate bond funds, we find that subsampling on the basis of AUM, cash holdings, or institutional base yields statistically weak differences. Overall, however, the deterioration in liquidity appears more pronounced in the aftermath of negative surprises for smaller funds, funds with lower initial cash holdings, and funds held by retail investors.

4.2   Event-Study around Specific Stress Events

Our methodology can be used to study the change in mutual fund liquidity profiles in response to any event of interest, not just macroeconomic announcements. In a second application, we consider three episodes that had the potential to affect the liquidity profile of selected mutual funds.

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[10]We use the Morningstar Direct binary variable "Institutional," which classifies funds as such if any of the following conditions are true: has the word "institutional" in its name; has a minimum initial purchase of \$100,000 or more; states in its prospectus that it is designed for institutional investors or those purchasing on a fiduciary basis.

Table 6. The Role of Size, Cash Holdings, and Institutional Base

	Negative News		Positive News	
Panel A	$\mathbf{AUM_{low}}$	$\mathbf{AUM_{high}}$	$\mathbf{AUM_{low}}$	$\mathbf{AUM_{high}}$
U.S. Large–Mid Cap	0.94*	0.83	−0.53	−0.60
	(1.80)	(1.63)	(−0.97)	(−1.07)
U.S. Small Cap	2.31**	1.81*	1.00	0.16
	(2.53)	(1.96)	(1.23)	(0.19)
Treasury	1.02	0.82	−0.54	−0.42
	(0.81)	(0.66)	(−0.33)	(−0.27)
Investment-Grade Corp. Bond	4.22**	3.03**	0.48	0.27
	(2.41)	(2.27)	(0.24)	(0.18)
High-Yield Corp. Bond	9.53***	9.44***	2.34	2.33
	(3.87)	(4.20)	(0.94)	(1.04)
Panel B	$\mathbf{CASH_{low}}$	$\mathbf{CASH_{high}}$	$\mathbf{CASH_{low}}$	$\mathbf{CASH_{high}}$
U.S. Large–Mid Cap	0.88*	0.85	−0.49	−0.47
	(1.78)	(1.57)	(−0.91)	(−0.80)
U.S. Small Cap	1.91**	1.97*	0.79	0.48
	(2.27)	(1.85)	(1.01)	(0.52)
Treasury	0.78	1.02	−0.27	−0.72
	(0.71)	(0.71)	(−0.20)	(−0.39)
Investment-Grade Corp. Bond	4.26***	3.25*	0.39	0.63
	(2.74)	(1.94)	(0.23)	(0.33)
High-Yield Corp. Bond	9.60***	9.46***	2.50	2.15
	(4.06)	(3.83)	(1.09)	(0.85)
Panel C	**INST**	**RETAIL**	**INST**	**RETAIL**
U.S. Large–Mid Cap	0.85*	0.84*	−0.51	−0.79
	(1.65)	(1.71)	(−0.94)	(−1.41)
U.S. Small Cap	1.95**	2.02**	0.76	0.27
	(2.13)	(2.28)	(0.88)	(0.33)
Treasury	1.14	0.93	−0.30	−0.41
	(0.85)	(0.77)	(−0.18)	(−0.27)
Investment-Grade Corp. Bond	3.85**	4.11**	0.60	0.48
	(2.70)	(2.54)	(0.36)	(0.27)
High-Yield Corp. Bond	9.46***	9.72***	2.52	2.42
	(4.03)	(4.10)	(1.06)	(1.02)

Source: Authors' calculations based on CRSP, WRDS, and Morningstar Direct.
Notes: The table shows the estimated coefficients from regression (1) for the indicated U.S. equity and fixed-income fund categories. We include all of the control variables introduced in tables 3 and 4 but, for the sake of brevity, only the standardized coefficients (in percentage) measuring the post-announcement change in the liquidity factor loadings β_Δ are reported. In panel A, we partition the sample based on fund AUM in the previous year. AUM_{low} and AUM_{high} refer to the samples where fund size is below and above the median value, respectively. In panel B, we similarly partition the sample based on average cash holdings relative to AUM in the previous four quarters. Finally, in panel C, we partition the sample based on whether the investors are retail or institutional. Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not reported.

First, we focus on the unexpected resignation of Bill Gross from PIMCO on September 26, 2014. He was PIMCO's chief investment officer and the portfolio manager of PIMCO's flagship and largest fixed-income fund, which experienced very large outflows in the aftermath of his resignation, totaling \$51 billion (25 percent of the fund's September-end AUM) through October 2014 (Herbst et al. 2015). Such large outflows might have had a significant effect on the liquidity profile of all fixed-income funds managed by PIMCO, whose investment philosophy was closely tied to the figure of Bill Gross.

Second, we study changes in the liquidity profile of high-yield bond mutual funds around the suspension of redemptions from Third Avenue's Focused Credit Fund on December 9, 2015. The fund halted redemptions after being unable to sell its illiquid assets at prices it deemed fair. We consider all high-yield bond funds, rather than just Third Avenue funds, because the troubles at Third Avenue might have been interpreted, by high-yield investors, as symptoms of broader market dysfunction.

Third, we focus on the bankruptcy of Lehman Brothers on September 15, 2008, and we study the funds managed by Neuberger Berman, an asset manager that was part of the Lehman Brothers corporate group and that remained in business after the parent company's bankruptcy. Uncertainty about the fate of Neuberger Berman likely led managers to expect high outflows and to manage their portfolios accordingly.

Table 7 reports the coefficients in equation (1) separately for each event.[11] The main coefficient of interest, β_Δ, is positive and statistically significant in the PIMCO and Third Avenue episodes, and negative for Lehman Brothers' bankruptcy. For Third Avenue, the magnitude of the coefficient is similar to that of macroeconomic announcements on high-yield bond funds, whereas the effect of Gross's resignation is much larger than what we report in table 4.

The results for Lehman Brothers' default are particularly interesting because the negative and statistically significant coefficient stands in sharp contrast with the largely positive β_Δ we reported in

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[11]Not all fund-specific variables are included in the regressions. Certain variables do not vary across months or quarters in the subsamples we study and cannot be included in a fixed-effect regression setting.

Table 7. Case-Study Analysis

	PIMCO	**Third Avenue**	**Lehman Brothers**
β	−24.43	15.21***	28.05***
	(1.64)	(4.37)	(4.05)
β_Δ	31.15**	8.61*	−29.75***
	(2.07)	(1.70)	(−3.25)
CDX	−0.30	−1.69***	
	(−0.39)	(−7.08)	
ΔLEVEL	9.85**	11.94**	
	(2.51)	(2.23)	
ΔSLOPE	−23.98	6.77	
	(−1.40)	(1.21)	
MKT			98.53***
			(30.88)
SMB			14.87***
			(3.68)
HML			−7.70
			(−0.77)
UMD			−1.12
			(−0.12)
AUM	−0.22	0.05	1.43**
	(−1.17)	(1.08)	(2.18)
AGE	−0.10		−1.29
	(−0.38)		(−0.66)
TEN	0.00		2.09**
	(0.04)		(2.70)
α	0.02	0.80***	0.02
	(0.16)	(7.52)	(0.24)
α_Δ	2.15	7.24***	−8.29
	(1.06)	(6.62)	(−1.51)
Obs.	1,015	4,918	631
Adj. $R2$	0.105	0.589	0.912

Source: Authors' calculations based on CRSP, WRDS, and Morningstar Direct.
Notes: The table reports the coefficients on asset pricing factors and fund characteristics around three events that are likely to have affected the liquidity profile of certain mutual funds. In the first column, the eight-week period used to estimate the coefficients is centered around September 26, 2014, when William H. Gross left PIMCO. We study the liquidity profile of PIMCO fixed-income funds. In the second column, the reference date is December 9, 2015, when withdrawals were suspended from the Third Avenue Focused Credit Fund in light of the fund's deteriorating liquidity position. In this case, we study the liquidity profile of broad-market high-yield funds. In the third column, we focus on the bankruptcy of Lehman Brothers on September 15, 2008, and we study the funds managed by Neuberger Berman, an asset manager affiliated with Lehman Brothers that survived the parent company's bankruptcy. Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively.

our various specifications so far. The event is also instructive because the portfolio managers were faced with clearly adverse conditions at both the macroeconomic and company-specific level, even though Neuberger Berman was one of Lehman Brothers' viable units (it was spun off and is currently in business). As a result, portfolio managers likely had an incentive to increase the holdings of liquid assets to better meet future redemptions and preserve the company's reputation as a viable going concern. An increase in liquid assets would have resulted in an improved liquidity profile and a negative β_Δ.

4.3   Monitoring Funds' Liquidity

We established that liquidity coefficients are useful to track the liquidity of mutual funds at a relatively high frequency around significant events. Our approach can also be used more generally—for instance, to monitor liquidity dynamics on a continuous basis without having to acquire holding-level inputs. These dynamics can be helpful to gauge current market developments. As an example, we find that changes in liquidity betas are correlated with contemporaneous changes in net flows to high-yield corporate bond funds.[12]

We focus on high-yield corporate bond funds because holdings of U.S. corporate bonds by mutual funds increased substantially over the past decade, raising concerns about the mismatch between daily redemptions allowed by these funds and the time required to sell their less-liquid assets. While mutual funds were able to meet redemptions during past periods of stress, including the recent period of market turmoil in December 2018, future redemptions amid weaker economic fundamentals could lead to greater stress.

We estimate a fund-specific liquidity coefficient at the quarterly and daily frequencies. That is, for a given quarter q and fund i, we compute $\beta_{i,q}^{fund}$ by regressing daily fund returns on market liquidity and other market and fund controls introduced in section 3:

$$RET_{i,t} = \alpha + \beta_{i,q}^{fund} LIQ_t + \gamma_Z Z_t + \gamma_X X_{i,q-1} + \varepsilon_t, \qquad (2)$$

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[12]Net flows vary around slow-moving trends, in particular increasing after the 2008 financial crisis. As a result, we consider changes in net flows, but changes in betas are also correlated with net flows.

Figure 3. Liquidity Beta and Fund Flows for High-Yield Funds

(a) Fund Beta (lhs) and Net Flows (rhs) – Quarterly Frequency

(b) Rolling Beta – Daily Frequency
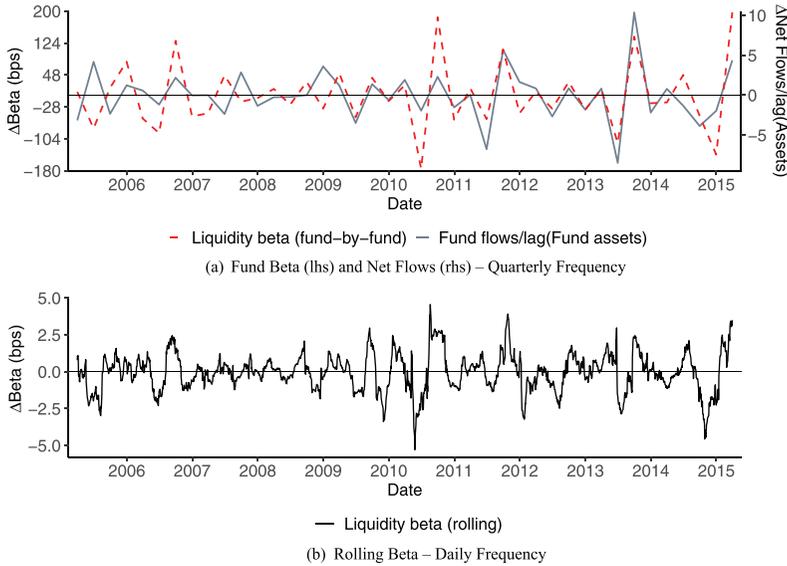
Source: Authors' calculations based on CRSP, WRDS, and Morningstar Direct.
Notes: Panel A shows the change in the cross-sectional average of fund betas $(\beta_{i,q}^{fund})$ estimated via equation (2) and changes in net flows, as a percentage of lagged assets, all at the quarterly frequency. Panel B depicts the 60-day moving average of changes in the cross-sectional average of daily fund-specific rolling liquidity betas $(\beta_{i,t}^{roll})$ throughout the sample period. Both betas are coefficients on the standardized aggregate liquidity factor and are expressed in basis points.

where $RET_{i,t}$ is the daily return for fund i on day t in quarter q, and LIQ_t is aggregate market liquidity on day t in quarter q, proxied by the Hu, Pan, and Wang (2013) noise measure. The coefficient $\beta_{i,q}^{fund}$ from this regression represents the liquidity profile of fund i in quarter q. We also estimate a similar regression using a 60-day rolling window to get daily fund-specific rolling liquidity betas $(\beta_{i,t}^{roll})$.

Figure 3 depicts the time series of changes in the cross-sectional averages of these coefficients, which are easier to visualize than individual liquidity loadings. Panel A shows changes in the average fund-by-fund beta over time at the quarterly frequency; panel B shows changes in the average rolling beta at the daily frequency. Changes

in the average $\beta_{i,q}^{fund}$ and $\beta_{i,q}^{roll}$ are highly correlated (over 90 percent). The rolling liquidity beta, $\beta_{i,t}^{roll}$, has the advantage of being computed in real time and can therefore potentially be used as a monitoring tool to understand whether high-yield funds (or specific funds) are changing their exposure to market liquidity, which implies tilting their portfolios toward more- or less-liquid assets. Panel A in figure 3 also shows the time-series relationship, at the quarterly frequency, between changes in average liquidity betas ($\beta_{i,q}^{fund}$) and changes in net flows scaled by lagged assets, revealing a high correlation (almost 60 percent) between the two variables. Once more, while fund flows are quarterly and observed with a lag, the daily rolling coefficients $\beta_{i,t}^{roll}$ could offer insights into how flows evolve in real time.

4.4   Robustness

We carry out a variety of robustness tests to gauge the sensitivity of our results to alternative econometric specifications.

In the first robustness exercise, we vary the length of the pre- and post-announcement window. While in the baseline specification we use a four-week window, we replicate the analysis with three- and five-week windows. Table 8 shows that the deterioration in the liquidity profile of mutual funds that we find following negative news for small-cap equity and corporate bond funds is consistent across different windows. Moreover, the effect dies out for small-cap equity funds as the window gets wider, while it increases for investment-grade and high-yield corporate bond funds. This finding highlights the different speeds at which the liquidity profiles of equity and fixed-income funds adjust.

In the second robustness check, we allow the coefficients on factors other than liquidity to change in the post-announcement period. For equity funds, we include $MKT_{post,t}$, $SMB_{post,t}$, $HML_{post,t}$, and $UMD_{post,t}$ in addition to $LIQ_{post,t}$ in equation (1). For fixed-income funds, we add $CDX_{post,t}$, $LEVEL_{post,t}$, and $SLOPE_{post,t}$ besides $LIQ_{post,t}$. As shown in columns 4 and 8 of table 8, the β_Δ coefficients are not affected once we allow for such a specification, and they are almost identical to the baseline specification.

Finally, we repeat the event study in section 4.2 using a differences-in-differences analysis where treated funds are compared

Table 8. Robustness

	Negative News				Positive News			
	Baseline (Four Week) (1)	Three-Week Window (2)	Five-Week Window (3)	All Loadings Can Change (4)	Baseline (Four Week) (5)	Three-Week Window (6)	Five-Week Window (7)	All Loadings Can Change (8)
U.S. Large–Mid Cap	0.81 (1.63)	0.59 (1.16)	0.81 (1.35)	0.90* (1.82)	−0.73 (−1.33)	−1.29** (−2.13)	−0.93 (−1.41)	−0.74 (−1.34)
U.S. Small Cap	1.95** (2.26)	2.19** (2.22)	1.74* (1.81)	1.94** (2.31)	0.42 (0.52)	0.37 (0.46)	1.08 (1.10)	0.11 (0.14)
Treasury	1.02 (0.82)	1.28 (0.94)	2.06 (1.58)	1.04 (0.83)	−0.46 (−0.29)	0.38 (0.21)	−1.08 (−0.65)	−0.41 (−0.26)
Investment-Grade Corp. Bond	3.70** (2.37)	3.65** (2.13)	5.90*** (3.60)	3.74** (2.39)	0.50 (0.28)	1.94 (0.96)	−1.47 (−0.77)	0.55 (0.31)
High-Yield Corp. Bond	9.45*** (4.05)	5.91** (2.27)	11.37*** (4.44)	9.42*** (4.05)	2.32 (0.99)	5.22* (1.87)	−2.84 (−0.99)	2.32 (0.99)

Source: Authors' calculations based on CRSP, WRDS, and Morningstar Direct.

Notes: The table shows the estimated post-announcement change in the liquidity factor loading coefficients, β_Δ, for the indicated U.S. equity and fixed-income fund categories. We include all of the control variables introduced in tables 3 and 4 but, for sake of brevity, only the standardized β_Δ coefficients (in percentage) are reported. In columns 1 and 5, we report the baseline specification with a four-week window pre- and post-announcement (eight weeks in total). We then show results for alternative window sizes: a three-week window in columns 2 and 6, and a five-week window in columns 3 and 7. Columns 4 and 8 show results for β_Δ from the specification where we allow all factor loadings (such as those on MKT or ΔSLOPE) to change in the post-announcement period. Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown.

with a set of control funds selected according to the specific event considered: Bill Gross's departure from PIMCO, the suspension of redemptions from the Third Avenue Focused Credit Fund, and the effect of Lehman Brothers' default on Neuberger Berman. We identify funds that behave similarly to our treated funds using daily return correlations over the full sample up to and including the month preceding the event in question (the control sample is the set of funds with higher correlations with the treated sample). We aggregate the funds in the treated sample by computing the value-weighted (by AUM) return of all funds in the treated sample, and we calculate the correlation of this return with the returns on funds suitable as controls (those in the same category as the treated funds). We value-weight returns on treated funds to make this exercise empirically feasible and to reduce the risk that we select the control sample on the basis of outlier correlations. Unreported results, available upon request from the authors, confirm our key findings and show that the change in liquidity that we report is indeed more pronounced in the treatment sample.

5.   Conclusions

We study open-end mutual funds' liquidity profiles, defined as the sensitivity of daily fund returns to aggregate market liquidity. We interpret an increase in sensitivity as a deterioration in the liquidity of the fund. We use our methodology to analyze how fund liquidity changes around two types of events that yield unanticipated information: (i) scheduled macroeconomic announcements that reveal unexpected news about the economy, and (ii) significant but unforeseen market events like Bill Gross's departure from PIMCO, Third Avenue's Focused Credit Fund's suspension of redemptions, and the collapse of Lehman Brothers.

Overall, we find that, in the aftermath of announcements that reveal unexpectedly negative information about the state of the economy, small-cap equity funds as well as investment-grade and high-yield corporate bond funds experience a deterioration in their liquidity profiles. We find similar results following adverse market events.

While there might be multiple reasons for this deterioration, we would need to observe managerial actions and portfolio changes at

a higher frequency to identify the exact mechanism. The changes we observe could arise because portfolio managers adjust the funds' holdings in light of unexpected news, purchasing higher-yielding illiquid assets after negative news as a wager that macroeconomic conditions will improve. Alternatively, these changes might also be triggered by unexpected outflows after negative surprises, and mutual funds might meet the associated redemptions by selling the most-liquid asset first. However, our analysis suggests that rapid changes in the liquidity characteristics of the assets held by mutual funds are unlikely to explain our results.

Irrespective of the exact drivers, understanding the dynamics of the liquidity profile of mutual funds is important because poorer fund liquidity might amplify certain vulnerabilities, especially at times of market stress. For example, if investors perceive that the liquidity of the fund they are invested in is at risk, they might run on the fund, in a process similar to a bank run. Our approach allows us to study the evolution of mutual fund liquidity at a higher frequency than possible when using regulatory asset-holding disclosures, and a natural application is monitoring fund liquidity around important events that could generate systemic risk.

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How Do Central Bank Projections and Forward Guidance Influence Private-Sector Forecasts?*

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We construct a 23-country panel data set to consider the effect of central bank projections and forward guidance on private-sector forecasts. Despite the strong arguments in the literature in favor of releasing central bank policy rate projections, we find that the provision of these projections reduces neither private-sector forecast dispersion nor forecast error. Further, the policy rate assumption that central banks use in their macroeconomic projections has not appeared to matter much for private-sector forecasts. We also find that forward guidance tends to reduce the dispersion and error of interest rate forecasts but less so for macroeconomic forecasts. This is consistent with the idea in the literature that forward guidance can lower interest rate forecast disagreement without reducing macroeconomic forecast disagreement because forward guidance can be interpreted by forecasters as either Delphic or Odyssean.

JEL Codes: D83, E37, E52, E58.

1.   Introduction

Central banks' ability to guide expectations is critical for the efficacy of the monetary policy transmission mechanism. In recent decades, central banks have employed an increasing number of both conventional and unconventional communication tools to help agents better anticipate future monetary policy actions. Numerous studies have assessed how this increased central bank transparency (via the provision of central bank projections, for example) has helped manage expectations by studying private-sector forecast disagreement (e.g., Crowe 2010; Ehrmann, Eijffinger, and Fratzscher 2012; Naszodi et al. 2016; Lustenberger and Rossi 2017, 2020). Less is understood, however, about the effectiveness of unconventional monetary policy tools and which types of central bank projections matter most for managing expectations.[1]

To study this issue, we construct a new, 23-country panel data set dating back to 1990 that records whether central banks provided six types of economic projections and three types of forward guidance. We also gather metadata about these projections, such as the policy rate path assumption used in economic projections (i.e., endogenous, constant, or market-implied). By constructing our own data set, we are able to assemble a more complete picture of monetary policy communication. Unlike other closely related studies, we incorporate the publication of additional economic projections, such as unemployment and policy rate projections, as well as qualitative, time-contingent, and state-contingent forward guidance. Our data are then used in conjunction with private-sector forecast data to estimate the impact of the provision of economic projections and forward guidance on private-sector forecast disagreement and forecast error. We are able to offer the following conclusions.

We find that the provision of central bank policy rate projections reduces neither private-sector forecast dispersion nor forecast error. In fact, when it comes to private-sector interest rate forecast dispersion, we find evidence that central bank policy rate projections

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[1]Three of the studies above pointed out that it would be useful to analyze how central bank projections affect private-sector forecasts in more detail. See Crowe (2010, p. 232), Ehrmann, Eijffinger, and Fratzscher (2012, p. 1028), and Naszodi et al. (2016, p. 166).

can actually increase forecast disagreement. It could be that central bank policy rate projections are difficult to interpret, especially in periods of heightened macroeconomic uncertainty. Central bank policy rate projections could also lose credibility over time if they have proven to be inaccurate in the past. Another possibility is that any signal conveyed by policy rate projections is dampened by the flood of information simultaneously released by central banks. The inclusion of wide confidence intervals around central banks' policy rate projections could add noise to the signal as well.

We also studied central bank inflation projections and found that they have tended to reduce both the forecast dispersion and forecast error of private-sector interest rate forecasts. Central bank inflation projections appear to have more influence over private-sector interest rate forecasts than macroeconomic forecasts, which suggests that inflation projections may primarily be used by private-sector forecasters to help forecast the path of monetary policy. In fact, central bank unemployment projections actually appear to increase private-sector disagreement and forecast error. One possibility is that some private-sector forecasters perceive unemployment projections as less important to inflation-targeting central banks than, for example, inflation projections or forward guidance. Surprisingly, central bank output gap projections appear to have fairly weak influence on private-sector forecast disagreement and forecast error. Nonetheless, the more projections a central bank released, the lower private-sector forecast dispersion and error tended to be, particularly for private inflation forecasts. This suggests that a larger set of central bank projections indeed provides more information.

We find that forward guidance tends to reduce private-sector interest rate forecast dispersion and forecast error, but the effect is weaker for inflation or domestic output forecast disagreement and error. These results add to the evidence provided by Andrade et al. (2019) that when the Federal Reserve used time-contingent forward guidance, private-sector short-term interest rate forecast disagreement fell to a historical low but some of those same forecasters revised their macroeconomic forecasts in opposite directions. One group, optimistic forecasters, tended to revise their macroeconomic forecasts upward. A second group, pessimistic forecasters, tended to revise their macroeconomic forecasts downward. Using the terminology of Campbell et al. (2012), forward guidance can be

Odyssean and signal a more accommodative stance of monetary policy in the future, which is good news, or it can be Delphic and signal that the macroeconomic outlook is worse than previously understood, which is bad news. Our paper suggests that the forecaster heterogeneity observed in the United States after the financial crisis in Andrade et al. (2019) is likely to be a more general phenomenon. As such, central banks should take great care in crafting their communication to avoid inadvertently providing Delphic forward guidance instead of the intended Odyssean forward guidance.

Finally, there are ongoing debates in the literature about whether a central bank should release its policy rate projection (e.g., Faust and Leeper 2005; Rudebusch and Williams 2008; Woodford 2013; Obstfeld et al. 2016) and about what policy rate path assumption a central bank should use in its macroeconomic projections (e.g., Goodhart 2009). We conclude that neither choice appears to have much influence on private-sector forecast disagreement or forecast error. At least when glimpsed through the lens of private-sector forecasts, these particular central bank communication choices are not obvious.

A relatively small literature has focused on private-sector forecaster expectations while incorporating forward guidance. Campbell et al. (2012) use survey data to show that the Federal Reserve has been able to influence private macroeconomic forecasts using forward guidance. The authors find that the responses of private-sector forecasts to unanticipated increases in forward guidance (or the "path factor;" see Gürkaynak, Sack, and Swanson 2005 for details) were opposite to those predicted by a standard New Keynesian model. They reason that private-sector forecasters must believe that central bank (the Federal Open Market Committee (FOMC) in this case) policy surprises must contain useful macroeconomic information. Kool and Thornton (2015) find that forward guidance reduced forecast dispersion in New Zealand, Sweden, and Norway, but not in the United States. Lustenberger and Rossi (2017) show that public information is less precise than private information during forward-guidance periods. Coenen et al. (2017) find that under effective lower bound (ELB) periods, state-contingent forward guidance reduced disagreement and that time-contingent forward guidance reduced disagreement if it was provided over relatively long horizons.

A number of theoretical papers have also considered the role of forward guidance at the zero lower bound. For example, Eggertsson and Woodford (2003) show that unconventional monetary policy can help avoid a major recession once the economy has hit the zero lower bound. By contrast, McKay, Nakamura, and Steinsson (2016) use an incomplete-markets model to show that forward guidance at the zero lower bound may not be as effective as implied by mainstream macroeconomic models and Eggertsson and Woodford (2003).

The forward-guidance analysis in our paper is closely related to Kool and Thornton (2015) and Coenen et al. (2017) but differs in several respects. First, our sample group includes a larger and more diverse set of economies. Second, our sample period extends back further and includes both ELB and non-ELB periods. Third, we include additional variables in our estimation, such as the provision of unemployment and policy rate projections, as well as numerous additional controls. Fourth, we address an econometric issue pointed out in Lustenberger and Rossi (2020). These differences allow us to offer a new perspective on the effect of forward guidance on private-sector forecasts. Our paper is organized as follows. Section 2 discusses our estimation methodology. Section 3 provides details on our data collection and the sample period used. Section 4 discusses our estimation results and section 5 concludes.

2.   Methodology

Central banks release macroeconomic projections for a number of reasons. Geraats (2005) argues that central banks have a strong incentive to publish forward-looking analysis to enhance their credibility as inflation targeters, thereby reducing inflationary bias. Morris and Shin (2005) illustrate how central banks could improve the public's understanding of the underlying state of the economy provided central banks are better informed than other agents in the economy. Rudebusch and Williams (2008) discuss how releasing interest rate projections could improve the public's understanding of the central bank's reaction function and thereby better align expectations.

Private-sector forecasters are typically the most avid analysts of central bank projections. Hubert (2015a) provides three hypotheses

as to why central bank inflation forecasts could influence private-sector forecasts. First, central bank projections may be more accurate than private ones. Second, central banks may have a different information set from that of private-sector forecasters. Third, central bank projections may be a form of monetary policy signal.[2]

Each of the preceding hypotheses, if true, could lead to lower private-sector forecast dispersion and forecast error. A number of papers have considered the role of central bank projections on private-sector forecasts. For example, Romer and Romer (2000) find that FOMC projections provide signals to private-sector forecasters, which causes private-sector forecasters to update their forecasts accordingly. To contribute to the literature, our approach aims to capture how the provision of central bank projections affects private-sector forecast disagreement and forecast error while incorporating a larger sample of economies and additional types of projections. To do so, we use the following two-way fixed-effects estimator:

$$y_{it} = \alpha + \mathbf{x_{it}}\boldsymbol{\beta} + \mathbf{c_{it}}\boldsymbol{\gamma} + \lambda_i + \lambda_t + \epsilon_{it}. \tag{1}$$

y_{it} refers to the natural logarithm of either private-sector forecast dispersion or private-sector absolute forecast error. x_{it} is a vector of central bank projection and forward-guidance dummy variables ($x_{it} \in \{0, 1\}$). c_{it} is a vector of control variables. λ_i refers to country fixed effects, λ_t refers to quarterly time fixed effects, and ϵ_{it} is an error term. This empirical approach is closely related to Ehrmann, Eijffinger, and Fratzscher (2012), Ehrmann (2015), Naszodi et al. (2016), and Lustenberger and Rossi (2020). We estimate the benchmark model using standard errors clustered at the country level that are robust to heteroskedasticity and serial correlation (see Stock and Watson 2008 and Lustenberger and Rossi 2020).[3]

Our main measure of forecast dispersion is the natural logarithm of the interdecile range, which is the difference between the ninth

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[2]Hubert (2014) found that publishing FOMC inflation forecasts reduced the dispersion of inflation expectations. In a five-country study, Hubert (2015a) suggests that although central bank projections influence private-sector forecasts, this effect cannot be attributed to forecasting performance. Hubert (2015b) provides evidence that European Central Bank inflation projections influence private-sector forecasts and that they convey useful monetary policy signals.

[3]The results are robust to bootstrapped standard errors as well. See the online appendix on the IJCB website (http://www.ijcb.org) for details.

and first deciles of a given forecast distribution. Forecast error is measured as the natural logarithm of the absolute value of the mean forecast error. By including both measures, we can glean whether less forecast disagreement has also coincided with less mean forecast error, which is important because it would not be desirable for central bank projections to reduce forecast disagreement at the cost of forecast accuracy.

The key variables of interest are the x_{it} variables, which denote binary dummy variables that indicate whether a central bank in country i provided a given type of macroeconomic projection or forward guidance in quarter t. These binary variables are tested jointly in an effort to disentangle the marginal effects of providing each type of central bank projection. If the release of a particular type of central bank projection is associated with a reduction in forecast dispersion or forecast error, then the corresponding β should be negative. Some multicollinearity issues prevent us from using all x_{it} variables. Specifically, we are able to include inflation, the output gap, unemployment, policy rate projections, and three types of forward guidance but must exclude domestic and global output projections. The correlation between the inflation and domestic output projections, for example, is 0.91, so it is not sensible to include both. Global output projections are excluded for a similar reason. Hence, we proceed with caution, knowing that it is difficult to disentangle the effects of central bank inflation projections from output projections because they so often appear together. However, we use all six central bank projections later in the paper when we replace the central bank projection dummy variables from x_{it} with a variable that counts the number of projections released by the central bank (we simply sum each of the six central bank projection dummy variables for a given quarter and country). This allows us to test the hypothesis that releasing more central bank projections provides more information and, if so, how so.

We include several control variables to adjust for different types of volatility. The control variables are denoted above by the vector c_{it}. First, following Ehrmann, Eijffinger, and Fratzscher (2012) and Naszodi et al. (2016), we include the conditional volatility of the realized macroeconomic data j in country i at time t. Following Capistrán and Timmermann (2009) and Capistrán and Ramos-Francia (2010), conditional volatility is estimated using a

GARCH(1,1) model (for more detail see subsection 3.5). Following Ehrmann, Eijffinger, and Fratzscher (2012) and Naszodi et al. (2016), we include the absolute value of the change in West Texas Intermediate (WTI) oil prices. As in Lustenberger and Rossi (2020), we attempt to control for some forms of financial market volatility by including the VIX (the implied volatility from options on the Standard & Poor's 500 stock index). Usefully, this volatility measure has low correlation with the various measures of conditional variance. As in all of the studies above and the related literature, we include country fixed effects, λ_i. Additionally, we also include quarterly time fixed effects, λ_t. When we use the forecast dispersion and error of either inflation or domestic output as dependent variables, we also add binary variables indicating the quarter (i.e., Q2, Q3, Q4) because of the fixed-event nature of these forecasts. We elaborate in subsection 3.2.

Next, we include a number of binary control variables (c_{it}) not included in the aforementioned (related) studies. We include a variable indicating whether a country's central bank had adopted an inflation target in a given quarter, as it is reasonable to assume that the presence of an inflation target may influence private-sector forecasts of macroeconomic variables. Periods at the effective lower bound may represent an exception to the normal relationship between the level of policy rates and forecast dispersion, for example, and so we include an indicator variable for the ELB in all regressions. For similar reasons, we include a variable that indicates whether a central bank had an active quantitative easing (QE) program in a given quarter and country. Although we implicitly adjust for the effect of many crisis periods by virtue of our numerous volatility variables and the ELB and QE variables, the global financial crisis probably represents a unique case and so we include an indicator variable for this period. We also seek to disentangle the influence of central bank projections and forward guidance from the publication of a monetary policy report or a monetary policy decision. Hence, we include one variable indicating whether a monetary policy report (or inflation report, other equivalent, etc.) was released in a given quarter and country and one variable indicating whether a central bank made a monetary policy decision in a given quarter and country. Finally, to account for different currency regimes, we include a variable indicating whether a country either had a

de facto currency peg or was a member of a currency union in a given quarter.

3.   Data

Our data analysis builds primarily on three papers. Ehrmann, Eijffinger, and Fratzscher (2012) is a 12-country study of central bank transparency and private-sector forecast dispersion. The authors provide evidence that announcing a quantified inflation target and publishing inflation and output forecasts reduces dispersion. Naszodi et al. (2016) is a 26-country study of central bank transparency and both private-sector accuracy and forecast dispersion. The authors provide evidence that central bank transparency reduces both. Using the sample from Ehrmann (2015), Coenen et al. (2017) find that, during ELB periods, state-contingent forward guidance reduced disagreement and that time-contingent forward guidance reduced disagreement if guidance was provided over relatively long horizons.

3.1   Sample Group

Our sample group consists of 23 economies: 15 advanced economies (Australia, Canada, the euro area, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the United Kingdom, and the United States) and 8 emerging market economies (Czech Republic, Hungary, Indonesia, Poland, Russia, Slovakia, South Korea, and Turkey). The sample group was chosen based on a number of criteria. First, we seek to maintain comparability to the literature. This sample group heavily overlaps with those from Capistrán and Ramos-Francia (2010), Ehrmann, Eijffinger, and Fratzscher (2012), Ehrmann (2015), and, especially, Naszodi et al. (2016). Second, we chose central banks that are, *at present*, judged to be particularly transparent (see, for example, Eijffinger and Geraats 2006 and Dincer and Eichengreen 2014). Such central banks are more likely to provide an array of central bank forecasts at some point in the sample period, thereby providing the data needed to test the effects of different types of central bank projections. Despite this, the sample group also provides some useful heterogeneity in terms of

transparency. As judged by the Dincer and Eichengreen (2014) central bank transparency index, scores range from 6.5 (Norway, early years) to 15 (Sweden, recent years). These scores have been trending upward as central banks release more and more macroeconomic projections and explain monetary policy decisions in greater detail. Third, historical macroeconomic data for each country are available from the Main Economic Indicators database on the Organisation for Economic Co-operation and Development (OECD) website, which allows us to use one data set to compute the forecast errors and conditional volatility for all countries and all periods.

3.2   Dependent Variables: Private-Sector Forecast Data

All private-sector forecast data come from Consensus Economics. The data are composed of point forecasts primarily from banks and economic research firms. We focus on private-sector forecasts of inflation, output, the three-month government bill rate, and the 10-year government bond yield. Each of the four types are forecasted at two horizons. In an attempt to reduce confusion, in this paper the term *projections* will always refer to *central bank* projections and the term *forecasts* will always refer to *private-sector* forecasts. The mean number of forecasts per sample is about 17 for output and inflation forecasts and about 11 for interest rate forecasts. Forecasts of the 10-year government bond yield are not available for some economies, such as the euro area, which of course, does not have a 10-year government bond. For the same reason, there is no Consensus Economics forecast of the euro-area three-month treasury bill either.[4] The survey participants are typically consistent over the sample period. Each of the four variables is forecasted at two horizons. The 3-month and 10-year yields are each projected 3 and 12 months into the future, respectively (fixed-horizon forecasts).[5] Both real gross domestic product (GDP) growth rates and inflation rates are forecasted on a full-year basis for both the current year and the next year (fixed-event forecasts).

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[4]The results are robust to the omission of the euro-area data (see the online appendix).

[5]More precisely, the projections are 3.5 and 12.5 months into the future, respectively.

To measure disagreement, we use the natural logarithm of the range, interdecile range, interquartile range, and standard deviation across all forecasters in country i and month t (each month corresponds to one quarter).[6] To measure forecast accuracy, we use the natural logarithm of the absolute value of the difference between the mean Consensus Economics forecast and the realized corresponding macroeconomic data (latest-available vintage).[7] The OECD's Main Economic Indicators database provided a rich data set of realized macroeconomic data for all of the countries in our sample group. The realized data for three-month government rates, 10-year yields, and WTI oil prices were obtained from Thomson Reuters Datastream.

3.3 Data Frequency

The forecast data are available on a monthly basis but, for the purposes of this study, are collapsed into a quarterly frequency. Hence, we use the survey results for every third month. This was done for two reasons. First, we better match the frequency of central bank projections, which, in general, are released quarterly. We hypothesize that the information effects conveyed by the release of central bank projections persist beyond just one month, probably for about one quarter.

Second, it would be very difficult to create a monthly version of our data. We choose Consensus Economics survey months to represent a given quarter so that they always *follow* the release of a central bank projection. This allows us to ensure that central bank projections could have influenced private-sector forecasts. For example,

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[6]The related forecast-dispersion literature uses a number of measures. Mankiw, Reis, and Wolfers (2003), Dovern, Fritsche, and Slacalek (2012), and Ehrmann, Eijffinger, and Fratzscher (2012) use interquartile range to avoid outliers. Naszodi et al. (2016) use standard deviation, which offers richer insight into the distribution but does include outliers. Ehrmann (2015), however, uses the interdecile range to gain a greater appreciation for changes in the full distribution while still excluding outliers (each 10 percent tail is discarded). In all cases, we use the natural logarithm of these measures of dispersion (see Lustenberger and Rossi 2020 for an explanation of how this leads to better-behaved residuals).

[7]This approach to measuring forecast accuracy is closely aligned with that of Ehrmann, Eijffinger, and Fratzscher (2012) and Naszodi et al. (2016). An alternate approach to calculating forecast error is to use the consensus forecast from December of a given year (akin to a nowcast) instead of the realized data. Our results are robust to this method (see the online appendix).

we begin by choosing the Consensus Economics surveys from April, July, and October of a given year, as well as January of the following year.[8] We attribute these surveys to the first, second, third, and fourth quarters of a given year, respectively.[9] In some cases, the central bank projection release date is known precisely, and in others it is known only approximately. For example, sometimes it was only possible to narrow the release date of a particular central bank projection down to a particular month. Although the approximate timing was adequate to assign central bank projections to their appropriate quarter, this would not be true for a monthly data frequency.

We then refine this survey forecast month selection approach in an additional step. We attempt to select the survey month that most immediately follows the corresponding central bank projections. Often, the April, July, October, and January survey months are appropriate for doing so (as discussed above). In many cases, however, a central bank released a projection early in the quarter and not again until the next quarter. In such cases, wherever practical, we choose a survey month earlier in the quarter to maintain roughly the same proximity between the central bank projection release and private-sector forecast release.[10] Accordingly, in some cases, the selection of survey month necessarily varies across country and time. Over the sample period, central banks occasionally release their projections in different months and at different frequencies. The patterns of these releases are very consistent within countries, but there are nonetheless many instances in which they vary. For example, in 2000 and 2001, the Bank of Canada released its projections in February, before switching to January for the rest of our sample period. In such cases, we are then forced to change the usual Consensus Economics survey month that we use for that

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[8]Each Consensus Economics survey is conducted near the beginning of the month.

[9]This is very similar to the approach taken by Andrade et al. (2016) to construct quarterly survey data from Blue Chip Financial Forecasts. For the fixed-event inflation and output forecasts, we make an exception for the January survey, which would correspond to a different set of projected variable-years. Hence, for the Q4 forecast data, we revert to the survey from the month before, December.

[10]Overall, our timing strategy is similar to that from Hubert (2015a) and other related studies.

country to ensure that it follows the new central bank projection release date.

3.4 Central Bank Projections Data and Forward Guidance

We constructed a new data set that records whether central bank i released a given macroeconomic projection in quarter t between 1990:Q1 and 2017:Q2. These data were hand-collected from more than 2,400 economic projection releases over the sample period. We recorded the existence of six types of macroeconomic projections: inflation, domestic output, global output, unemployment, the output gap, and the policy rate. Each variable is a binary variable that takes the value of one when a macroeconomic projection was released by the central bank and zero otherwise. The primary source for these data are monetary policy reports, inflation reports, central bank bulletins, and other related central bank periodicals. For older forecasts, some of the periodicals were not available online, so to source the material, we reached out to a number of central banks, which kindly offered us their support.

Historically, central banks have often begun by first releasing inflation and domestic output projections, often following later with some combination of global output, unemployment, output gap, and, in some cases, policy rate projections (among other types of projections). Usefully, this release pattern varies widely from central bank to central bank. Some central banks chose to add extra types of projections only very gradually over time, while others decided to begin releasing a full suite of projections all at once. In general, the patterns of central bank releases are fairly systematic, but there is a great deal of variation both longitudinally and cross-sectionally. Over the years, central bank projection release patterns have changed. For instance, historically, releases switched frequency (e.g., from semiannually to quarterly) and schedule (e.g., from Q1 to Q2). This variation affords us a great deal of heterogeneity in this large data set, which is plotted in figure A.1 in the online appendix.

To assemble euro-area central bank projections and forward-guidance data, we took two basic approaches. First, for central bank projections, we used the domestic projections released by the national central banks. The private-sector forecasters in our sample

provide forecasts for their respective countries. We argue that when it comes to forecasting domestic output growth in the Netherlands, for example, central bank projections for the Netherlands are more relevant than projections for the euro area as a whole. Hence, when De Nederlandsche Bank provided domestic projections, we recorded this in our data. However, there is one important exception to this approach. We also included private-sector forecasts for the euro area as a whole in our sample. For this broader region, we used the projections for the euro area as a whole, which are provided by the European Central Bank (ECB). For forward guidance, we use the forward guidance of the ECB. That is, when the ECB released forward guidance, this forward guidance would be reflected not only in our euro-area data but also in our data for each euro-area country in our sample.[11] Because the ECB sets monetary policy for the euro area as a whole, ECB forward guidance should influence private-sector forecasts in each euro-area country.

We recorded all instances of output gap projections, but many central banks provide output gap estimates, so a key distinction must be made. Whereas some central banks only provide an estimate of the current output gap, others provide both this estimate and a projection. The purpose of this paper is to better understand the role of central bank projections in private-sector forecasts. So, for two reasons, we only scored output gap *projections* as a one and left aside *estimates*. Our hypothesis is that central bank projections of the future state of the economy affect private-sector forecast dispersion and/or forecast error. We also did so for consistency: all other central bank projections were counted as a one only when a forward-looking projection was provided.

We recorded all instances of forward guidance in each country. Central banks often provide discussions of the likely path of the policy rate or a policy bias in press releases. We scored all such cases as a one and a zero otherwise. To do this, we read all monetary policy press releases from each central bank in our sample period and assigned a score of one when forward guidance was used and zero otherwise. Forward guidance is often conceptualized as an unconventional monetary tool to be used at the effective lower bound. In

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[11]Naturally, the same logic applies for quantitative easing.

fact, forward guidance is often used during periods away from the effective lower bound.

We categorized each instance of forward guidance as having either time-contingent attributes, state-contingent attributes, qualitative attributes, or some combination thereof. In our scoring methodology, forward guidance is simply any statement that articulates the probable future stance of monetary policy.[12] Specifically, time-contingent forward guidance is a statement that provides information about the probable stance of monetary policy at a specific time in the future. State-contingent forward guidance is any forward-looking statement that provides information about the central bank's monetary policy reaction function that is either more specific than (e.g., quantitative) or substantially different from the central bank's mandate. Typically, this state is closely related to the central bank's inflation target, but in some cases it is not. Qualitative forward guidance is that which does not fall into either category but nonetheless meets the definition of forward guidance above.

Most examples of forward guidance are fairly clear, but, admittedly, it was necessary to use judgment in some cases.[13] Occasionally, central banks provided both a policy rate projection and time-contingent forward guidance, such as the Riksbank and the Reserve Bank of New Zealand. Most of the better-known cases of forward guidance are documented in Moessner and Nelson (2008), Campbell et al. (2012), Woodford (2013), Charbonneau and Rennison (2015), Kool and Thornton (2015), Obstfeld et al. (2016), and Moessner, Jansen, and de Haan (2017), so we record these accordingly. Whenever possible, we also relied on studies published by each central bank to corroborate our scoring (e.g., Andersson and Hofmann 2009, Brubakk, ter Ellen, and Xu 2017, and Coenen et al. 2017). Many less-frequently documented cases, such as forward guidance in Poland (see Baranowski and Gajewski 2016), Australia, and earlier instances in New Zealand, however, also merited scores of one. We offer some examples of forward guidance and how they were categorized below.

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[12] "Forward guidance in monetary policy means providing some information about future policy settings" Svensson (2015).

[13] For more in-depth discussion of the definitions of forward guidance, the forward-guidance literature, and forward-guidance examples, see Sutherland (2020), available online.

The Federal Open Market Committee is a good example because it has used all three types of forward guidance in its history. Earlier in the history of the Committee's use of forward guidance, it tended to favor qualitative forward guidance, such as this example from December 13, 2005:

> The Committee judges that some further measured policy firming is likely to be needed to keep the risks to the attainment of both sustainable economic growth and price stability roughly in balance.

The FOMC later introduced time-contingent forward guidance, such as this statement on August 9, 2011:

> The Committee currently anticipates that economic conditions—including low rates of resource utilization and a subdued outlook for inflation over the medium run—are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013.

Finally, the FOMC introduced perhaps the quintessential example of state-contingent forward guidance on December 12, 2012:

> To support continued progress toward maximum employment and price stability, the Committee expects that a highly accommodative stance of monetary policy will remain appropriate for a considerable time after the asset purchase program ends and the economic recovery strengthens. In particular, the Committee decided to keep the target range for the federal funds rate at 0 to 1/4 percent and currently anticipates that this exceptionally low range for the federal funds rate will be appropriate at least as long as the unemployment rate remains above 6-1/2 percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's 2 percent longer-run goal, and longer-term inflation expectations continue to be well anchored.

Of course, examples from other central banks abound. There are numerous examples of forward guidance in earlier years, such as this time-contingent forward guidance from the Reserve Bank of New Zealand (RBNZ) on September 1, 1997: "Our projections point to further, but quite small, easings in the first two quarters of

1998 before emerging inflationary pressures lead us to expect monetary conditions to enter another tightening phase." This particular RBNZ forward guidance was also released alongside a projection of the 90-day bank-bill yield. On April 12, 2005, the Bank of Canada used a good example of qualitative forward guidance: "In line with this outlook, a reduction of monetary stimulus will be required over time." On August 7, 2013, the Bank of England used the following state-contingent forward guidance: "In particular, the MPC intends not to raise Bank Rate from its current level of 0.5% at least until the Labour Force Survey headline measure of the unemployment rate has fallen to a threshold of 7%, subject to the conditions below."

We also consider policy rate projections and quantitative easing in our analysis. First, we recorded all instances when central banks released quantitative projections of their policy rates. Such projections are typically released in monetary policy reports. Rate projections were first released by the Reserve Bank of New Zealand (1997), then by Norges Bank (2005), followed by Sveriges Riksbank (2007), the Czech National Bank (2008), and most recently, by the FOMC (2012). These are identified as "Rate Projection" in the results tables. Second, we created a dummy variable indicating when a central bank was engaged in an active quantitative easing program. We define a quantitative easing program as the expansion of reserves to purchase bonds or other assets. The examples of quantitative easing in our sample include the Federal Reserve, the Bank of England, Sveriges Riksbank, the Bank of Japan, and the European Central Bank.

3.5   Control Variables

Conditional volatility is included because forecaster dispersion is likely to be higher in times of volatile macroeconomic conditions. Following Capistrán and Timmermann (2009), Capistrán and Ramos-Francia (2010), Ehrmann, Eijffinger, and Fratzscher (2012), and Naszodi et al. (2016), our conditional volatility measures are the predicted values from a GARCH(1,1) model of the realized data (π_{it} below) for a given country i and quarter t. We estimate the following model for each type of dependent variable (inflation, domestic

output, three-month rate, 10-year yield) in each country (23 countries times four types of dependent variable[14]:

$$\pi_{it} = \lambda_0 + \lambda_1 \pi_{i,t-1} + \lambda_2 \pi_{i,t-2} + \epsilon_{it} \tag{2}$$

$$\epsilon_{it} \sim N(0, \sigma_{it}^2) \tag{3}$$

$$\sigma_{i,t+1}^2 = \omega + \alpha_1 \epsilon_{it}^2 + \beta_1 \sigma_{it}^2. \tag{4}$$

In the mean equation, we include the first two lags of the relevant variable (e.g., realized inflation, or domestic output, etc.) as in Ehrmann, Eijffinger, and Fratzscher (2012) and Naszodi et al. (2016).

Similarly, Ehrmann, Eijffinger, and Fratzscher (2012) hypothesize that large changes in oil prices would also be associated with heightened forecaster uncertainty and therefore greater forecast dispersion. To maintain comparability to their model and that of Naszodi et al. (2016), we also include the absolute value of the change in the price of WTI oil from the end of one month to the next. We also hypothesize that financial market volatility might contribute to forecaster disagreement and test this by including the level of VIX. This variable is typically not included in other closely related studies, but we find that this control is usually significant (as do Lustenberger and Rossi 2020). Both the oil and VIX data were obtained from Thomson Reuters Datastream. We also include a binary variable for the financial crisis of 2008 to 2009 and we use the dates from Chor and Manova (2012) to create this variable.

As discussed, we include a control variable for inflation-targeting periods. All 23 central banks in our sample become inflation targeters at some point in the sample. Fortunately, the transition dates from non-inflation targeters to inflation targeters vary widely. As in most related studies (e.g., Capistrán and Ramos-Francia 2010, Crowe 2010, and Ehrmann, Eijffinger, and Fratzscher 2012), we use the date of adoption to mark the beginning of inflation targeting. The dates were gathered primarily from Roger and Stone (2005), Bank for International Settlements (2009), and Hammond (2012). The first central bank to adopt an inflation target, the Reserve

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[14]In our panel regressions, we use the same estimate of conditional volatility for both forecast horizons for a given type of dependent variable.

Table 1. Inflation-Targeting and Effective Lower Bound Periods by Central Bank

Country	Inflation Targeting	Effective Lower Bound
Australia	1993:Q1–2017:Q2	
Canada	1991:Q1–2017:Q2	2009:Q2–2010:Q2
Czech Republic	1998:Q1–2017:Q2	2012:Q4–2017:Q2
Euro Zone	1999:Q1–2017:Q2	2012:Q3–2017:Q2
France	1999:Q1–2017:Q2	2012:Q3–2017:Q2
Germany	1990:Q1–2017:Q2	2012:Q3–2017:Q2
Hungary	2001:Q2–2017:Q2	
Indonesia	2005:Q3–2017:Q2	
Italy	1999:Q1–2017:Q2	2012:Q3–2017:Q2
Japan	2012:Q1–2017:Q2	1999:Q3–2000:Q3
		2001:Q2–2006:Q2
		2016:Q1–2017:Q2
Netherlands	1999:Q1–2017:Q2	2012:Q3–2017:Q2
New Zealand	1990:Q1–2017:Q2	
Norway	2001:Q1–2017:Q2	
Poland	1998:Q1–2017:Q2	
Russia	2015:Q1–2017:Q2	
Slovakia	2005:Q1–2017:Q2	2012:Q3–2017:Q2
South Korea	1998:Q2–2017:Q2	
Spain	1995:Q1–2017:Q2	2012:Q3–2017:Q2
Sweden	1993:Q1–2017:Q2	2014:Q4–2017:Q2
Switzerland	2000:Q1–2017:Q2	2003:Q1–2004:Q2
		2009:Q2–2017:Q2
Turkey	2006:Q1–2017:Q2	
United Kingdom	1992:Q4–2017:Q2	2009:Q1–2017:Q2
United States	2012:Q1–2017:Q2	2012:Q3–2015:Q4

Bank of New Zealand, happened to do so in the first quarter of our 110-quarter sample (1990:Q1). The last central bank to adopt an inflation target in our sample, the Central Bank of the Russian Federation, did so in the first quarter of 2015. The other 21 transitions are scattered rather evenly across our sample period (see table 1).

Further, we created a control variable indicating whether a central bank was at the effective lower bound in a given quarter. Nearby

rates forecasts may become less dispersed and more predictable because the scope for rate cuts is effectively absent. Rate increases may also be perceived as less likely in the short term (particularly if forward guidance is employed, but this should be detected by our forward-guidance variables). Similarly, nearby macroeconomic forecasts might be less dispersed as low-growth, low-inflation periods are anticipated. Conversely, forecasters might disagree on how long economic conditions will take to stabilize and, for that matter, how long it will take for central banks to unwind highly accommodative monetary policy. This could actually result in *more* forecaster disagreement and error for longer-term forecasters. To detect these dynamics, we include an ELB variable in our panel regressions. The dummy variable takes the value of one when the policy rate reached either the *announced ELB*, or, in the absence of such a clear guideline, the zero lower bound. We searched central bank websites for announcements that quantify the ELB. There are numerous examples of central banks operating at an announced ELB in our sample, such as the Bank of Canada (2009–10) and, less explicitly, the European Central Bank (2014–17).

We also created an MPR (monetary policy report) dummy variable as well as a policy rate decision dummy variable. To create the MPR dummy, we went through our records and, where necessary, central bank websites, to determine when a central bank released its monetary policy report and when it did not. When the report was released, the MPR dummy takes the value of one and zero otherwise. There are some cases when the form of the MPR is less obvious than others. For example, for the Swiss National Bank, we use the press release as the monetary policy report. There are some other examples where we use, for example, an economic bulletin that strongly resembles a monetary policy report. This typically happens in earlier years. To create a policy rate decision dummy variable, we created three separate dummy variables and then combined them. First, we created a dummy variable to indicate when a scheduled policy rate decision occurred. Second, we created a dummy variable to indicate when an unscheduled policy rate decision occurred. Third, for earlier years before scheduled policy rate decision dates, we follow the approach of Champagne and Sekkel (2018) and consider that changes in the central bank's policy rate target variable (for example, a three-month Treasury-bill rate) are essentially de facto policy

rate decisions. We combine (sum) these three variables into our final policy rate decision dummy variable.

3.6   Central Bank Projections: Policy Rate Path Assumptions and Source

Many papers have argued that central bank projections that rely on an endogenous policy rate path assumption are more informative than those that use market-implied or constant policy rate path assumptions (e.g., Svensson 2006, Galí 2011, and Woodford 2013). Although there is a lively debate in the literature about this issue, the consensus appears to be that, at a minimum, central banks should make efforts to provide at least some information about their policy rate path assumptions (e.g., Goodhart 2009). With an endogenous rate path assumption, the public would, in theory, know that the central bank projections account for the likely policy response of that central bank to a given projected macroeconomic variable. Hence, the projection may be more realistic; it may be the central bank's best estimate of the progression of the projected macroeconomic variable. With an exogenous rate path assumption (i.e., a market-implied or constant rate), the assumed policy rate path may differ from the one the central bank would actually take given the projected evolution of the macroeconomic variables.

To the extent that the central bank may ultimately deviate from the assumed, exogenous path, and, to the extent that this deviation could affect the projected macroeconomic variables, the central bank's projection may be unrealistic. Accordingly, the projection may be less informative and ultimately increase private-sector forecast dispersion and/or private-sector forecast error. We attempt to test that hypothesis.

First, we recorded the rate path assumptions used by central banks in their projections. The projection rate path assumptions are primarily sourced from Hammond (2012). We must also account for the time-varying nature of these assumptions, as many central banks changed their policy rate assumption over our sample period (1990 to 2017). We update the data from Hammond (2012) with the central banks' respective monetary policy (inflation) reports and with discussion from Bank for International Settlements (2009), Woodford

(2013), and Hubert (2015a, 2015b). We categorize central bank projections into one of three categories: those that use an endogenous, a market-implied, or a constant policy rate path assumption.[15] We then use these categorizations to sort our benchmark panel regressions from equation (1) into three sample groups. These data are depicted in figure A.2 in the online appendix.[16]

The *source* of central bank projections may also be important to private-sector forecasters. Projections provided by monetary policy decisionmakers may be judged to have greater monetary policy signal content (Romer and Romer 2000 and Ellison and Sargent 2012). Alternatively, committee-provided projections may be perceived as less accurate than staff-produced forecasts (Romer and Romer 2008). At the same time, projections provided by monetary policy decisionmakers may be seen as biased (Romer and Romer 2008 and Ellison and Sargent 2012). One reason is that policymakers may have different information sets and heterogeneous preferences, as outlined in Hansen, McMahon, and Rivera (2014). To test some of these hypotheses, we gathered data on projection source from Hammond (2012), the central banks' respective monetary policy (inflation) reports, and discussion from Bank for International Settlements (2009), Woodford (2013), and Hubert (2015a). We categorized central bank projections into one of three types: committee provided (i.e., monetary policy decisionmakers), staff provided, or more generally, central bank provided. We then use these to sort our benchmark panel regressions from equation (1) into two groups: (i) monetary policy committee projections or (ii) central bank projections (i.e., staff projections or those from the central bank).

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[15]Central bank projections that use an endogenous policy rate path assumption are also referred to as unconditional forecasts in the literature, whereas those that use either a market-implied or a constant policy rate path assumption are also referred to as conditional forecasts in the literature.

[16]This figure also shows that the Bank of England releases two sets of projections: one set that uses a market-implied policy rate assumption and another set that uses a constant policy rate assumption. Initially, the Bank of England only released projections that used a constant policy rate assumption. Later, it added a second set that use a (in some cases more realistic) market-implied policy rate assumption.

4.　Results

Our benchmark results (equation (1)) can be found in table 2 and table 3. The results for the same regressions but using the natural logarithm of the range and standard deviation as the dependent variables (instead of the interdecile range) are shown in table 4 and table 5. The results for the natural logarithm of the interquartile range are included in the online appendix to economize on space. The results for the control variables can also be found in the online appendix.

4.1　Central Bank Policy Rate Projections

Many argue along the lines of Svensson (2015) that "a published policy rate should affect market expectations of future policy rates and thereby the yield curve and longer market rates that have an impact on economic agents' decision and this way contribute to a more effective implementation of monetary policy." To test this the idea, table 2 and table 3 each include a line for "Rate Projection." Overall, we find that the provision of central bank policy rate projections reduces neither private-sector forecast dispersion nor forecast error. In fact, when it comes to private-sector interest rate forecast dispersion, we find evidence that policy rate projections can actually increase forecaster disagreement.

　　More specifically, policy rate projections tended to increase dispersion particularly for short-term rate forecasts and particularly at short-term forecast horizons. This suggests that central bank policy rate projections probably have the most influence on private-sector forecasts of nearby policy rate decisions. The increase in dispersion is much more prominent when considering forecasts clustered toward the central portion of the forecast distribution. That is, the effect is most significant when using the interquartile range of short-term rates forecasts, less significant when using the interdecile range, and not significant when using the range or standard deviation (although the estimated effect is still positive).[17]

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[17]The results using the interquartile range are shown in the online appendix. Note that we use the natural logarithm of each of the aforementioned dispersion measures as the dependent variable in our regressions.

Table 2. Private-Sector Rate Forecasts: Natural Logarithm of the Forecast Dispersion and Absolute Forecast Error

| | 3-Month Government Bill Rate | | | | 10-Year Government Bond Yield | | | |
| | 3-Month Forecast Horizon | | 12-Month Forecast Horizon | | 3-Month Forecast Horizon | | 12-Month Forecast Horizon | |
	Dispersion (1)	Error (2)	Dispersion (3)	Error (4)	Dispersion (5)	Error (6)	Dispersion (7)	Error (8)
Inflation	−0.20**	−0.28*	−0.19**	−0.29**	−0.23***	−0.38*	−0.10	−0.23
	(0.09)	(0.14)	(0.07)	(0.12)	(0.07)	(0.21)	(0.07)	(0.16)
Output Gap	−0.14	−0.17	−0.06	−0.07	−0.06	0.16	−0.06	0.05
	(0.10)	(0.16)	(0.08)	(0.12)	(0.09)	(0.13)	(0.05)	(0.09)
Unemployment	0.15	0.45***	0.11	0.46***	0.19**	0.18	0.15*	0.20
	(0.09)	(0.14)	(0.08)	(0.16)	(0.08)	(0.18)	(0.08)	(0.16)
Rate Projection	0.21*	−0.01	0.19*	−0.13	0.06	−0.09	0.15	0.07
	(0.11)	(0.23)	(0.11)	(0.22)	(0.08)	(0.17)	(0.09)	(0.16)
FG Time Contingent	−0.17	0.04	−0.14	0.29	−0.07	−0.00	−0.19*	0.11
	(0.14)	(0.20)	(0.11)	(0.25)	(0.06)	(0.16)	(0.09)	(0.13)
FG Qualitative	−0.02	−0.11	−0.09	−0.16	0.01	0.04	−0.01	0.08
	(0.09)	(0.07)	(0.06)	(0.11)	(0.03)	(0.06)	(0.03)	(0.09)
FG State Contingent	0.17	0.19	0.06	−0.33*	−0.09	0.09	−0.13**	0.11
	(0.15)	(0.18)	(0.12)	(0.17)	(0.06)	(0.16)	(0.05)	(0.10)
Quantitative Easing	−0.27	0.08	−0.34	0.45	−0.01	−0.01	0.01	−0.15
	(0.22)	(0.34)	(0.24)	(0.27)	(0.08)	(0.09)	(0.05)	(0.11)
Effective Lower Bound	−0.33**	0.02	−0.18**	−0.25	0.14*	0.24	0.24***	0.27*
	(0.15)	(0.15)	(0.08)	(0.18)	(0.07)	(0.16)	(0.05)	(0.14)
Adjusted R^2	0.42	0.22	0.49	0.27	0.27	0.30	0.25	0.40
N	1,864	1,827	1,868	1,761	1,536	1,505	1,536	1,457

Notes: Panel regressions with country and quarterly fixed effects. Standard errors (parentheses) are clustered by country. Control variables are suppressed. Column interpretation: "3-Month Government Bill Rate, 3-Month Forecast Horizon (Dispersion)": In this case the dependent variable is the natural logarithm of the interdecile range of *private forecasts* of the three-month government bill rate in three months' time. Row interpretation: rows correspond to binary variables indicating the presence of a *central bank projection*, forward guidance, quantitative easing, or the effective lower bound. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Private-Sector Macro Forecasts: Natural Logarithm of the Forecast Dispersion and Absolute Forecast Error

| | Inflation Rate | | | | Real Gross Domestic Product | | | |
| | Current-Year Forecast | | Next-Year Forecast | | Current-Year Forecast | | Next-Year Forecast | |
	Dispersion (1)	Error (2)	Dispersion (3)	Error (4)	Dispersion (5)	Error (6)	Dispersion (7)	Error (8)
Inflation	-0.14	-0.08	-0.11	-0.36*	-0.10*	-0.26*	-0.11**	-0.16
	(0.11)	(0.13)	(0.09)	(0.18)	(0.05)	(0.15)	(0.05)	(0.14)
Output Gap	-0.13	-0.23	-0.16	0.04	-0.03	0.19	-0.07	0.02
	(0.11)	(0.15)	(0.10)	(0.16)	(0.05)	(0.12)	(0.05)	(0.17)
Unemployment	0.03	0.12	0.06	0.22	0.19***	0.13	0.06	0.37**
	(0.15)	(0.17)	(0.13)	(0.20)	(0.05)	(0.15)	(0.06)	(0.14)
Rate Projection	-0.28	-0.37	-0.19	-0.47	-0.07	-0.18	-0.00	0.11
	(0.22)	(0.32)	(0.20)	(0.29)	(0.07)	(0.18)	(0.07)	(0.26)
FG Time Contingent	0.12	0.04	0.12	0.15	0.08	0.21	0.01	-0.08
	(0.12)	(0.15)	(0.12)	(0.20)	(0.08)	(0.21)	(0.07)	(0.18)
FG Qualitative	-0.00	0.04	0.03	0.04	-0.03	0.12	-0.05	-0.12
	(0.06)	(0.10)	(0.05)	(0.11)	(0.03)	(0.09)	(0.04)	(0.11)
FG State Contingent	-0.07	-0.15	-0.03	-0.22*	-0.01	0.20	-0.12	0.02
	(0.10)	(0.15)	(0.08)	(0.12)	(0.04)	(0.25)	(0.07)	(0.18)
Quantitative Easing	0.25*	0.29*	0.12	-0.11	0.08	-0.03	0.05	-0.36
	(0.12)	(0.17)	(0.09)	(0.22)	(0.08)	(0.16)	(0.05)	(0.22)
Effective Lower Bound	-0.08	-0.03	0.12	0.20	0.04	-0.20	0.18***	-0.23
	(0.19)	(0.13)	(0.11)	(0.16)	(0.04)	(0.15)	(0.06)	(0.20)
Adjusted R^2	0.28	0.24	0.25	0.17	0.55	0.16	0.29	0.22
N	2,070	2,026	2,079	1,934	1,971	1,929	1,971	1,841

Notes: Panel regressions with country and quarterly fixed effects. Standard errors (parentheses) are clustered by country. Control variables are suppressed. Column interpretation: "Inflation Rate, Current-Year Forecast (Dispersion)": In this case the dependent variable is the natural logarithm of the interdecile range of *private forecasts* of the inflation rate (current year). Row interpretation: rows correspond to binary variables indicating the presence of a *central bank projection*, forward guidance, quantitative easing, or the effective lower bound. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Private-Sector Rate Forecasts: Natural Logarithm of the Forecast Range and Standard Deviation (S.D.)

| | 3-Month Government Bill Rate | | | | 10-Year Government Bond Yield | | | |
| | 3-Month Forecast Horizon | | 12-Month Forecast Horizon | | 3-Month Forecast Horizon | | 12-Month Forecast Horizon | |
	Range (1)	S.D. (2)	Range (3)	S.D. (4)	Range (5)	S.D. (6)	Range (7)	S.D. (8)
Inflation	−0.20*	−0.25**	−0.18**	−0.17**	−0.22***	−0.24***	−0.09	−0.13*
	(0.10)	(0.09)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
Output Gap	−0.16	−0.11	−0.10	−0.10	−0.08	−0.07	−0.05	−0.05
	(0.10)	(0.12)	(0.08)	(0.07)	(0.09)	(0.08)	(0.06)	(0.05)
Unemployment	0.15	0.24**	0.10	0.11	0.19**	0.20**	0.11	0.14*
	(0.12)	(0.10)	(0.08)	(0.07)	(0.08)	(0.09)	(0.06)	(0.08)
Rate Projection	0.14	0.14	0.10	0.13	0.04	0.04	0.14	0.13
	(0.14)	(0.11)	(0.10)	(0.09)	(0.10)	(0.08)	(0.09)	(0.09)
FG Time Contingent	−0.25*	−0.26	−0.14	−0.12	−0.06	−0.04	−0.21**	−0.15**
	(0.15)	(0.17)	(0.12)	(0.10)	(0.09)	(0.06)	(0.08)	(0.06)
FG Qualitative	−0.03	−0.09	−0.08*	−0.08*	0.02	0.00	0.01	−0.00
	(0.08)	(0.11)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
FG State Contingent	0.14	−0.21	0.01	0.03	−0.09	−0.09	−0.13***	−0.13***
	(0.14)	(0.28)	(0.11)	(0.10)	(0.05)	(0.05)	(0.03)	(0.04)
Quantitative Easing	−0.21	−0.42	−0.27	−0.29	−0.01	−0.02	0.02	0.01
	(0.20)	(0.28)	(0.19)	(0.19)	(0.08)	(0.07)	(0.07)	(0.06)
Effective Lower Bound	−0.28**	−0.09	−0.14*	−0.16**	0.13*	0.16**	0.18***	0.22***
	(0.13)	(0.20)	(0.07)	(0.07)	(0.07)	(0.06)	(0.04)	(0.04)
Adjusted R^2	0.43	0.21	0.50	0.52	0.26	0.31	0.23	0.28
N	1,866	1,867	1,869	1,869	1,536	1,536	1,536	1,536

Notes: Panel regressions with country and quarterly fixed effects. Standard errors (parentheses) are clustered by country. Control variables are suppressed. Column interpretation: "3-Month Government Bill Rate, 3-Month Forecast Horizon (S.D.)": In this case the dependent variable is the natural logarithm of the standard deviation of *private forecasts* of the three-month government bill rate in three months' time. Row interpretation: rows correspond to binary variables indicating the presence of a *central bank projection*, forward guidance, quantitative easing, or the effective lower bound. $*p < 0.10$, $**p < 0.05$, $*** p < 0.01$.

Table 5. Private–Sector Macro Forecasts: Natural Logarithm of the Forecast Range and Standard Deviation

	Inflation Rate				Real Gross Domestic Product			
	Current-Year Forecast		Next-Year Forecast		Current-Year Forecast		Next-Year Forecast	
	Range (1)	S.D. (2)	Range (3)	S.D. (4)	Range (5)	S.D. (6)	Range (7)	S.D. (8)
Inflation	−0.13	−0.14	−0.11	−0.12	−0.13***	−0.13***	−0.06	−0.10*
	(0.09)	(0.10)	(0.09)	(0.09)	(0.04)	(0.05)	(0.06)	(0.05)
Output Gap	−0.15	−0.13	−0.14	−0.14	−0.02	−0.00	−0.06	−0.05
	(0.11)	(0.10)	(0.10)	(0.10)	(0.04)	(0.04)	(0.05)	(0.04)
Unemployment	−0.03	0.01	0.01	0.05	0.09*	0.12**	−0.05	0.02
	(0.14)	(0.13)	(0.13)	(0.13)	(0.05)	(0.05)	(0.06)	(0.06)
Rate Projection	−0.26	−0.27	−0.26	−0.22	−0.13*	−0.09	−0.11	−0.06
	(0.24)	(0.23)	(0.21)	(0.20)	(0.07)	(0.07)	(0.07)	(0.07)
FG Time Contingent	0.18	0.16	0.13	0.13	0.10	0.08	−0.02	−0.02
	(0.14)	(0.13)	(0.13)	(0.13)	(0.06)	(0.06)	(0.08)	(0.06)
FG Qualitative	0.01	0.01	0.02	0.03	−0.02	−0.00	−0.02	−0.03
	(0.07)	(0.07)	(0.05)	(0.05)	(0.03)	(0.03)	(0.05)	(0.05)
FG State Contingent	−0.04	−0.04	0.01	−0.01	0.06	0.03	−0.08	−0.09
	(0.07)	(0.07)	(0.09)	(0.08)	(0.04)	(0.04)	(0.06)	(0.06)
Quantitative Easing	0.13	0.13	0.12	0.12	0.06	0.05	0.03	0.02
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.06)	(0.05)
Effective Lower Bound	0.09	0.11	0.13	0.15	0.06	0.07	0.13	0.17**
	(0.10)	(0.10)	(0.11)	(0.11)	(0.06)	(0.05)	(0.08)	(0.06)
Adjusted R^2	0.45	0.49	0.24	0.28	0.52	0.58	0.25	0.33
N	2,079	2,079	2,079	2,079	1,971	1,971	1,971	1,971

Notes: Panel regressions with country and quarterly fixed effects. Standard errors (parentheses) are clustered by country. Control variables are suppressed. Column interpretation: "Inflation Rate, Current-Year Forecast (S.D.)": In this case the dependent variable is the natural logarithm of the standard deviation of *private forecasts* of the inflation rate for the current year. Row interpretation: rows correspond to binary variables indicating the presence of a *central bank projection*, forward guidance, quantitative easing, or the effective lower bound. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

An interesting and important caveat is in order. In the first half of our sample (pre-2006), rate projections actually reduced dispersion and forecast error. Again, the effect is most prominent for short-term rates and at shorter forecast horizons. For context, this estimated (pre-2006) effect should be dominated by the policy rate forecast of the Reserve Bank of New Zealand (released from 1997 onward). In the second half of our sample (2006 and beyond), the availability of policy rate projections tended to increase forecast dispersion and error. This latter half of the sample includes policy rate projections from all countries that released them in our sample.

A number of alternatives could explain this observed effect. Perhaps central bank policy rate projections ceased to lower forecast dispersion and error at some point (with the effect eventually transitioning from negative to positive). The global financial crisis and, later, the European financial crisis took place in the latter half of our sample period, so although we adjust for three forms of volatility and include a dummy variable for the global financial crisis, higher levels of uncertainty may influence the interpretation of policy rate projections. Mokhtarzadeh and Petersen (2017) perform an experimental study that considers how particular central bank projections affect macroeconomic expectations. The authors find that in relatively certain periods (low variability in aggregate-demand shocks), central bank policy rate projections tend to improve subjects' forecasts. In relatively uncertain periods (high variability in aggregate-demand shocks), central bank policy rate projections may become more difficult to interpret.

Central bank policy rate projections could also lose credibility over time if they have proven to be inaccurate in the past.[18] Market-implied policy rate paths (e.g., those extracted from forward-rate curves) frequently differ from central banks' policy rate paths. Svensson (2015) demonstrates these discrepancies in the United States, New Zealand, and, especially, Sweden. In particular, the paper argues that the Sveriges Riksbank's policy rate path projections were not credible in September 2011 and other subsequent

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[18]"The public might focus on, say, a projected interest rate one year ahead, and become disillusioned when, inevitably, the forecast turned out to be inaccurate" Sims (2010, p. 176).

periods.[19] It is possible that the policy rate projections of the Norges Bank (introduced 2005), the Sveriges Riksbank (2007), the Czech National Bank (2008), and the FOMC (2012) tended to increase forecast dispersion while those of the Reserve Bank of New Zealand (1997) tended to decrease forecast dispersion. This seems unlikely, however, given that Svensson (2015) also found discrepancies between the policy rate projections of the Reserve Bank of New Zealand and the market-implied policy rate paths.

Another possibility is that other information communicated simultaneously by the central bank (e.g., central bank projections, forward guidance, the text from monetary policy reports, the text from press releases, the dialogue in press conferences, etc.) dominates these quantitative projections, as policy rate path projections are often accompanied by verbal forward guidance as well.[20]

Finally, the inclusion of wide confidence intervals around central banks' rate path projections could add too much noise to the signal.[21] Whatever the underlying reason, the evidence presented in this paper suggests that policy rate path projections do little to reduce forecast dispersion and forecast error, and in the case of interest rate forecasts, even increase dispersion and error. These possibilities do not, however, necessarily imply that central banks' policy rate path projections do not affect policy rate expectations more broadly. Brubakk, ter Ellen, and Xu (2017), for example, find that policy rate projections provided by the Norges Bank and Sveriges Riksbank succeeded in guiding market-implied interest rate projections in the desired direction.

The effect of policy rate projections on private-sector inflation and domestic output forecasts is less clear. Policy rate projections may decrease both forecast dispersion and error for private-sector

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[19]Svensson (2015, p. 28) defines credibility as "the extent to which market expectations are in line with the published interest rate path, regardless of whether the interest rate path is appropriate in achieving the monetary policy objectives."

[20]"But central banks that have taken this course have done so in the context of detailed, regularly updated, inflation reports, of which interest rate forecasts are only one element, and often not the most newsworthy one" Sims (2010, p. 176).

[21]"Interest rate forecasts are usually displayed as 'fan charts' that inhibit their interpretation as simple numerical targets" Sims (2010, p. 176).

inflation forecasts (at both horizons), but the corresponding standard errors are too large to draw any meaningful conclusions. Overall, policy rate projections have had an unclear effect on private-sector growth forecasts. In the first half of our sample, policy rate projections appeared to reduce the dispersion of private-sector growth forecasts, especially for the current-year forecasts (see the online appendix). This suggests that, during this subsample at least, policy rate projections provided information to private-sector forecasters about the outlook for the economy.

4.2 Central Bank Inflation, Output Gap, and Unemployment Projections

Overall, central bank inflation projections have tended to reduce both the forecast dispersion and forecast error of private-sector interest rate forecasts (table 2). Central bank inflation projections also appear to have reduced dispersion and forecast error of private-sector macroeconomic forecasts, but the effect is not as strong. That central bank inflation projections appear to have more influence over private-sector interest rate forecasts suggests that inflation projections may primarily be used by private-sector forecasters to help forecast the path of monetary policy.

Central bank unemployment projections actually appear to increase private-sector disagreement and forecast error. Again, the effect is stronger for private-sector interest rate forecasts. The effect of unemployment projections on interest rate forecasts appears to be driven, to some extent, by projections using a constant policy rate assumption, the first half of the sample (pre-2006), and forecasts coming from the Monetary Policy Committee. One possibility is that some private-sector forecasters perceive unemployment projections as less important to inflation-targeting central banks than, for example, inflation projections or policy rate projections. As such, the interpretation of these projections may be particularly diffuse.

Overall, central bank output gap projections appear to have fairly weak influence on private-sector forecast disagreement and forecast error. The majority of coefficients on output gap projections are negative, but the standard errors are large. This is a somewhat surprising result because output gap projections often feature

heavily in central bank communication. In principle, output gap projections should be rather important for the future path of monetary policy. In light of this, more research on the influence of output gap projections, such as that in Mokhtarzadeh and Petersen (2017) and Champagne, Poulin-Bellisle, and Sekkel (2018) would be useful.

4.3 Forward Guidance

Overall, we find that forward guidance tends to reduce private-sector interest rate forecast dispersion and forecast error. This is apparent in table 2 and is clearer in table 4. By contrast, table 3 and table 5 show that forward guidance does not appear to significantly reduce inflation or domestic output forecast disagreement or error. This suggests that although central banks can reduce forecaster disagreement about the future path of monetary policy, it may be more difficult to reduce forecaster disagreement about future inflation rates and domestic output growth. Why might this be?

Andrade et al. (2019) find that when the Federal Reserve used time-contingent forward guidance, private-sector short-term interest rate forecast disagreement fell to a historical low. That is, forecasters agreed that the policy rate would remain low for long. Interestingly, when the authors analyzed how those same forecasters revised their macroeconomic forecasts, they observed two distinct groups. One group, optimistic forecasters, tended to revise their macroeconomic forecasts upward. A second group, pessimistic forecasters, tended to revise their macroeconomic forecasts downward. In other words, although these two groups of forecasters were exposed to the same central bank signal, they arrived at two different conclusions about what this meant for the future state of the economy.

This implies that, using the terminology of Campbell et al. (2012), dovish forward guidance, for example, can be *Odyssean* and signal a more accommodative stance of monetary policy in the future, which is good news, or it can be *Delphic* and signal that the macroeconomic outlook is worse than previously understood, which is bad news. Andrade et al. (2019) is confined to the United States and to the few years following the global financial crisis. The results shown in this paper, which considers data that span 23 countries and over 27 years, suggests that the forecaster heterogeneity observed in Andrade et al. (2019) is likely to be a more general phenomenon. As

such, central banks should take great care in crafting their communication to avoid inadvertently providing Delphic forward guidance instead of the intended Odyssean forward guidance.

Notably, these reductions in dispersion and error are not especially limited to or concentrated within any particular attribute of forward guidance. It is somewhat surprising that it was not possible to detect that three different approaches to forward guidance lead to distinct outcomes. As such, some more research on the influence of forward guidance and its attributes, such as that in working papers Coenen et al. (2017) and Sutherland (2020), would be useful. Although not the focus of this paper, it is interesting to note that quantitative easing does not appear to influence private-sector forecast disagreement very much. Subsample analysis suggests that the quantitative easing results vary greatly by country, however, so a country-by-country approach would probably be better. Interestingly, at the effective lower bound, private-sector forecast dispersion of the three-month Treasury-bill rate is lower, but forecast dispersion of the 10-year Treasury-bond yield is higher.

4.4   Central Bank Policy Rate Assumptions

Many argue that an endogenous policy rate path assumption in projections should be more informative than an exogenous one. The results shown in our online appendix, however, suggest that endogenous rate path assumptions are no more useful for professional forecasters at least. Our estimates show that the magnitudes of reduction in forecast dispersion and forecast accuracy associated with each type of policy rate assumption—although negative, statistically significant, and economically significant in many cases—are, in general, statistically indiscernible from one another. Our results are also broadly consistent with results from Knüppel and Schultefrankenfeld (2017). To study this issue, the authors compare the predictive accuracy of Bank of England projections with those of the Banco Central do Brasil and find no statistical difference. From this, the authors conclude that "the choice of the interest rate assumption appears to be of minor relevance empirically." Our results, which are based on a much larger sample group and sample period, are aligned with this conclusion and suggest that the policy rate path assumption may not be so important after all.

4.5   The Source of Central Bank Projections

Similar to the results discussed above, we find that projections provided by monetary policy decisionmakers do not have any greater impact than those provided by the staff or the central bank more generally (these results are included in the online appendix). What might explain these results? One interpretation is that projections are already a source of noisy information (Sims 2003). The macroeconomic projection, regardless of rate path assumption, is still the central bank's published projection. The difference in projection source or rate path assumption may simply make an already noisy signal only slightly more or less noisy.[22] The overall value of central bank projections as monetary policy signals may remain intact regardless of the policy rate path assumption or projection source.

4.6   Does the Number of Central Bank Projections Matter?

We have already considered how particular central bank projections influenced private-sector forecasts. What about the aggregate effect of numerous central bank projections? When central banks provide a whole set of projections, does this provide more information than merely providing one or two important projections, such as inflation or output? To analyze this question, we create a new variable that simply counts the number of projections released by a given central bank in a given quarter. To do so, we sum our six binary central bank projections variables. Accordingly, the minimum value is zero and the maximum value is six.

We find that, in general, the more central bank projections a central bank provided, the lower forecast dispersion and forecast error tended to be (see the online appendix for details). This result is strongest for private-sector inflation forecast dispersion and error. Perhaps a larger suite of central bank projections allows private-sector forecasters to understand the assumptions underlying, say, a central bank's inflation projection. This display of technical ability

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[22] "Since people are unlikely to have loss functions that make minor deviations of forecast from actual interest rates important to them, they are unlikely to focus narrow attention on interest rate point forecasts when these are just one part of a richer presentation of information" Sims (2010, p. 176).

could not only increase the credibility of a given central bank projection but also allow private-sector forecasters to compare the central bank's other macroeconomic assumptions with each of their own. To the extent that central banks have strong analytical capabilities, a larger set of central bank projections could also help private-sector forecasters better understand the prevailing macroeconomic landscape and thereby improve their forecasts.

4.7   Limitations

Before concluding, we must acknowledge two key limitations. First, in this paper the provision of different macroeconomic projections are scored as dummy variables (as in much of the literature; see Ehrmann, Eijffinger, and Fratzscher 2012, Naszodi et al. 2016, Coenen et al. 2017). We are unable to distinguish between the provision of output and inflation forecasts as, for the majority of central banks, they have always been released together. Hence, the significance we see on the inflation coefficient also captures the provision of output projections.

Second, there may be an endogeneity issue related to forward guidance. By definition, forward guidance—an unconventional monetary policy tool—is often released in times of financial or economic stress. As such, it is difficult to isolate the true ceteris paribus effects of the provision of forward guidance. However, this issue should make it more, not less, difficult to observe reductions in forecast disagreement because forward guidance should tend to coincide with times of greater uncertainty and likely greater forecaster disagreement.

5.   Conclusion

In this paper, we have presented estimates of the effect of publishing various types of central bank projections and forward guidance on private-sector forecast disagreement and forecast error. We draw a number of conclusions. First, we find that the provision of central bank policy rate projections reduces neither private-sector forecast dispersion nor forecast error. In fact, when it comes to private-sector interest rate forecast dispersion, we find evidence that central bank policy rate projections can actually increase forecaster disagreement.

It could be that policy rate projections are difficult to interpret, especially in periods of heightened macroeconomic uncertainty. Central bank policy rate projections could also lose credibility over time if they have proven to be inaccurate in the past. Another possibility is that any signal conveyed by policy rate projections is dampened by the flood of information simultaneously released by central banks. Additionally, the inclusion of wide confidence intervals around central banks' policy rate projections could add too much noise to the signal.

We also studied central bank inflation projections and found that they have tended to reduce both the forecast dispersion and forecast error of private-sector interest rate forecasts. That central bank inflation projections appear to have more influence over private-sector interest rate forecasts than macroeconomic forecasts suggests that inflation projections may primarily be used by private-sector forecasters to help forecast the path of monetary policy. Central bank unemployment projections actually appear to increase private-sector disagreement and forecast error. One possibility is that private-sector forecasters perceive unemployment projections as less important to inflation-targeting central banks than, for example, inflation projections or forward guidance. Surprisingly, central bank output gap projections appear to have fairly weak influence on private-sector forecast disagreement and forecast error. Nonetheless, the more projections a central bank released, the lower private-sector forecast dispersion and error tended to be, particularly for private inflation forecasts. This suggests that a larger set of central bank projections indeed provides more information.

We also find that forward guidance tends to reduce private-sector interest rate forecast dispersion and forecast error, but it does not appear to significantly reduce inflation or domestic output forecast disagreement or error. These results add to the evidence provided by Andrade et al. (2019) that when the Federal Reserve used time-contingent forward guidance, private-sector short-term interest rate forecast disagreement fell to a historical low but some of those same forecasters revised their macroeconomic forecasts in opposite directions. One group, optimistic forecasters, tended to revise their macroeconomic forecasts upward. A second group, pessimistic forecasters, tended to revise their macroeconomic forecasts downward.

Using the terminology of Campbell et al. (2012), forward guidance can be *Odyssean* and signal a more accommodative stance of monetary policy in the future, which is good news, or it can be *Delphic* and signal that the macroeconomic outlook is worse than previously understood, which is bad news. Our paper suggests that the forecaster heterogeneity observed in the United States after the financial crisis in Andrade et al. (2019) is likely to be a more general phenomenon. As such, central banks should take great care in crafting their communication to avoid inadvertently providing Delphic forward guidance instead of the intended Odyssean forward guidance.

Finally, there are ongoing debates in the literature about whether a central bank should release its policy rate projection and about what policy rate path assumption a central bank should use in its macroeconomic projections. We conclude that neither choice appears to have much influence on private-sector forecast disagreement or forecast error. At least when glimpsed through the lens of private-sector forecasts, these particular central bank communication choices are not obvious.

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Credit Risk, Liquidity, and Lies[*]

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We examine the relative effects of credit risk and liquidity in the interbank market using bank-level panel data on LIBOR submissions and CDS spreads, allowing for the possibility that LIBOR-submitting firms may strategically misreport their funding costs. We find that interbank spreads were very sensitive to credit risk at the peak of the crisis. However, liquidity premiums constitute the bulk of those spreads on average, and Federal Reserve interventions coincide with improvements in liquidity at short maturities. Accounting for misreporting, which is large at times, is important for obtaining these results.

JEL Codes: E43, G21, L14.

1.   Introduction

Bank funding markets came under extraordinary pressure during the financial crisis that began in 2007, threatening both the stability of important financial institutions and the functioning of the financial system as a whole. Because of the critical role of these markets in financial stability and monetary transmission, central banks around the world responded with a number of emergency measures. These

included both efforts to inject funds directly into short-term markets, intended to relieve *liquidity* strains, and efforts to ensure the solvency of the banking system, intended to reduce perceptions of *credit risk*. In this paper, we empirically investigate the extent to which these two factors drove interbank pressures during the crisis in order to shed light on the functioning of this market and, by extension, the potential efficacy of policy interventions.

We add to the literature investigating the relative importance of credit risk and liquidity by exploiting cross-bank and term structure dimensions of the data. The richness of our large panel data set greatly increases the power and flexibility of our identification relative to pure time-series approaches, such as Taylor and Williams (2009). In particular, it allows us to examine differences in liquidity conditions across maturities and changes over time in the degree to which credit risk passes through to interbank spreads. Our main finding is that although interbank spreads were very sensitive to counterparty credit risk at the height of the crisis, liquidity premiums constitute the bulk of those spreads on average. Furthermore, Federal Reserve interventions designed to bolster funding markets coincided with improvements in liquidity at short maturities. These results help to reconcile papers like Afonso, Kovner, and Schoar (2011) and Angelini, Nobili, and Picillo (2011), which ascribe a large importance to credit risk during the crisis, with papers like Acharya and Merrouche (2013), McAndrews, Sarkar, and Wang (2017), and Schwarz (2019), which emphasize liquidity hoarding and the effectiveness of central bank liquidity programs. We find that both credit risk and liquidity have been important in different contexts.

We measure bank funding costs using individual banks' submissions to the London interbank offered rate (LIBOR) panel across a spectrum of maturities over the period 2007–13, and we measure the same banks' credit risk using credit default swaps (CDS) written on their debt. A key innovation of our paper is to match these two data sources as closely as possible to each other while taking care to address the various sources of measurement error that arise at this level of granularity. For instance, the five-year CDS spread is commonly used in the literature to measure interbank credit risk because of that contract's superior liquidity, but five-year credit risk may differ substantially from the short-term credit risk that is relevant for interbank contracts. We use all available CDS quotes on

each day to estimate the entire term structure of credit risk, allowing us to match the maturity of each bank's reported funding costs exactly while still incorporating as much information as possible. A separate measurement issue concerns the well-publicized attempts of panel banks to manipulate the LIBOR data during this time. Previous studies in this liquidity versus credit risk literature that have used LIBOR as a measure of funding costs have largely ignored this complication, potentially biasing their results. We construct a model that accounts for misreporting incentives, and build it into our estimation to control for and measure these effects.

To identify the time-varying liquidity and credit risk components of interbank spreads across maturities, we apply state-space methods to our panel data. We calculate how large and volatile each of the two components was and show how they changed with market conditions, including Federal Reserve interventions. Over our sample, the estimated liquidity premium constitutes the majority of the funding spread (on average) at most maturities. It tends to be larger at longer maturities than at short maturities, consistent with Gorton, Metrick, and Xie (2014), who argue that lenders in money markets shifted from long to short maturities during the crisis. During the time that Federal Reserve liquidity facilities were in force, our measures of liquidity premiums dropped significantly for the maturities at which those programs were targeted. For example, when the Term Auction Facility (TAF), which primarily extended 28-day loans, expanded rapidly in 2008, our one-month liquidity premium plunged by over 100 basis points, but liquidity premiums at longer maturities did not decline. We do find that credit risk has been important at times; for example, it accounted for most of the spike in interbank spreads around the failure of Lehman Brothers in September 2008 and most of the decline in spreads after the Federal Reserve's bank "stress tests" in May 2009. But for much of the subsequent sample, the sensitivity of funding costs to CDS spreads was close to zero. Consequently, on average this component makes up only about a fifth of the aggregate interbank spread.

Although the aggregate LIBOR rate is perhaps the most widely used interest rate benchmark in the world, the underlying microdata have been relatively unexploited by researchers. Instead, in previous bank-level studies, the most common method for measuring rates paid by banks to each other is to infer them from funds

transfers in payments-systems records, as in Furfine (1999). However, recent research suggests that the payments-based procedure may suffer from significant measurement error in some situations (see Armantier and Copeland 2012 and also Kovner and Skeie 2013). In addition, that approach cannot be applied when no transactions occur, as was frequently the case in term funding markets during the period we study. A key benefit of the LIBOR data is that, in principle, they provide the only source of information about banks' shadow borrowing costs when no borrowing is actually taking place.

As noted above, however, these data do come with complications. As is now well known, at least some of the LIBOR-reporting banks frequently lied about their borrowing rates either for reputational reasons or in an attempt to influence the direction of the market for financial gain.[1] Because the incentives to misreport can be related to credit risk, accounting for misreporting is necessary to obtain unbiased estimates of the credit and liquidity factors in the model. To do this, we build on recent work regarding how banks choose to report in the LIBOR survey (Snider and Youle 2012, Chen 2013, Youle 2014, Bonaldi 2017, Gandhi et al. 2019). We find that the effect of misreporting varies across time, maturities, and banks, but we estimate that it was most pronounced—biasing the aggregate rate downward by as much as 35 basis points—during the height of the crisis. Given our use of bank-level data, controlling for these misreporting effects turns out to be important. A version of the model that sets the misreporting terms to zero produces results that indicate credit risk plays little to no role interbank spreads, in conflict with the findings of Afonso, Kovner, and Schoar (2011) and others. Furthermore, we find that this alternative model is also strongly rejected by the data in favor of our baseline model that does give a role to misreporting.

Our paper contributes to the growing literature on the behavior of the interbank market during the crisis and the policy responses to its breakdown. In one of the first and best known of these studies, Taylor and Williams (2009) argue that wide interbank spreads mostly reflected counterparty credit risk among borrowing institutions, not a lack of liquidity in the market, and that consequently efforts by central banks to boost market liquidity were essentially

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[1]See Hou and Skeie (2014) and Duffie and Stein (2015) for overviews.

useless. While a number of subsequent papers support this general conclusion, a separate set of studies has taken the opposite position, arguing that funding stress has primarily been a liquidity problem, not a credit risk problem.[2] Our results show that both credit risk and liquidity played important roles at different times and different maturities, and we obtain these findings in the context of arguably better measures of both credit risk and borrowing costs. Our finding that sensitivity to credit risk varies significantly over time complements Afonso, Kovner, and Schoar (2011) by confirming (with much different data) that attention to credit risk in the interbank market increased in the immediate aftermath of the Lehman Brothers default. However, as noted above, we also find that this attention eventually returned to negligible levels.[3] Finally, our results may help to assess theoretical models of the interbank market in which credit risk and liquidity play a role, such as Eisenschmidt and Tapking (2009), Acharya and Skeie (2011), and Heider, Hoerova, and Holthausen (2015).

Three previous papers have used the cross-sectional aspects of the LIBOR data to study bank funding costs. Filipović and Trolle (2013) and Christensen, Lopez, and Rudebusch (2014) exploit variation in LIBOR in the maturity dimension, but they impose no-arbitrage cross-equation restrictions that we relax. (Given the dysfunction in funding markets during much of the sample, the no-arbitrage assumption seems strong.) Gefang, Koop, and Potter (2011) use LIBOR variation across both banks and maturities, but they do not match individual CDS and LIBOR spreads as we do. Rather, they model credit risk as a single unobserved factor driving both LIBOR and CDS, with different loadings at each bank. Thus,

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[2]Afonso, Kovner, and Schoar (2011), Angelini, Nobili, and Picillo (2011), and Smith (2012), like Taylor and Williams, emphasize the prominence of credit risk in these markets, and Brunetti, di Filippo, and Harris (2011) provide additional evidence that central bank interventions were ineffective. In contrast, Gefang, Koop, and Potter (2011) and Schwarz (2019) estimate a large liquidity premium in interbank spreads; Acharya and Merrouche (2013) document liquidity hoarding by large settlement banks; and Wu (2011), Rai (2013), Christensen, Lopez, and Rudebusch (2014), and McAndrews, Sarkar, and Wang (2017) all find that central bank liquidity facilities significantly reduced bank funding rates.

[3]Angelini, Nobili, and Picillo (2011) also present evidence that lending banks may have paid more attention to credit risk at some times during the crisis than at others.

their identification comes mostly from the time-series component of the data and does not fully exploit the within-bank correlations. Moreover, all three papers employ single factors for credit and liquidity that affect all maturities proportionally. Our approach allows for different factors at each maturity, which turns out to be particularly important for the liquidity results.

2.   Matching LIBOR and CDS Data

U.S. dollar LIBOR is calculated based on a survey of a panel of banks in North America, Europe, and Japan that—during the period we examine—was conducted daily by the British Bankers Association.[4] Broadly speaking, the panel consists of the largest global banks that are active in dollar funding markets. The survey question is: "At what rate could you borrow funds, were you to do so by asking for and then accepting inter-bank offers in a reasonable market size just prior to 11 am?" Every day, this question is answered by a respondent at each of the panel banks for 10 maturities (up to one year).[5] During our sample, the individual bank-level responses were made public at the same time that the reference rate was published.

The primary data in this paper consist of the bank-level LIBOR submissions and matched CDS spreads on a subset of the dollar-LIBOR-panel banks. We follow standard practice and subtract overnight index swap (OIS) rates, matched by maturity, from each bank's LIBOR quote on each day to remove the short-rate expectations and term premium components associated with the risk-free rate.[6] We label the difference between LIBOR quotes and OIS rates as "LOIS" spreads.

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[4]Responsibility for the administration of LIBOR was handed over to Intercontinental Exchange Benchmark Administration Ltd. on January 31, 2014. For more information, see https://www.theice.com/iba/libor.

[5]The composition of the survey panel varies across currencies and changes over time. The aggregate value that is published as "the" LIBOR reference rate for each currency at each maturity on each day is calculated as the trimmed mean of the survey responses, where the trimming excludes the 25 percent highest and 25 percent lowest submissions rounded to the nearest integer number of respondents.

[6]We obtain dollar-denominated CDS quotes for the senior debt of the banks from Markit and the LIBOR and OIS data from Bloomberg.

2.1   Using CDS as a Proxy for Credit Risk

As in prior literature that investigates the credit and liquidity components of short-term funding costs, we use CDS spreads to proxy for credit risk. Some of the earlier papers in this literature (e.g., Taylor and Williams 2009) use five-year CDS spreads alongside short-term LOIS rates. The idea that five-year CDS proxy well for credit risk comes from the more active primary and secondary market for this tenor. For example, Culp, van der Merwe, and Stärkle (2016) show that single-name CDS with one to five years remaining to maturity accounted for the largest proportion of CDS outstanding over our sample period. However, while the approach of using five-year CDS draws information from the segment of the CDS market with the greatest liquidity, it also accepts a mismatch in maturity between funding rates and CDS spreads that may introduce measurement error relative to true short-term credit risk. Other papers do match the maturities of CDS and interbank rates more closely, but this may come at the cost of potential measurement error in individual short-term credit risk, as short-term CDS contracts are more thinly traded.[7] Although some evidence suggests that the relative liquidity of short-term CDS may have improved over time, their low trading volumes imply that short-maturity CDS contracts, in isolation, may provide a noisier signal of short-term credit risk than five-year contracts do.[8]

Our approach is to fit a Nelson and Siegel (1987) curve to the full term structure of each bank's CDS. These curves utilize all of the available CDS data, including quotes from the most-liquid portion of the market (the five-year maturity). Our CDS data provider, Markit, requires multiple, fresh quotes in order to post a CDS spread for any given firm-maturity combination on a specific day. Bearing this in mind, we build the term structure under the following constraints:

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[7]Eisenschmidt and Tapking (2009), Filipović and Trolle (2013), Sul (2015), McAndrews, Sarkar, and Wang (2017), and Schwarz (2019) all make use of six-month and/or one-year CDS spreads to measure the credit risk of the banks in their studies alongside short-term funding rates.

[8]Culp, van der Merwe, and Stärkle (2016) show that, over the period of our sample, CDS with one year or less remaining maturity become a more significant portion of the single-name outstanding. See exhibit 7 and the related discussion in that paper.

(i) The Nelson-Siegel curve is fitted weighing the CDS data by inverse maturity. That is, the penalty for poor fit at the 30-year tenor is 1/60 the size of the penalty at six months.

(ii) We only build CDS curves for bank-day combinations for which we have *both* 6- and 12-month CDS quotes for that bank.[9]

(iii) As a bad fit of the Nelson-Siegel curve may be indicative of a day in which CDS is a particularly poor proxy of actual credit risk, we eliminate any observations where the CDS curve fitting errors were large, choosing a cutoff of 25 percent of the CDS spread. Such days may be due to poor CDS liquidity (see, e.g., Hu, Pan, and Wang 2013; Musto, Nini, and Schwarz 2018), or represent other conditions that could drive a wedge between CDS spread and credit risk, and their removal helps assure that our results are not driven by observations not well approximated by our methods.[10]

Given that we use the information from all tenors to construct our daily term structure curves and exclude any days for which 6- or 12-month CDS quotes are unavailable (days which were left blank by Markit due to unavailable or stale quotes), our CDS curve should mitigate concerns about illiquidity-induced measurement error to the extent possible. Therefore, in our baseline model, we take exact maturity-matched reads off of these curves as our measures of short-term credit risk. We then offer a variety of tests to verify robustness to this approach.[11]

It is important to note a feature of the Markit CDS data, which are used in most studies in this literature, including ours. These

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[9]This eliminates about 12 percent of the sample.

[10]This resulted in the elimination of roughly 4 percent of the underlying data.

[11]We thank the referee for raising issues which helped lead to the filtering procedures outlined here. It is important to clarify that we fit a separate curve to the data available for each bank on each day and do not rely upon historical correlations in any way when constructing these curves. That is, every bank gets a completely new CDS curve on every day, based on the quotes that are reported only on that day. Usually there are 11 quotes on each day for each bank, covering maturities of six months to 30 years. See the online appendixes on the IJCB website (http://www.ijcb.org) for more detail.

data are quotes obtained from dealers, who are the primary CDS market makers, and likely reflect a mix of transaction- and model-based information. To the extent that dealers report model-based—as opposed to transaction-based—quotes (in the absence of trading), there exists the potential to introduce noise into our proxy of credit risk that could affect our results. The size of this potential noise is a function of two things: the relative quantities of transaction-based quotes versus model-based quotes, and the presence of any systematic divergence between these quote "categories" over our sample. We do not know the magnitude of the effect this may have on the underlying results in this literature, including our paper, but to the extent that the data in model- and transaction-based quotes diverged systematically and/or persistently, our results on the contribution of credit risk to interbank spreads could be slightly misstated, with the direction and magnitude of misspecification depending on the properties of the divergence.[12] To the extent that the noise induced by model-based quotes was instead more "two sided" and idiosyncratic, thereby more a function of CDS market liquidity, the impact should be detectable by examining how CDS market liquidity affects our results. We conduct robustness tests for this in section 5.3.2.

Finally, while the procedure to filter CDS data ensures that the credit risk proxy used in the analysis is as free as we can make it of the effects of CDS liquidity, it removes credit risk data completely for those bank-day observations. To the extent that there is correlation between CDS market liquidity and the broader credit

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[12]One potential example of a systematic distortion: dealers could post model-based quotes that are generally more conservative than executed transactions. If model-based quotes represent the offer side of the bid/ask spread which is prone to widening quickly in response to market volatility, for example, these model-based quotes may also move up faster at times when the conservative dealer sees the risk as having changed (i.e., the bid/offer spread widens when CDS spreads rise). If model-based quotes were a dominant fraction of the total data, and they consistently behave as we speculate here, they could potentially mute our perceived sensitivity of interbank lending markets to credit risk, or influence our measures of its time variation. This type of measurement error also demonstrates the importance of basing the credit risk component on information using as much of the maturity spectrum as possible, allowing us to improve the likelihood that we are using some transaction-based information for each bank-day observation. Finally, we note again that this issue is one confronted by all users of CDS data at a single-name level.

risk and liquidity discussion which is the focus of the paper, this
removal could bias our results. We are able to provide something
of a test for filter-generated bias by running the analysis with and
without the filter in step (iii) above. We find that the filter does not
fundamentally alter our results.

We start the sample in August 2007. Prior to that date, there
was virtually no interesting variation in either LOIS or CDS spreads.
Moreover, the CDS data become sparse as we go back further in time.
We stop the sample in June 2013 because of the significant changes
to the LIBOR procedures (i.e., the elimination of same-day report-
ing of the underlying submissions) instituted at that time. Over the
sample period, 21 different banks participated in the panel, which
contained 16 to 20 banks at any given time. We have LIBOR quotes
for every bank that was in the panel on each day during this period.
The CDS data, on the other hand, are sometimes missing because
of the rules imposed by Markit regarding quote quality discussed
above. The state-space methods used in our estimation allow us to
estimate parameters regardless of occasional missing CDS data.[13]

2.2 Empirical Features of LIBOR and CDS Spreads

To illustrate some key features of these data, figure 1 plots the
one-week and 12-month LOIS spreads and (Nelson-Siegelized) CDS
quotes, respectively. In each case, the solid lines show the cross-
sectional average on each day, and the dashed lines show the range
across banks. Although we do not use them in our subsequent analy-
sis, we show the data prior to August 2007 to illustrate the mag-
nitude of the structural break that occurs at the beginning of our
sample.

The LOIS and CDS data have some clear commonalities. Rel-
ative to the post-2007 sample, both series are much closer to zero
with little cross-sectional variation prior to August 2007. After that
time, the average levels of both series rise significantly, and the dis-
persion widens. We see increases in both series after the default of
Lehman Brothers in September 2008, as well as smaller increases
around the times of tensions in Europe in mid-2010 and late 2011.

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[13]The online appendixes contain a more detailed discussion of the data coverage
and sources.

Figure 1. Dispersion of CDS and LIBOR-OIS Submissions
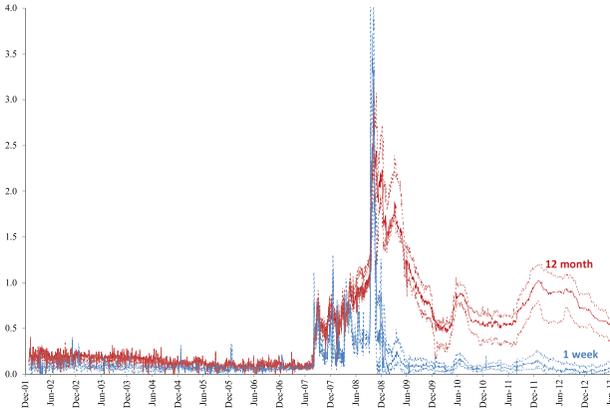
A. Dispersion of LIBOR-OIS Submissions
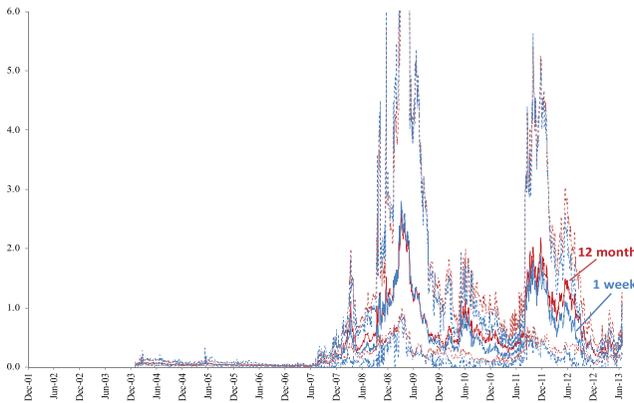
B. Dispersion of Nelson-Siegelized CDS Quotes

Note: The solid lines show the cross-section average on each day and the dashed lines show the range across banks.

These co-movements might suggest that at least part of the reason for the movement in LOIS has to do with the same counterparty credit risk factors that are driving CDS spreads.

However, there are also some important differences between the two series. Most significantly, figure 1A shows that the term spread for LOIS widens substantially in the post-2007 period—the difference between the one-week and 12-month series rises to over 150

basis points in 2009—whereas figure 1B shows that the term spread in CDS remains close to zero, at least on average. Thus, at least at this superficial level, it does not seem that credit risk can fully account for the widening of both short- and long-term LOIS spreads. In addition, there are distinct differences in the timing and relative magnitudes of movements in the two series. For example, the jump in LOIS spreads in August 2007 is quite abrupt, but in CDS spreads it is more gradual; after the collapse of Lehman, both spreads widen, but the LOIS spread peaks relatively quickly, in October 2008, while the average CDS spread peaks in mid-2009. During the European crisis in 2011, CDS spreads widen to about the same levels that they had reached in the aftermath of Lehman, but LOIS spreads widen by a much smaller amount than they had in 2008. Finally, while the cross-sectional variation of the LOIS spreads increases somewhat after August 2007, the increase in the dispersion of the CDS spreads is far more dramatic. For example, the coefficient of variation for the 12-month CDS spread averages 0.5 after that date, while that for the corresponding LOIS spread averages just 0.1.

Despite the co-movement between the aggregate LOIS and CDS time series, the cross-sectional correlation between LOIS and CDS spreads is weak at best. Daily cross-sectional correlations between LOIS and CDS spreads average less than 0.15 at all maturities over our sample.[14] This pattern is puzzling because interbank lenders to a given bank and the writers of CDS contracts on that bank face losses in the same states of the world. In the United States, for example, the National Depositor Preference Act of 1993 treats both bonds and interbank loans as "general or senior liabilities," which stand together in the same place in line in the event of insolvency (after depositors but before subordinated debtholders) and receive the same pro rata recovery rate.[15] This strict correspondence may be muddled by variations in failure-resolution statutes across countries and in corporate structure across institutions. Nevertheless, a bank's default on one claim is nearly always associated with defaults on other claims, particularly those of similar maturity, so we would still generally expect the correlation between matched LOIS and

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[14]Michaud and Upper (2008) also note the weak cross-sectional correlation between CDS and LIBOR quotes.

[15]See Federal Deposit Insurance Act, section 11(d).

CDS spreads to be very high. Furthermore, it seems particularly odd that the spreads should not be correlated in the cross-section given the strong correlation that the aggregate series display over time. On its face, that observation would seem to suggest that lending banks demand a premium to compensate them for the aggregate default probability of the banking sector but not for the default probabilities of the particular banks they are lending to.

It is tempting to appeal to information asymmetries to explain these discrepancies, as in Heider, Hoerova, and Holthausen (2015). But this cannot be the whole story. Interbank lenders generally have access to contemporaneous CDS quotes when negotiating lending terms, and, during our sample period, CDS dealers also had access to contemporaneous bank-level LIBOR submissions. Indeed, many of the lending banks in the interbank market are the banks that are also making markets in CDS, and the same information sets should thus be priced into both instruments. For example, the LIBOR panel contains 11 of the G-14 dealer banks, which were collectively responsible for about 80 percent of all CDS activity during our sample period.[16] An alternative possibility, considered below, is that at least part of the discrepancy between LOIS and CDS spreads might be due to banks not reporting their true funding costs in the LIBOR survey.

3. Modeling Credit Risk, Liquidity, and Misreporting

In this section we develop a model of LIBOR determination to motivate and interpret our empirical tests. We first discuss our generalization of the standard empirical interbank-modeling framework to a panel context and our interpretation of the reduced-form parameters in that framework. We then extend the model to incorporate misreporting incentives.

3.1 "Fundamental" Determinants of Interbank Costs

We begin by extending the basic time-series framework that has been used in many previous studies of interbank funding costs, following Taylor and Williams (2009), to incorporate cross-sectional heterogeneity in the bank and maturity dimensions. Specifically, let L_{imt}

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[16]See Chen et al. (2011).

be the spread of the interbank rate paid by bank i in time t for a loan of maturity m, relative to the risk-free rate at the same maturity. Let C_{imt} be a measure of the counterparty credit risk for the same bank, at the same time, at the same maturity (i.e., the default risk on that bank's borrowings at horizon m). In our case, L_{imt} will be measured as the bank-level LIBOR-OIS spread, and C_{imt} as the CDS spread. We posit that each bank's interbank borrowing rate is determined as follows:

$$L_{imt} = \lambda_{mt} + \phi_{imt} C_{imt}, \qquad (1)$$

where λ_{mt} is a maturity-specific liquidity premium, and ϕ_{imt} is a measure of interbank sensitivity to credit risk. λ_{mt} and ϕ_{imt} will be the central objects of interest in our estimation. By definition, λ_{mt} does not vary across banks—it is a marketwide liquidity premium that reflects the scarcity of funds at a given point in time. In principle, ϕ_{imt} could vary across both banks and maturities, but we argue below that it is a priori reasonable to restrict it to vary only in the time dimension. That is still a generalization of previous specifications, which have typically assumed this parameter to be constant over time.

Following the previous empirical literature, the key identifying assumption of equation (1) is that the liquidity premium λ_{mt} is not bank specific. This reflects the observation that, although individual banks' liquidity needs may differ, the price that they pay for liquidity in equilibrium should primarily depend upon the aggregate demand for and supply of reserves. To be more precise, consider a stylized environment with a set of I risk-neutral banks, each of which at time t chooses to hold a quantity of reserves x_{it} and each of which can borrow or lend without constraint at maturity m in the interbank market. Assume that the interbank market is competitive and denote each bank's gross borrowing rate R_{imt}. Assume that the aggregate supply of reserves is fixed by the central bank and that reserves pay the instantaneous gross risk-free rate R_{0t}^f. The m-period risk-free rate is

$$R_{mt}^f = \frac{1}{m} \int_0^m E_t[R_{0t+s}^f] ds. \qquad (2)$$

Banks have some incentive to hold reserves because each bank faces a random cash outflow during the period over which its interbank loans are outstanding. Let this outflow be distributed with a density f_{imt} that possibly varies across time, maturities, and banks. If the cash outflow exceeds the reserves that the bank has chosen to hold in any period, the bank pays a (possibly bank-specific) cost k_{it}. This cost could reflect the cost of asset fire sales, penalties associated with borrowing from the central bank, or, in the extreme, bankruptcy.[17] Under these assumptions, the expected return on an m-maturity interbank loan made by bank i is $R^f_{mt} + k_{it}f_{imt}(x_{it})$, where the term $k_{it}f_{imt}(x_{it})$ is the expected marginal cost of a cash shortfall. Since banks are risk neutral and the market is competitive, expected returns must be equal across all banks. Thus, the equilibrium allocation of reserves solves $k_{it}f_{imt}(x_{it}) = k_{jt}f_{jmt}(x_{jt})$ for all i, j. The corresponding equilibrium spread is our liquidity premium, λ_{mt}. It reflects the balance of aggregate reserve supply with the demand that results from precautionary hoarding to protect against liquidity outflows. It will vary over time as banks' perceptions of the probability of such outflows changes.

Now suppose that banks default on their obligations with some exogenous probability. Let the probability that a loan at maturity m to bank i defaults be ρ_{imt}, with the lending bank losing a fraction δ^L_{imt} of the loan and interest in the event of such a default, and further assume that any borrowing bank defaults on its bonds in the same states of the world that it defaults on its interbank loans, although possibly with a different conditional loss rate δ^C_{imt}. Thus, m-maturity CDS holders on bank i expect to pay out at rate $\rho_{imt}\delta^C_{imt}$.

Given risk neutrality, the equilibrium interest rate on an interbank loan to bank i is equal to the expected return on that loan, adjusted for its expected losses:

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[17]Although it is quite stripped down, the funding-cost portion of this model shares the intuition of other models of the interbank market, such as Allen, Carletti, and Gale (2009) and Eisenschmidt and Tapking (2009), in which banks choose their reserve holdings to cover expected liquidity needs. Of course, as studied by Cocco, Gomes, and Martins (2009), Acharya, Gromb, and Yorulmazer (2012), and others, departures from perfect competition could also be important in this market.

$$R_{imt} = \frac{R_{mt}^f + k_{it}f_{imt}(x_{it})}{1 - \pi_{imt}\delta_{imt}^L}. \tag{3}$$

Let C_{imt} be the time-t spread on a CDS contract that insures the bonds of bank i over the subsequent m periods. Since bonds default in the same state of the world as interbank loans, we have $\pi_{imt}\delta_{imt}^L = \phi_{imt}C_{imt}$, where $\phi_{imt} = \frac{\delta_{imt}^L}{\delta_{imt}^C}$ is the relative expected conditional loss rates on the two instruments. Substituting ϕ_{imt} and λ_{mt} into equation (3) and defining $L_{imt} = \log R_{imt} - \log R_{mt}^f$ produces equation (1), up to an approximation error due to Jensen's inequality.

While our empirical exercises begin directly with equation (1) and are not dependent upon the specific structural model just described, that model does motivate certain parameter restrictions and help to interpret our results. First, the assumption that the "liquidity premium" λ_{mt} does not vary across banks is a key identifying restriction of the empirical tests, and the structural model clarifies why that assumption is reasonable: this parameter reflects the marginal opportunity cost of interbank lending, which does not depend on borrower characteristics and must be identical across lenders in equilibrium. Second, the structural model implies that the coefficient ϕ_{imt} should only vary across banks and maturities to the extent that the *relative* conditional loss rates between CDS holders and interbank lenders differ in those dimensions. Since there is no particular reason to suspect such variation, we will assume this coefficient to be constant across i and m (that is, we set $\phi_{imt} = \phi_t$ for all values of i and m), a restriction that also greatly improves the identification of the model.[18]

The flexibility of our framework, in which λ_{mt} and ϕ_{imt} are allowed to vary over states of the world, also makes the model amenable to alternative structural interpretations. For example, fluctuations in the value of a bank's relationships, as emphasized by Acharya and Merrouche (2013), could be another reason for changes

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[18]If lenders are not risk neutral, fluctuations in their risk aversion will also likely be reflected in our estimates of ϕ_t. Time variation in this sensitivity could also be consistent with the model of Heider, Hoerova, and Holthausen (2015), in which lenders' incentives to monitor depend in part on the level of credit risk. Again, however, there is no obvious reason that this should cause differences in pricing across borrowing banks.

in its credit risk sensitivity. Similarly, if the value of interbank relationships is correlated with funding market liquidity, it will show up in estimates of λ_{mt}. This possibility is consistent with our interpretation of λ_{mt} in the sense that a deterioration in the value of relationships that is systematic across banks (but uncorrelated with credit risk) could be fairly characterized as a drop in liquidity. Thus, we think of changing relationships across banks as one possible source of the fluctuations we document in liquidity and credit risk sensitivity.

Finally, the above structural framework produces at least one important testable hypothesis. Namely, central bank liquidity programs that provide funds to banks at or below the market rate must cause the liquidity premium to fall if they are large enough. (For any k_{it} and $f_{imt}, \lim_{x \to \infty} k_i f_i(x) = 0$.) Intuitively, such programs reduce the demand for loans in the interbank market, putting downward pressure on the rate. At the same time, they unambiguously reduce probabilities of cash shortfalls.

3.2 Reporting Incentives in LIBOR

In the spring of 2008, the *Wall Street Journal* published a series of articles calling into question the veracity of LIBOR quotes.[19] The *Journal* articles pointed to the weakening relationship between LIBOR and CDS quotes specifically as prima facie evidence of misreporting. The authors went on to point out several specific banks for which LIBOR quotes seemed particularly out of line with CDS spreads and speculated that "one possible explanation for the gap is that banks understated their borrowing rates . . . At times of market turmoil, banks face a dilemma. If any bank submits a much higher rate than its peers, it risks looking like it's in financial trouble."

In addition to reputational concerns, banks may have direct financial incentives to misreport. Many of the banks on the LIBOR panel make markets or hold positions in LIBOR-linked financial products, such as interest rate derivatives and syndicated loans. If large enough, such positions could net the banks, their clients, or their traders substantial sums of money in short periods of

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[19]C. Mollenkamp, "Bankers Cast Doubt on Key Rate Amid Crisis," *Wall Street Journal*, April 16, 2008; C. Mollenkamp and M. Whitehouse, "Study Casts Doubt on Key Rate," *Wall Street Journal*, May 29, 2008.

time, even from a few-basis-point move in LIBOR. The incidence of position-driven misreporting is attested to by the numerous exchanges between LIBOR respondents and traders, which have come to light through recent legal investigations, wherein LIBOR submitters repeatedly comply with requests from traders at their banks for particular configurations of LIBOR quotes.[20]

Subsequent to the *Wall Street Journal* story, most of the banks on the LIBOR panel have been investigated, with 10 having settled allegations of malfeasance with U.S. and U.K. authorities as of this writing, and numerous individual bankers face or have pled guilty to criminal charges. Meanwhile, U.K. regulators have undertaken a set of reforms of the reporting process intended to discourage future misreporting (Wheatly 2012), and a number of academic studies have attempted to uncover evidence of the misreporting ex post in the data (Abrantes-Metz et al. 2012; Kuo, Skeie, and Vickery 2018; Snider and Youle 2012; Poskitt and Dassanayake 2015; Gandhi et al. 2019). A smaller literature has also emerged focusing on the game played by banks in setting rates and the consequences for the shape of the resulting rate distribution (Snider and Youle 2012; Chen 2013; Youle 2014; Bonaldi 2017). These models generally view the decision to misreport as reflecting a potential benefit (either reputational or position driven) traded off against a potential cost of deviating from the truth.

To incorporate into our model the possibility that banks may strategically misstate their funding costs in the LIBOR survey, we borrow from the theoretical literature on misreporting. Specifically, we distinguish between each borrowing bank i's "true" funding cost at each maturity, L_{imt}, and the cost that it reports for LIBOR purposes, $\widehat{L}_{imt}$.[21] The bank's reported value for LIBOR purposes may reflect several considerations, including that the bank may have a portfolio-specific reason to distort LIBOR in one direction or the

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[20]See, for example, L. Vaughan and G. Finch, "Secret Libor Transcripts Expose Trader Rate-Manipulation," *Bloomberg*, December 13, 2012, and the many instances cited in Arvedlund (2014). Gandhi et al. (2019) estimate that the panel banks collectively gained $33 billion from position-driven manipulation over the 2001–10 period.

[21]For ease of exposition, we suppose that each bank reports its spread over the time-t, m-maturity risk-free rate, but this makes no difference since the risk-free rates are assumed to be common knowledge.

other. Except at the trimming quantiles, the marginal effect of any bank's quote on aggregate LIBOR is constant (either zero or $2/I$), so we assume that the benefits from distortion are approximately linear. We also consider that banks may receive reputational or signaling benefits from reporting a low value for LIBOR. Again, we assume that these benefits are linear in $\widehat{L}_{imt}$ at each point in time. Thus, in any period, both incentives to misreport are captured by an expression of the form

$$\text{misreporting benefits}_{imt} = \gamma_{0imt} + \gamma_{1imt}\widehat{L}_{imt}. \qquad (4)$$

In theory, the marginal benefit of misreporting $\gamma_{1,imt}$ can take either sign. We assume that each bank may face a quadratic cost of reporting a value far away from the truth. This cost may reflect potential regulatory or legal penalties, or simply the psychological and moral costs of lying. We define "far away" in terms of the cross-sectional dispersion of LIBOR quotes at each point in time. This reflects the idea that more heterogeneity in the market is associated with greater financial market uncertainty and lowers the probability of a lie being detected. Thus, we have

$$\text{cost of lying}_i = \frac{\gamma_{2t}}{2} \frac{\left(\widehat{L}_{imt} - L_{imt}\right)^2}{\text{std}_{mt}\left[\widehat{L}_{imt}\right]}, \qquad (5)$$

where std_{mt} denotes the time-t standard deviation across banks at maturity m. For simplicity, we assume that the parameter γ_{2t} is the same across banks and maturities, since there is no obvious reason to expect that the penalties for fraudulent behavior should depend on the identity of the perpetrator or the specific contract that was lied about.

Banks may have misreported not just for financial gain but simply because they did not want to appear different from their peers. Indeed, investigations into the LIBOR scandal suggest that misreporting out of fear of differentiating oneself from the competition was a strong motivating factor. Arvedlund (2014) reports numerous examples that illustrate this point. In transcripts and other documents released by government agencies, traders and LIBOR submitters speak of "fit[ting] in with the rest of the crowd," not

"draw[ing] unwanted attention to [them]selves," and "not want[ing] to be an outlier in the LIBOR fixings, just like everybody else."[22] An additional reason that banks may have reported LIBOR numbers similar to their peers is that they may have engaged in outright collusion in an attempt to influence aggregate LIBOR rates in order to boost their portfolio returns. This type of activity has also come to light in post-crisis legal investigations. For example, the 2012 settlement between the Commodity Futures Trading Commission and UBS noted that that bank "colluded with at least four other panel banks to make false submissions" in yen-related LIBOR contracts.[23] Such behavior is also not well captured by a model in which banks only trade off their own immediate profits against the costs of lying. Rather, in order for the cartel to be successful, the colluding banks must effectively face a cost of deviating too far from each other.

In light of these observations, we expand the misreporting model to allow for the possibility that banks may worry that reporting a value much different from other banks (in either direction) may bring unwanted scrutiny by markets or regulators or that they may be engaged in implicit or explicit collusion with other banks that would subject them to some cost if their submission deviates too much from the rest of the cartel. We capture these incentives with a second cost function:

$$\text{cost of being an outlier}_{imt} = \frac{\gamma_{3t}}{2} \frac{\left(\widehat{L}_{imt} - \overline{\widehat{L}_{mt}} \right)^2}{\text{std}_{mt}\left[\widehat{L}_{imt} \right]}, \qquad (6)$$

where γ_{3t} is a cost parameter and $\overline{\widehat{L}_{mt}}$ is the cross-sectional mean of reported LIBOR spreads. We assume that the moments $\overline{\widehat{L}_{mt}}$ and

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[22]In one particularly telling instance, two UBS employees engaged in the following exchange via text message:

   TRADER: [A senior manager] wants us to get in line with the competition by Friday . . .
   TRADER-SUBMITTER: . . . if you are too low you get written about for being too low . . . if you are too high you get written about for being too high. . .
   TRADER: middle of the pack there is no issue. . .

[23]See http://www.cftc.gov/PressRoom/PressReleases/pr6472-12.

$std_{mt}[\widehat{L}]$ are known to all banks when they do their optimization. Since traders usually have a good sense of the conditions in the day's market before submitting their quotes, this seems a reasonable approximation.[24] We note that this formulation will effectively make banks' misreporting incentives a function of their credit risk. In particular, it gives banks with high credit risk an incentive to underreport LIBOR in order to remain close to the other banks.

3.3   Banks' Choice Problem

In each period, each borrowing bank chooses $\widehat{L}_{imt}$ at each maturity to maximize benefits less costs in each period. Assuming that the true funding costs are determined from equation (1), the appendix in this main paper shows that this maximization produces bank-level LIBOR submissions that can be written in reduced form as a linear function of the liquidity premium, bank-level CDS spreads, and the cross-sectional mean and standard deviation of all banks' CDS. In particular,

$$\widehat{L}_{imt} = \lambda_{mt} + \phi_t C_{imt} + \beta_{1imt}\sigma_{mt}^C + \beta_{2t}\left(C_{imt} - \overline{C}_{mt}\right), \quad (7)$$

where $\overline{C}_{mt}$ and σ_{mt}^C are the cross-sectional mean and standard deviation of CDS spreads at each maturity, $\beta_{2t} = -\phi_t\gamma_{3t}/(\gamma_{2t} + \gamma_{3t})$, and β_{1imt} is a complicated function of the structural parameters, including γ_{1imt}. Equation (7) will be the target of our estimation.

If banks always told the truth, $\widehat{L}_{imt}$ would simply be equal to $\lambda_{mt} + \phi_t C_{imt}$. Thus, the last two terms in equation (7) reflect the bank-level misreporting bias. Note, however, that since the last term of equation (7) always averages to zero, the *aggregate* bias in LIBOR is simply equal to $\bar{\beta}_{1mt}\sigma_{mt}^C$, where $\bar{\beta}_{1mt}$ is the cross-sectional average of the β_{1imt} terms. The result that the size of the bias should increase with the cross-sectional dispersion of true funding costs also

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[24]For example, in its May 29, 2008 article, the *Wall Street Journal* noted, "When posting rates to the BBA [British Banker's Association], the 16 panel banks don't operate in a vacuum. In the hours before banks report their rates, their traders can phone brokers at firms such as Tullett Prebon PLC, ICAP PLC and Compagnie Financière Tradition to get estimates of where brokers perceive the loan market to be."

appears in Chen (2013), although it arises through a slightly different mechanism.[25]

Finally, we note that the applicability of our model does not depend on the amount of lending that actually takes place in equilibrium. Anecdotally, interbank volumes were very low, perhaps zero, at longer maturities during much of our sample. This is a possible outcome of our model, one in which the equilibrium rate is too high for any bank to find it worthwhile to borrow. In this case, the equilibrium rate is still a well-defined object, albeit one that cannot be observed from market prices. One advantage of the LIBOR data is that, assuming misreporting can be corrected for, they provide a source of information *even when* volumes are zero. Of course, one might wonder how informed the LIBOR reporters really are about their borrowing costs when they are not actually doing any borrowing. But this lack of information does not cause any particular problems for our model either. Indeed, one can reinterpret the model as one in which a bank is unsure of its own true funding cost and (in addition to possible strategic misreporting behavior) makes an informed guess about its value by looking at the distribution of other banks' submissions, which it weights by the term γ_{3t}. Consequently, we expect our model to produce unbiased and meaningful estimates of λ_{mt} and ϕ_t even when there are no underlying interbank transactions.

4.   Estimation

We estimate the model by treating equation (7) as a measurement equation and the reduced-form parameters as unobserved state variables. We impose a final set of cross-equation restrictions to further reduce the dimension of the system by assuming that β_{1imt} is the same across all maturities for each bank (that is, we assume

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[25]Since our estimation will allow us to infer λ_{mt} and ϕ_{imt}, equation (7) allows us to estimate each bank's "true" LIBOR values. Of course, if we can back out "true" LIBOR rates as econometricians, we should recognize the possibility that market participants can also do it. Our model is essentially unchanged if we permit all banks to have full knowledge of all of the L_{imt} in real time. Of course, in this case, it would not make sense to consider reputational benefits of misreporting, but equation (4) still holds as an approximation to possible trading gains.

$\beta_{1imt} = \beta_{1it}$ for all values of m). Given our other assumptions, maturity variation in this parameter could only come from variation in γ_{1imt}. Thus, this restriction implies that marginal misreporting benefits at a given bank are the same across all maturities and any point in time. Specifically, we estimate

$$\widehat{L}_{imt} = \lambda_{mt} + \phi_t C_{imt} + \beta_{1it}\sigma_{mt}^C + \beta_{2t}\left(C_{imt} - \overline{C}_{mt}\right) + \epsilon_{imt}, \quad (8)$$

where ϵ_{imt} is a normally distributed iid error with variance matrix $\mathbf{R}$, which we assume to be diagonal.[26] Since these equations are linear in the observables C_{imt}, σ_{mt}^C, and $\overline{C}_{mt}$, we can use the Kalman filter to infer the values of the time-varying parameters λ_{mt}, ϕ_t, β_{1it}, and β_{2t} (for all i and m). Estimation is joint over 17 banks and five maturities, and we thus have 85 measurement equations and 24 state variables.

The fixed parameters of the model are estimated by Gibbs sampling, following Kim and Nelson (1999), much in the style of the state-space modeling used in the time-varying vector autoregression literature (e.g., Cogley and Sargent 2002). Following that literature, we collect our state variables in the vector $\boldsymbol{\theta}_t$, and we approximate their evolution with independent random walks:

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\nu}_t, \quad (9)$$

where $\boldsymbol{\nu}_t \sim N(0, \mathbf{Q})$ and $\mathbf{Q}$ is a diagonal matrix. As noted earlier, some observations are missing for some banks, either because we lack CDS data or because banks entered or departed the LIBOR panel. Missing observations are handled through the Kalman-filter-based imputation procedure demonstrated in Aruoba, Diebold, and Scotti (2009). In our results presented below, we estimate the model on weekly averages of the daily data. Online appendix C provides additional detail on the estimation procedure.

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[26]The assumption of uncorrelated measurement errors is common in the state-space and term structure literatures as a necessary way to reduce the number of parameters that need to be estimated. If we attempted to estimate the full $\mathbf{R}$, rather than a diagonal version, it would require us to estimate an additional 3,570 terms, which would be weakly identified at best.

Figure 2. Estimated Path of Liquidity Premiums (λ_{mt}), by Maturity, with 5th and 95th Percentiles (shown in percentage points)
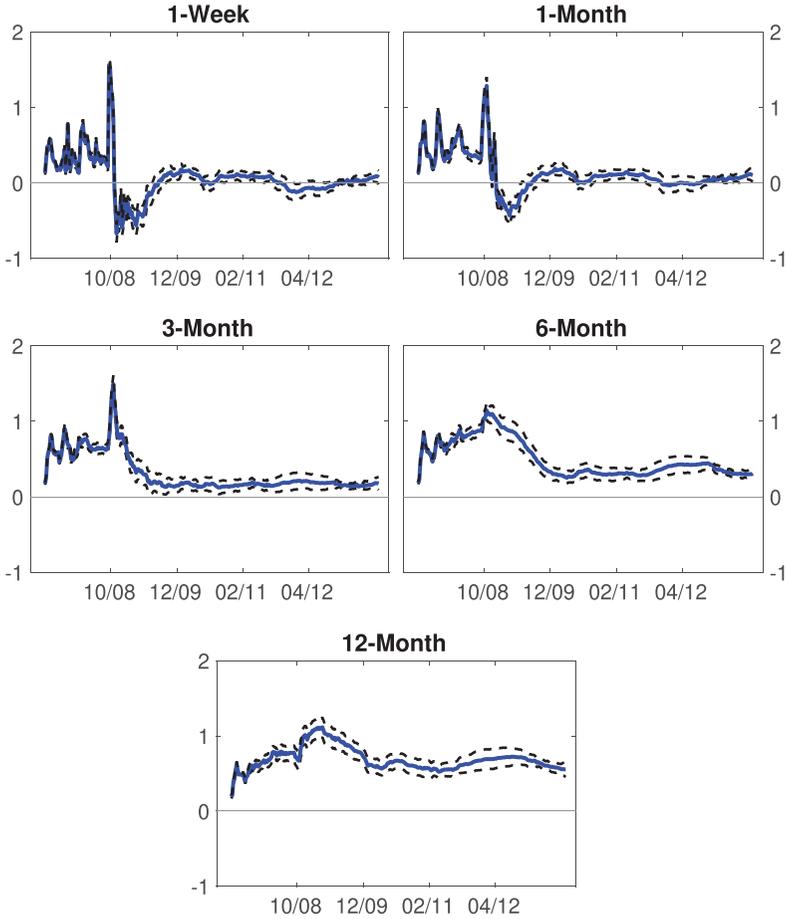
5.   Results

5.1   State Variable Estimates

Figure 2 shows our smoothed estimates of the liquidity premiums λ_{mt} across maturities by plotting the median of the posterior distributions, along with 5th and 95th percentiles. These premiums are fairly tightly estimated. They are generally increasing in

maturity. This result is perhaps not surprising given figures 1A and 1B, which showed the steep term structure of LOIS spreads that was not matched by the term structure of the CDS data. It is also consistent with anecdotes and evidence that liquidity was particularly strained and trading volumes particularly low in longer maturities during the crisis (e.g., Gorton, Metrick, and Xie 2014). The one-week and one-month liquidity premiums drop precipitously, and indeed take negative values, in mid-October 2008. This observation, to which we return later, suggests that Federal Reserve interventions in funding markets around this time significantly ameliorated liquidity strains at short maturities. On the other hand, even by the end of the sample, the 6- and 12-month liquidity premiums had not fully retraced their upward moves during the crisis.

Figure 3 shows the results for the credit risk component of the estimated model. Specifically, panel A shows our estimate of the sensitivity to credit risk, ϕ_t. This series displays significant variation over time. Indeed, our estimate of the weekly standard deviation of changes in ϕ is 0.11.[27] Specifically, credit risk sensitivity spikes during a relatively brief episode immediately following the Lehman bankruptcy when we estimate ϕ_t to jump to a value of about 2.5.[28] We discuss these results further in section 6.

Panel B combines our point estimate of ϕ_t with the CDS data to produce the aggregate credit risk components $\phi_t \overline{C}_{mt}$. Unlike liquidity, credit risk exhibits virtually no differences across maturities. Although credit risk contributes substantially to LOIS spreads during certain episodes, the path of ϕ_t causes it to spend a significant amount of time close to zero. Indeed, outside of the period from late 2008 to mid-2009, average interbank credit spreads rarely rise above 50 basis points at any maturity.

Figure 4 shows the average misreporting bias $(\overline{\beta}_{1t}\sigma_t^C)$, which varies considerably over time. On average, it is slightly negative, consistent with previous empirical work. In particular, we find that

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[27]This is obtained from the corresponding element of **Q**.

[28]Afonso, Kovner, and Schoar (2011) use entirely different measures of bank funding costs and credit risk—and a broader sample of banks—to examine the response of the interbank market immediately after the collapse of Lehman. Their results are consistent with ours in the sense that they conclude that sensitivity to credit risk increased during that period, although they argue that most of this sensitivity took the form of quantity rationing rather than differences in spreads.

Figure 3. Credit Risk
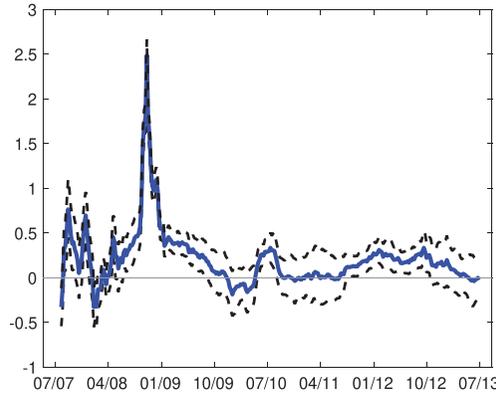
A. Estimated Path of Credit Risk Sensitivity (ϕ_t), with 5th and 95th Percentiles (shown in percentage points)
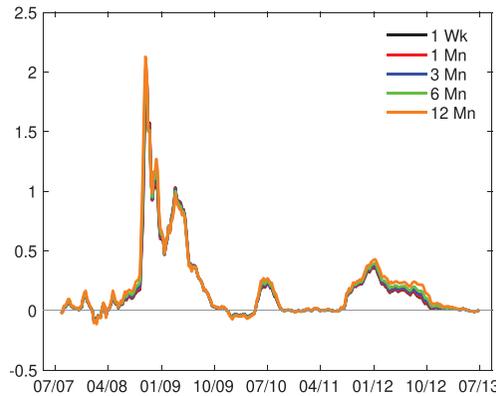
B. Aggregate Credit Risk Component, $\phi_t \overline{C}_{mt}$ (shown in percentage points)

the bias (based on the medians of our posterior distributions) averages around –5 basis points at all maturities. It attains its largest magnitudes of –25 to –30 basis points in early 2009 (about the same time that bank CDS spreads reach their peaks). These magnitudes are similar to those estimated by Kuo, Skeie, and Vickery (2018) and Youle (2014). The finding that the bias was greater during the crisis period is consistent with opportunistic misreporting. However, we also estimate that misreporting biases were considerably smaller and not statistically significant in the period of stress beginning in mid-2011, even though the levels and dispersion of CDS spreads

Figure 4. Estimated Path of the Average Misreporting Bias $(\overline{\beta}_{1t}\sigma_t^C)$, by Maturity, with 5th and 95th Percentiles (shown in percentage points)
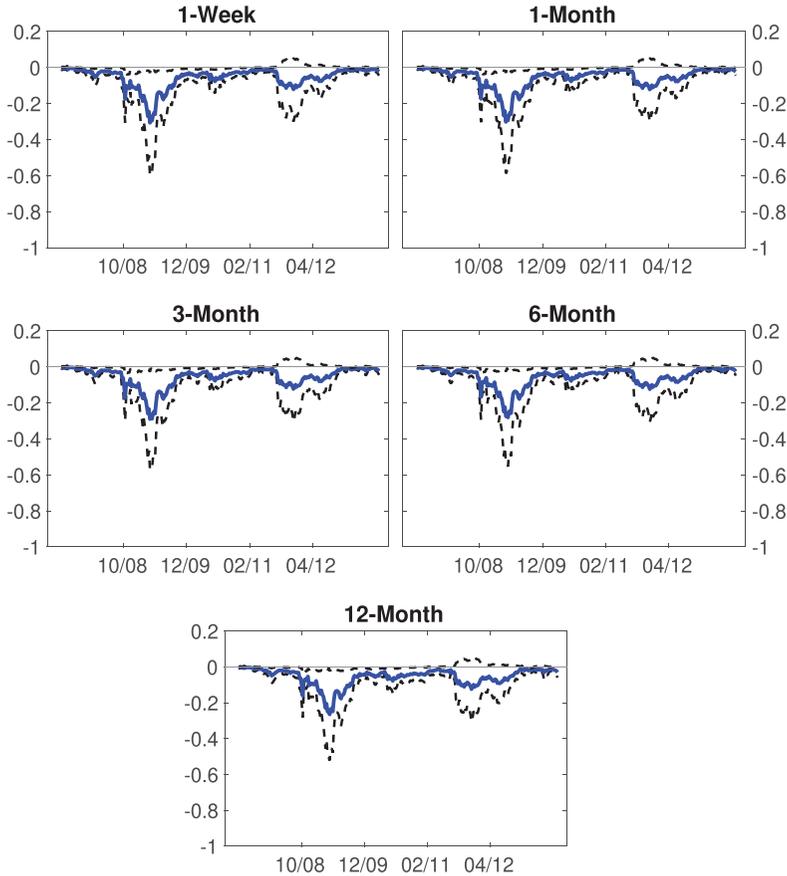
over that period were similar to the 2008–09 period. This suggests, perhaps, that banks made more of an effort to report correctly in an environment of enhanced regulatory attention to this problem, a finding consistent with the results of Gandhi et al. (2019).

Recall that our estimate of the reduced-form parameter β_{2t} allows us to infer the ratio of the perceived cost of lying to the perceived cost of deviating from other banks $(\gamma_{2t}/\gamma_{3t})$. The estimate of this ratio averages 0.04 over the sample, never exceeds 1, and is rarely statistically significant (see figure D.1 in the online

Table 1. Model Results: Relative Contributions of Model Components

	1 Week	1 Month	3 Months	6 Months	12 Months
A. Average Value					
Liquidity	0.069	0.135	0.313	0.499	0.691
Credit Risk	0.175	0.177	0.181	0.188	0.201
Misreporting	−0.054	−0.054	−0.054	−0.054	−0.055
B. Average Fraction of "True" LOIS Spread					
Liquidity	36%	54%	76%	83%	85%
Credit Risk	63%	47%	24%	17%	15%
Misreporting	−30%	−23%	−14%	−8%	−6%

Notes: Panel A shows the average level of each of the indicated components of the average LOIS spread at each maturity, reported in percentage points. Panel B shows the unweighted average value of each component when normalized by the contemporaneous value of the bias-corrected LOIS spread. The contributions are calculated using the medians of the posterior distributions of the estimates.

appendixes). This result implies that the perceived cost of differing from other banks was always much greater than the perceived cost of lying per se. This finding supports our extension of the misreporting model to include a penalty for deviating from the group and helps to explain the relatively tight cross-sectional variance of LOIS spreads compared with that of CDS spreads through both the numerator and the denominator of the ratio. All else equal, a value of γ_{2t}/γ_{3t} close to zero would imply that banks do not vary their reported LIBOR quotes commensurately with their credit risk, but that they would all want to report similar values.

5.2   Decomposition of LOIS Spreads

Table 1 summarizes the relative contributions of the liquidity, credit risk, and misreporting components, based on our estimates of $\lambda_{mt}, \phi_t,$ and $\bar{\beta}_{1t},$ to overall LOIS spreads. Panel A reports our median point estimates of the three components averaged over time. Panel B reports the average ratios of each component to the "true"

LOIS spread.[29] The liquidity component dominates the true LOIS spread at all maturities greater than one week. At horizons greater than one month, it accounts for roughly 80 percent of the level of the spread on average. At the one-month maturity, the liquidity premium constitutes a larger fraction of the average spread than the credit risk premium does (54 percent versus 47 percent), though its average value is slightly smaller (13.5 basis points versus 17.7 basis points). This tension, which also exists to a lesser extent at other maturities, reflects the fact that the average credit risk component is pulled upward by a relatively brief episode in 2008 and 2009; for most of the sample and at most maturities it is lower than the liquidity risk component. Meanwhile, the average misreporting component is modestly negative, as noted above. It is similar in magnitude, on average, across maturities, although as a fraction of the overall LOIS spread it is less important at longer maturities.

Table 2 decomposes the time-series variance of the (true) LOIS spread into the variance of the liquidity and credit risk components and the covariance between them. The variance of the credit risk component is further decomposed, to a first-order approximation, into the variation due to credit risk itself (as measured by CDS spreads) and the variation due to changes in credit risk sensitivity (ϕ_t).[30] Again, this decomposition is performed using the medians of the distributions of our estimated state variables.

Although liquidity seems to be the largest component of the longer-run *levels* of spreads, it is fluctuations in the credit risk component that drive the *movements* over time on average. In addition, movements in credit risk itself (as captured by CDS spreads) account for less than half of this variation. Most is due to movements in credit risk *sensitivity*, represented by the time-varying parameter ϕ_t. As noted above, fluctuations in ϕ_t played a large role in driving LOIS spreads during the crisis. This variation would be missed in specifications that assume a constant coefficient on CDS spreads. Aside from the one-month horizon, the covariance terms contribute

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[29] "Truth" is defined as the estimate we obtain by subtracting the estimated misreporting bias from the reported quote.

[30] The latter decomposition is not exact because ϕ_t and $\overline{C_t}$ are multiplied together, and it is accomplished by holding each of those components constant at its sample mean while allowing the other component to vary.

Table 2. Model Results: Variance Decomposition

	1 Week	1 Month	3 Months	6 Months	12 Months
Liquidity	0.074	0.063	0.064	0.058	0.024
Credit Risk (ϕ and $\bar{C}$)	0.096	0.096	0.098	0.1	0.107
ϕ Only	0.038	0.039	0.042	0.046	0.057
$\bar{C}$ Only	0.012	0.012	0.012	0.012	0.012
Liq./Credit Risk Cov.	−0.047	0.006	0.088	0.107	0.073
Liquidity	60%	38%	26%	22%	12%
Credit Risk (ϕ and $\bar{C}$)	78%	58%	39%	38%	53%
ϕ Only	31%	23%	17%	17%	28%
$\bar{C}$ Only	10%	7%	5%	5%	6%
Liq./Credit Risk Cov.	−38%	4%	35%	40%	36%

Notes: The table shows the contribution of each of the indicated components to the overall time-series variance of the average LOIS spread at each maturity. Contributions are calculated using the medians of the posterior distributions of the estimates. Units in the top panel are percentage points squared. The contributions of liquidity, credit risk, and their covariance sum identically to the total variation in LOIS. The contributions of the credit risk components, ϕ and $\bar{C}$, are based on linear approximations. The bottom panel expresses the variance decomposition as a percentage of the total variance of each LOIS spread.

significantly to the variance of LOIS spreads. Most of this covariance derives from correlation between λ_{mt} and $\overline{C}_{mt}$ (rather than λ_{mt} and ϕ_t). In particular, the negative covariance at shortest maturities primarily results from the drop in short-term liquidity premiums in late 2008, at the same time that aggregate CDS spreads were rising.

5.3   Validation Exercises

5.3.1   Regression Validation of Liquidity Estimate

Our measure of liquidity in the interbank market follows an often-implemented approach of measuring the liquidity component of LOIS spreads as a "residual." That is, in our setup, the common component of what remains in the LOIS data after accounting for credit and misreporting is labeled liquidity. An alternative

approach—taken, for example, by Schwarz (2019)—is to use direct proxies for liquidity itself in the estimation.[31] We validate our model-based estimates of liquidity using a similar rationale by comparing them with other liquidity measures external to our model. We also view this validation as strengthening the case for the correct identification of the other model components. That is, the fact that our estimated liquidity series correlates well with external measures of liquidity also lends credence to our estimates of credit risk and misreporting.

We validate our liquidity component by examining how well it is explained by two short-term liquidity variables that are completely unrelated to any form of credit risk. First, we use a time series of the total available lending capacity from the TAF. This measure is based on the total volume for collateralized loans made available by the Federal Reserve during our sample. This total capacity number is constructed by aggregating the total sizes of each of the auctions whose funding would have been available at a given point in time. This number reflects total funding made available by the Federal Reserve and does not reflect the any individual bank's choices about how much funding to attempt to obtain. Since these auctions were for loans which were primarily made at 28-day maturities (with none exceeding 84 days), they should have had a beneficial effect on liquidity at the one-week and one-month horizon, though not necessarily at the longer horizons in our sample. The second liquidity variable we use is the spread between rates on recently issued Treasury bills and the off-the-run Treasury coupon curve. This spread measure is similar to the Schwarz (2019) liquidity proxy and has also been used in a different context by Greenwood, Hanson, and Stein (2015) as an indicator of excess demand for liquidity at short horizons. An advantage of this series is that we can match it exactly to the maturities of the LIBOR data.[32]

Table 3 shows the results of these regressions. Because the errors in the model displayed very high serial correlation, resulting in

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[31]In Schwarz's paper, a liquidity metric for the German bund market serves as a proxy for liquidity in the interbank market, under the assumption that liquidity conditions in the two markets are likely to be highly correlated.

[32]We note, however, that data on bill rates do not exist at the one-year horizon for part of our sample or at the one-week horizon at all.

Table 3. External Validation of λ

	1 Week			1 Month			3 Months			6 Months			12 Months[c]		
Intercept	0.02**	0.01	0	0	0.01**	0.01**	0.01**	0.01***	0.01***	0.01***	0.01***	0.01***	0.00***	0.01***	0.01***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
T-Bill Spread[a]	0.28***		0.28***	0.16***		0.16***	0.12***		0.12***	0.11***		0.11***	−0.15***		−0.17***
	(0.05)		(0.05)	(0.03)		(0.03)	(0.03)		(0.03)	(0.04)		(0.04)	(0.03)		(0.03)
TAF Total Capacity		−0.66***	−0.69***		−0.76***	−0.73***		−0.06	−0.1		0.21**	0.20***		0.29***	0.31***
		(0.24)	(0.23)		(0.22)	(0.21)		(0.15)	(0.15)		(0.09)	(0.09)		(0.05)	(0.05)
Error AR(1)	0.9	0.89	0.88	0.96	0.96	0.95	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.98	0.98
Adj. R^2[b]	0.36	0.66	0.57	0.82	0.34	0.83	0.25	0.07	0.32	0.69	0.69	0.7	0.06	0.94	0.95
N. Obs.	308	308	308	308	308	308	308	308	308	308	308	308	264	264	264

Notes: Regression performed using Cochrane and Orcutt (1949) procedure to account for serial correlation in the errors. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.
[a] In the regression for the one-week horizon, we use the one-month Treasury note-bill spread, which is the shortest maturity available; all other maturities are matched exactly.
[b] Adjusted R^2 for Cochrane-Orcutt procedure excludes contribution of lagged error term.
[c] Twelve-month data only available since 2008.

Durbin-Watson statistics in the range of 0.1, we report results using the Cochrane and Orcutt (1949) procedure.[33] In nearly all cases, the coefficients are statistically significant with the expected signs. In particular, periods in which the Treasury bill/coupon spread is larger are also periods in which our measure of the liquidity premium is higher at the corresponding maturity. Increases in the total capacity of the TAF are associated with improvements in our liquidity premium at short maturities but deterioration at long maturities. This is consistent with activity migrating from long-term lending to the one-week and one-month sectors of the market, which were being supported by the Federal Reserve.

5.3.2   Checking the Effects of CDS Liquidity

A concern raised about models such as these which use CDS spreads to proxy for credit risk is that—particularly when the credit risk sensitivity parameter is time varying—the model may confuse deviations between the empirical proxy for credit risk (CDS spreads) and actual credit risk with changes in the sensitivity to credit risk (ϕ_t). While our approach to the credit risk proxy attempts to make the best use of *all* available CDS information, here we pause to investigate concerns that the link between CDS and credit risk may be weakened by poor liquidity in the CDS market.

If fluctuations in CDS liquidity were an important driver of our results, then the estimates of liquidity and credit risk sensitivity factors produced by our model would be significantly correlated with CDS liquidity. To check for this possibility, we run regressions of our estimates of liquidity (λ_t) and credit risk sensitivity (ϕ_t) on two measures of CDS liquidity: Nelson-Siegel curve fitting errors for the shortest observable maturities and a sample of CDS bid/ask spreads. As discussed in section 2.1 above, fitting errors for the CDS term

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[33]Using ordinary least squares (OLS) with Newey-West correction produces consistent standard errors in the presence of serial correlation, but it does not overcome the inefficiency of the OLS coefficient estimate in such a situation. Moreover, it does not correct for the spurious correlation that biases R^2 upward. Cochrane-Orcutt is a feasible generalized least-squares regression that explicitly models the autocorrelation of the error term and is asymptotically efficient in the presence of (first-order) serial correlation. For comparison, the OLS regression results with Newey-West autocorrelation-consistent standard errors are reported in the online appendixes.

structure curves represent a measure of CDS liquidity which we have used already as a preliminary screen by dropping any observation for which the fitting error was greater than 25 percent of the overall CDS spread. Here, we include in each regression the mean of the cross-sectional distribution of the absolute value of these curve fitting errors. The CDS bid/ask spreads are constructed by Markit for each contract at each maturity on each day that they receive sufficient quotes. Unfortunately, Markit only began collecting these data in 2010, and we only have observations for the three U.S. banks in the LIBOR panel. While this limitation is significant, one might expect CDS liquidity to be highly cross-sectionally correlated across banks. We construct indexes of bank-CDS liquidity at the 6- and 12-month horizons by averaging the three bid/ask spreads that we observe at each of those maturities on each day.[34]

Table 4 reports the results.[35] The coefficients shown are in a sense upper bounds on the contamination of our results, because we expect measures of CDS liquidity to be correlated with actual conditions in bank funding markets. Nonetheless, in most cases, the external liquidity measures have little to no significant correlation with the model estimates. The adjusted R^2's (which exclude the effect of serial correlation) are all fairly close to zero. Even in the cases where the coefficients are statistically significant, their economic magnitudes are low. In short, although it is true that liquidity in CDS may create some concern that CDS spreads reflect more than pure credit risk, we find no evidence that the resulting noise in the data is driving our results.

5.4   Does Accounting for Misreporting Matter?

Even though our estimate of the aggregate misreporting bias is modest on average, including the misreporting terms in our model has a large influence on both the fit and the qualitative results. To see this, we reestimated the model under the assumption that γ_{1it} and γ_{3t} are always zero (i.e., there is no benefit to misreporting and no

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[34]The online appendixes contain further details and a table of summary statistics on these two liquidity proxies.

[35]Again, we use Cochrane-Orcutt regression because of the highly serially correlated errors, with autocorrelation-consistent OLS results reported in the online appendixes.

Table 4. Checking for Contamination from CDS Illiquidity

	λ^{6M}		λ^{12M}		ϕ	
	Full Sample	**Since 2010**	**Full Sample**	**Since 2010**	**Full Sample**	**Since 2010**
Intercept	0.01***	0.01***	0.02***	0.01***	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
6-Month Avg.	−0.01	0.02			0.39	0.23*
Fit Err.	(0.12)	(0.03)			(0.48)	(0.14)
6-Month B/A		−0.15				−0.76
		(1.31)				(15.5)
12-Month Avg.			−0.08	−0.11*	−0.52	−0.15
Fit Err.			(0.13)	(0.06)	(0.65)	(0.28)
12-Month B/A				1.41		3.18
				(2.62)		(27.90)
Error AR(1)	0.99	0.99	0.97	0.99	0.95	0.96
Adj. $R^{2\,\text{a}}$	0.00	0.01	0.00	0.17	0.01	0.12
N Obs.	308	167	308	167	308	167

Notes: Regression performed using Cochrane and Orcutt (1949) procedure to account for serial correlation in the errors. The labels "6-Month Avg. Fit Err." and "12-Month Avg. Fit Err." correspond to the mean absolute fitting error of the Nelson-Siegel curve used to fit the CDS data; they are the mean from the cross-sectional distribution (of sample banks) at the 6- and 12-month maturity, respectively. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.
ᵃAdjusted R^2 for Cochrane-Orcutt procedure excludes contribution of lagged error term.

cost of deviating from other banks). These assumptions are sufficient to make the β_{1it} and β_{2t} terms in equation (7) equal to zero. Consequently, the model that we now estimate contains only the liquidity and credit risk terms.

Figure 5A plots the posterior trace of **R** for this restricted model versus the baseline model estimated above.[36] This is a summary measure of how closely either model is able to match the LOIS quotes.[37] Including the misreporting terms reduces the estimate of

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[36]For color versions of the figures, see the paper on the IJCB website (http://www.ijcb.org).

[37]Our prior distribution in both cases is essentially flat over the region depicted in figure 5A.

Figure 5. Model without Misreporting
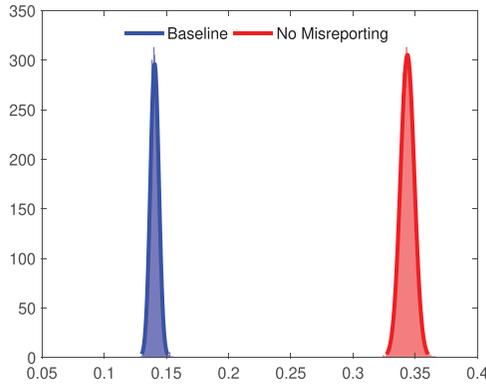
A. Posterior Distributions of the Trace of **R** under the Baseline Model (left) and the Model with Misreporting Terms Set to Zero (right)
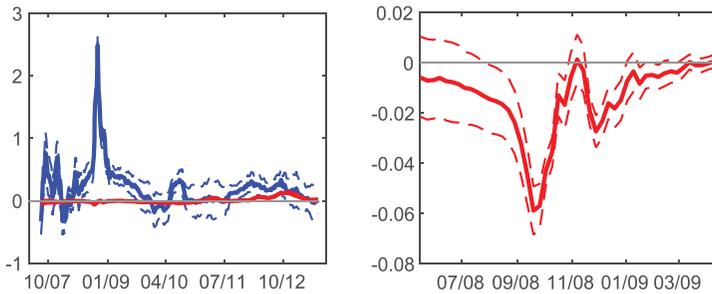
B. Estimated Path of Credit Risk Sensitivity (ϕ_t), with 5th and 95th Percentiles (shown in percentage points)

Notes: Panel B: On the left, ϕ_t is shown for both the baseline model (blue) and the model with misreporting terms set to zero (red) for a period of roughly a year around the peak of the crisis. On the right, we show only the model with the misreporting terms set to zero—for a period of roughly a year around the peak of the crisis—in order to show the dip below zero at the appropriate scale.

the trace by more than half, indicating that these terms are important for fitting the data.

Apart from the significantly better econometric fit of including misreporting in the model, figure 5B shows the economic intuition behind including the misreporting mechanism by looking at the estimate of credit risk sensitivity during a period of roughly one year during the peak of the financial crisis. The panel on the left shows

Table 5. Model Results without Controlling
for Misreporting: Relative Contributions of
Model Components

	1 Week	1 Month	3 Months	6 Months	12 Months
A. Average Value					
Liquidity	0.196	0.245	0.439	0.646	0.849
Credit Risk	0.002	0.002	0.002	0.003	0.005
Misreporting	0	0	0	0	0
B. Average Fraction of "True" LOIS Spread					
Liquidity	96%	89%	100%	103%	101%
Credit Risk	0%	0%	0%	0%	0%
Misreporting	0%	0%	0%	0%	0%

Notes: Panel A shows the average level of each of the indicated components of the average LOIS spread at each maturity, reported in percentage points. Panel B shows the unweighted average value of each component when normalized by the contemporaneous value of the bias-corrected LOIS spread. The contributions are calculated using the medians of the posterior distributions of the estimates. Using the model that excludes the misreporting terms, the table shows the contribution of each of the indicated components to the overall time-series variance of the average LOIS spread at each maturity. Units in panel A are percentage points squared.

estimates of ϕ_t under both the baseline model and the model without misreporting terms. Without accounting for misreporting, the model is best fit by credit risk sensitivity that always hovers much closer to zero. In addition, as seen by focusing exclusively on the model without misreporting in the panel on the right, we see that without accounting for misreporting the sensitivity to credit risk actually becomes slightly negative—indicating a risk-*loving* attitude among interbank lenders—at the peak of the crisis. Such a finding would also be at odds with previous research, including Afonso, Kovner, and Schoar (2011), which finds heightened credit risk sensitivity at exactly this time. Due to the credit risk sensitivity being driven to zero in the absence of misreporting, this model puts essentially all of the level and variation in the LOIS spread in the liquidity term, rather than giving credit risk an important role. This can be seen in tables 5 and 6, which reproduce tables 1 and 2 for the model that excludes misreporting.

Table 6. Model Results without Controlling for Misreporting: Variance Decomposition

	1 Week	1 Month	3 Months	6 Months	12 Months
Liquidity	0.123	0.153	0.227	0.236	0.165
Credit Risk	0	0	0	0	0.001
ϕ Only	0.001	0.001	0.001	0.001	0.001
$\bar{C}$ Only	0	0	0	0	0
Liq./Credit Risk Cov.	-0.008	0.001	-0.002	-0.004	0.006
Liquidity	107%	99%	101%	101%	96%
Credit Risk	0%	0%	0%	0%	0%
ϕ Only	1%	0%	0%	0%	1%
$\bar{C}$ Only	0%	0%	0%	0%	0%
Liq./Credit Risk Cov.	-7%	1%	-1%	-2%	4%

Notes: Using the model that excludes the misreporting terms, the table shows the contribution of each of the indicated components to the overall time-series variance of the average LOIS spread at each maturity. Contributions are calculated using the medians of the posterior distributions of the estimates. Units in the top panel are percentage points squared. The contributions of the credit risk components, ϕ and $\bar{C}$, are based on linear approximations. The contributions of liquidity, credit risk, and their covariance sum identically to the total variation in LOIS. The bottom panel expresses the variance decomposition as a percentage of the total variance of each LOIS spread.

There are at least two statistical reasons that accounting for misreporting matters. First, while the effects of misreporting on the aggregate level of LIBOR are modest, the effects on individual banks' submissions can be large. The flexibility introduced by the misreporting terms helps us to fit the cross-sectional data much better, since (as noted in section 2) the differences between banks can generally not be explained by credit risk alone. It therefore sharpens our estimates of λ and ϕ. Second, the time-series correlation between the levels and dispersion of CDS quotes (C_{it} and σ_t^C) is quite high—on the order of 80 percent across maturities in our data. Thus, leaving out the β_1 term in equation (8) introduces omitted-variable bias. While in theory that bias could go in either direction, in practice it pushes our estimates of ϕ_t toward zero, with the λ_t terms picking up most of the slack.

Figure 6. Posterior Distribution of ϕ in the Specification where ϕ Is Not Time Varying
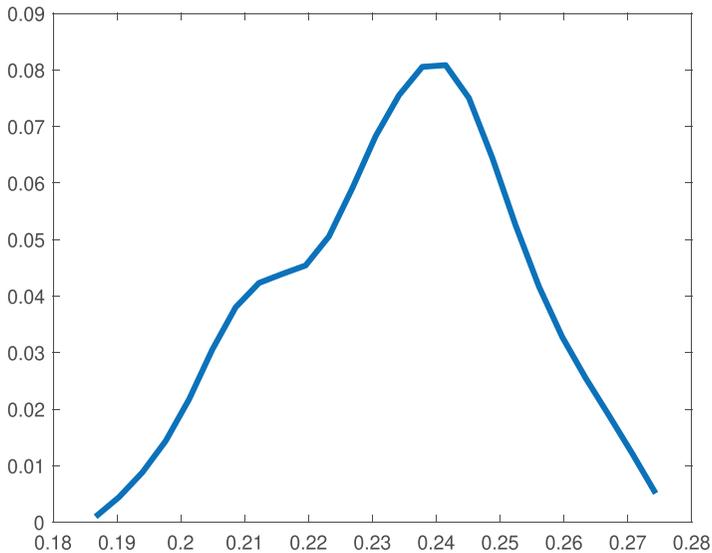
5.5 *Is Time Variation in Credit Risk Sensitivity Important?*

The baseline model articulated in equation (8) allows ϕ to vary over time. That is, in the baseline setup, the sensitivity of inter-bank spreads to bank credit risk can be different in the crisis than it is in the recovery. As a robustness check, we estimated a version of the model in which ϕ was fixed. This was done through the inclusion of an additional Gibbs step to the estimation. That is, we extracted ϕ from the θ_t vector, creating θ_t^* (and Q^*), which continues to evolve according to equation (9), and drawing a fixed ϕ in a separate step.

The resulting posterior distribution for the fixed ϕ peaks at a value slightly above the time-series average of the median path of the time-varying ϕ_t for the baseline model. Figure 6 shows that the posterior distribution also has a hint of bimodality below the peak, which we view as owing to the potential for different sensitivities to credit risk at different points in time in the sample. We build the Bayes factor to do formal model comparison and find a log-Bayes factor of 120, indicating that the data prefer the baseline

specification under the strictest selection criteria.[38] This aligns with evidence from Afonso, Kovner, and Schoar (2011) suggesting that attention to credit risk was higher during the crisis than at other times, and that earlier work decomposing credit risk and liquidity which assumes a constant level of sensitivity to credit risk may be misspecified.[39]

6.   Event Studies

We use the results of our model to examine the drivers of funding pressures in different episodes during and after the financial crisis. Among other things, this exercise provides suggestive evidence on the efficacy of various policy measures taken during that time. Specifically, table 7 reports the decomposition of changes in average LOIS spreads around five events that garnered wide attention by showing changes in the three fundamental components of those spreads (λ_{mt}, $\overline{C}_{mt}$, and ϕ_t) in the weeks surrounding each event.

The first event ("Beginning of Crisis") includes the suspension of redemption of funds by BNP Paribas that marked the start of the financial crisis and that corresponded to the sudden jump in LOIS spreads that was evident in figure 1A. The table shows that, during the month of August 2007, LOIS spreads at all but the shortest maturities exhibited increases that were in the 99th percentile. Our decomposition shows that these increases were due to a deterioration in liquidity, but also to the rise in ϕ. Similarly, the second column shows the breakdown for the period around the introduction of the TAF in December 2007. In the weeks following the TAF announcement, LOIS spreads fell across the board. We attribute a sizable portion of the fall at the one- and three-month maturities to improved liquidity. Again, movement in ϕ is also estimated to have played a role, though the total shift in credit risk was not large. The Federal Reserve expanded the TAF and introduced a host of new liquidity facilities targeted at relatively short maturities in October

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[38]For reference, Kass and Raftery (1995) suggest a log-Bayes factor of 5 as the most stringent threshold for evidence against a model. We construct the log-Bayes factor by building the log-marginal data densities via the harmonic mean method.

[39]These results and replications of tables 1 and 2 under a fixed-ϕ regime are included in the online appendixes.

Table 7. Decomposition of Model Results across Various Time Periods

		Beginning of Crisis	TAF	Fed Facilities	SCAP	European Crisis
	Start →	7/30/07	12/3/07	9/29/08	4/27/09	7/25/11
	End →	8/31/07	1/4/08	11/7/08	5/22/09	9/9/11
LOIS	1 Week	0.5	−0.27	−2.01***	−0.05	0.01
	1 Month	0.53**	−0.65***	−1.00***	−0.12	0.04
	3 Months	0.54***	−0.35*	−0.63***	−0.31*	0.11
	6 Months	0.59***	−0.22	−0.36*	−0.33**	0.13
	12 Months	0.45***	−0.11	−0.28*	−0.35***	0.17
λ	1 Week	0.44*	−0.13	−1.90***	0.25	−0.08
	1 Month	0.46***	−0.51***	−0.78***	0.16	−0.05
	3 Months	0.47***	−0.20**	−0.33***	−0.04	0.01
	6 Months	0.51***	−0.07	0.06	−0.06	0.02
	12 Months	0.37***	0.05	0.30***	−0.05	0.05
Total Credit Risk	1 Week	0.06	−0.11	−0.17**	−0.37***	0.12
	1 Month	0.06	−0.06	−0.21	−0.37***	0.12
	3 Months	0.06	−0.04	−0.31*	−0.37***	0.13
	6 Months	0.07	−0.01	−0.44***	−0.37***	0.13
	12 Months	0.09	−0.01	−0.64***	−0.36***	0.14
$\bar{C}$	1 Week	0.01	−0.03	0.16	−0.74***	0.96***
	1 Month	0.01	−0.03	0.14	−0.74***	0.97***
	3 Months	0.02	−0.02	0.07	−0.75***	0.99***
	6 Months	0.02	−0.02	−0.01	−0.76***	1.01***
	12 Months	0.02	−0.01	−0.13	−0.75***	1.01***
ϕ		0.53***	−0.65***	−0.47**	−0.09	0.09

Notes: The table shows cumulative changes in the LOIS spread and CDS spread data and in the medians of the posterior distributions of our state-variable estimates during certain episodes or interest. Asterisks indicate values that are in the top or bottom 5, 2.5, and 0.5 percentiles, based on the distributions observed during our sample period. LOIS, liquidity, and CDS spreads are reported in percentage points.

2008.[40] As shown in the third column, LOIS spreads narrowed significantly around this time, and, in the first two maturities likely strongly influenced by the TAF, our model attributes most of this narrowing to an improvement in liquidity (seen by comparing the sizes of the λ contribution with the size of the contribution from the total credit risk effect). These results compliment Wu (2011), who also found liquidity improvements in response to the TAF. Interestingly, in both the December 2007 and October 2008 episodes, liquidity improvements at the short end were not accompanied by such improvements at the long end. Indeed, if anything, longer-term liquidity deteriorated during these periods, particularly for the 12-month maturity. This result, which echoes our regression findings in table 3, may reflect a substitution by banks into the maturities where the facilities were targeted and away from longer-term funding, which was not generally supported by these programs.

To see more plainly how short-term liquidity spreads changed during the period when the TAF was operational, figure 7 plots our estimates of $\lambda_{1wk,t}$ and $\lambda_{1mn,t}$ against the level of total capacity for TAF loans by the Federal Reserve. The decreases in liquidity premiums during the two TAF-related windows considered in the table are evident, but, as suggested by the regression results reported in table 3, the correspondence between the series extends over the entire life of the facility. Again, no such relationship exists with the longer-maturity liquidity spreads (not shown).

As seen by the relatively muted movements in the $\overline{C}$ panel of the table for the first three events, CDS spreads did not move substantially in any of the episodes discussed so far. The final two columns of the table consider events in which they did. First, in May of 2009, the Federal Reserve announced the results of the Supervisory Capital Assessment Program (SCAP) (also known as the bank "stress tests"), and bank CDS spreads narrowed significantly in response. Simultaneously, LOIS spreads narrowed, particularly at longer maturities, and we estimate that this occurrence was entirely due to the improvement in credit risk; we do not see any improvement in liquidity around this time. Similarly, we do not

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[40]The new facilities included the Commercial Paper Funding Facility, the Money Market Investor Funding Facility, and new or increased liquidity swap lines with numerous foreign central banks.

Figure 7. The Estimated Path of the Short-Maturity Liquidity Premiums (λ_t) and the Level of Total Capacity for TAF Loans at the Federal Reserve
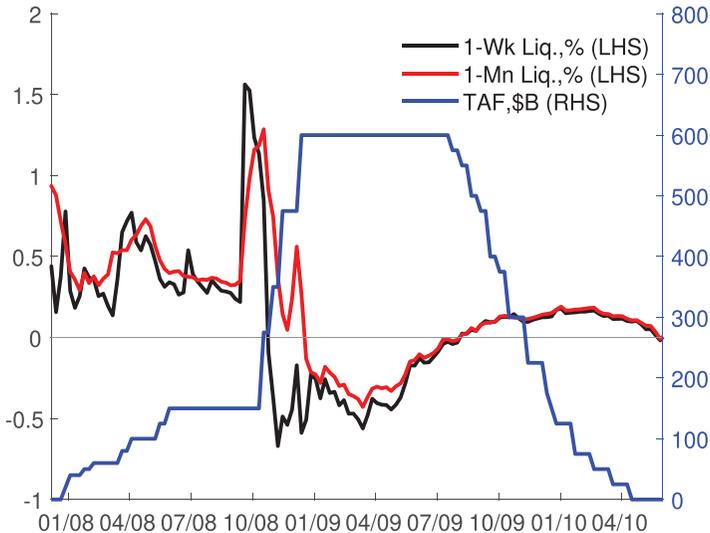
find a significant deterioration in liquidity in response to the turbulence in European sovereign debt markets that arose in August 2011, even though bank CDS spreads widened dramatically. Moreover, the CDS widening did not pass through to a significant degree into LOIS spreads because our estimate of ϕ was near zero around this time.

7.   Conclusion

This paper develops a model that combines the fundamental determinants of interbank spreads given by LIBOR data with the possible costs and benefits of strategic misreporting by LIBOR-submitting firms. It also maximizes usage of the information about banks' short-term credit risk by utilizing the full CDS information set. By explicitly modeling misreporting as we reexamine the credit risk and liquidity debate about short-term funding spreads, we merge two growing strands of the literature and place this important decomposition for policymakers onto firmer footing.

We conclude that, during the period examined, liquidity was the largest component of bank funding costs, especially at longer maturities. Furthermore, we find that, at shorter maturities, liquidity improved significantly following Federal Reserve interventions in short-term funding markets, in contrast to some previous studies, such as Taylor and Williams (2009), that suggest the Federal Reserve's actions had limited effects. Thus, it appears that policymakers have had ample scope to affect bank borrowing costs and funding market pressures through liquidity interventions. However, we also find that most of the *variation* in LOIS spreads during the crisis was due to the credit risk component and that much of the fluctuations in that component stem from movements in the interbank rate's sensitivity to credit risk, rather than from changes in the level of credit risk per se. This suggests policymakers' ex ante regulatory actions to prevent credit risk and ex post actions (such as the SCAP examinations of 2009) to clarify the magnitude of actual credit risk may also help calm funding markets. In particular, we find very high sensitivity to credit risk around the failure of Lehman Brothers, but not subsequently.

We find the misreporting bias to be modest on average, but our results indicate that accounting for it is of first-order importance when disentangling the credit and liquidity factors in models which examine bank-level data. Additionally, it appears important to account for the possibility that banks perceive a cost of being outliers in the distribution of LIBOR submissions, rather than just a cost of not telling the truth.

Appendix. Derivation of Measurement Equations

Each bank's first-order condition is

$$\gamma_{1imt} - \gamma_{2t}\left(\frac{\widehat{L}_{imt} - L_{imt}}{\mathrm{std}_{mt}\left[\widehat{L}_{imt}\right]}\right) - \gamma_{3t}\left(\frac{\widehat{L}_{imt} - \overline{\overline{L}}_{mt}}{\mathrm{std}_{mt}\left[\widehat{L}_{imt}\right]}\right) = 0. \quad \text{(A.1)}$$

Solving for $\widehat{L}_{imt}$ and substituting equation (1) (imposing $\phi_{imt} = \phi_t$ for all i and m) gives

$$\widehat{L}_{imt} = \frac{\gamma_{1imt}\mathrm{std}_{mt}\left[\widehat{L}_{imt}\right] + \gamma_{2t}\left(\lambda_{mt} + \phi_t C_{imt}\right) + \gamma_{3t}\overline{\widehat{L}}_{mt}}{\gamma_{2t} + \gamma_{3t}}. \quad (A.2)$$

Averaging across banks and rearranging delivers

$$\overline{\widehat{L}}_{mt} = \lambda_{mt} + \phi_t\overline{C} + \frac{\overline{\gamma}_{1t}}{\gamma_{2t}}\mathrm{std}_{mt}\left[\widehat{L}_{imt}\right], \quad (A.3)$$

where $\overline{\gamma}_{1t}$ is the cross-sectional mean of γ_{1i}. Substituting back into equation (A.2),

$$\widehat{L}_{imt} = \lambda_{mt} + \phi_t\frac{\gamma_{2t}C_{imt} + \gamma_{3t}\overline{C}_{mt}}{\gamma_{2t} + \gamma_{3t}}$$
$$+ \left(\frac{\gamma_{1imt}}{\gamma_{2t} + \gamma_{3t}} + \frac{\gamma_{3t}\overline{\gamma}_{1mt}}{\gamma_{2t}(\gamma_{2t} + \gamma_{3t})}\right)\mathrm{std}_{mt}\left[\widehat{L}_{imt}\right]. \quad (A.4)$$

The cross-sectional variance is therefore

$$\mathrm{var}_{mt}\left[\widehat{L}_{imt}\right] = \left(\frac{\phi_t\gamma_{2t}}{\gamma_{2t} + \gamma_{3t}}\right)^2(\sigma_{mt}^C)^2 + \frac{\mathrm{var}_{mt}\left[\widehat{L}_{imt}\right]\mathrm{var}_{mt}\left[\gamma_{1imt}\right]}{(\gamma_{2t} + \gamma_{3t})^2}$$
$$= \frac{(\phi_t\gamma_{2t})^2}{(\gamma_{2t} + \gamma_{3t})^2 - \mathrm{var}_{mt}\left[\gamma_{1imt}\right]}(\sigma_{mt}^C)^2. \quad (A.5)$$

Thus, we can write equation (7), by defining

$$\beta_{1imt} = \left(\frac{\gamma_{1imt}}{\gamma_{2t} + \gamma_{3t}} + \frac{\gamma_{3t}\overline{\gamma}_{1mt}}{\gamma_{2t}(\gamma_{2t} + \gamma_{3t})}\right)\frac{\phi_t\gamma_{2t}}{\sqrt{(\gamma_{2t} + \gamma_{3t})^2 - \mathrm{var}_{mt}\left[\gamma_{1imt}\right]}} \quad (A.6)$$

and

$$\beta_{2t} = -\frac{\phi_t\gamma_{3t}}{\gamma_{2t} + \gamma_{3t}}. \quad (A.7)$$

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How Would U.S. Banks Fare in a Negative Interest Rate Environment?*

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The effectiveness of negative interest rates as a monetary policy tool depends importantly on the response of the banking sector. This paper offers unique new insights for U.S. banks by using supervisory data to examine bank-level expectations regarding the impact of negative rates on profitability through net interest margins. The main results show that the largest U.S. banks differ significantly in how they respond to negative interest rates. The most significant channel of adverse exposure comes from the pass-through of the negative policy rate to interest rates on short-term liquid assets held on the balance sheet. At the same time, on the liability side, banks that rely more heavily on short-term wholesale funding, including financing through the repo market, may benefit through a reduction in funding costs. In the aggregate, these effects likely wash out as liquidity provision is sufficiently well diversified across the banking sector as a whole.

JEL Codes: E43, E44, G21.

1. Introduction

Since the financial crisis a number of central banks, including the European Central Bank (ECB), Danmarks Nationalbank, the

Swedish Riksbank, the Swiss National Bank, and the Bank of Japan, have implemented negative interest rate policies with the aim of generating monetary stimulus for real economic activity.[1] In the United States, a negative interest rate policy, though never implemented, has been discussed amongst academics as well as in broad policy circles.[2] While the immediate urgency of this debate has diminished as the post-crisis expansion continues, it is still the case that the federal funds rate remains near historic lows. As such, a series of adverse shocks would likely put unconventional policy tools, including negative interest rates, back under consideration.

In principle, the transmission of monetary policy as implemented through negative interest rates can work through a number of possible transmission channels, but one that has received particular attention operates through the banking sector. The idea is that by charging a fee for holding excess reserves at the central bank, a negative interest rate policy can be used to encourage banks to substitute out of reserves and into other assets. Under a certain set of assumptions, doing so can influence the loan supply schedule such that the resulting increase in bank credit lowers the cost of capital for bank-dependent borrowers. This, in turn, has a stimulative effect on the rest of the macroeconomy. The bank lending channel of monetary policy transmission is articulated in Bernanke and Blinder (1988) and discussed more generally in Bernanke and Gertler (1995). Empirical support is provided by Bernanke and Blinder (1992), Kashyap and Stein, (1995, 2000) and Jimenez et al. (2012), among others.

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[1]Bech and Malkhozov (2016) point to a desire to manage inflation and inflation expectations as a key motivation behind the ECB and the Riksbank implementing negative interest rates, while the the Swiss and Danish National Banks were motivated by a desire to mitigate appreciation pressure on their respective currencies.

[2]From an academic perspective, Goodfriend (2000) is an early contribution on the implementation of negative interest rates and Goodfriend (2017) provides a discussion of the evolution of the literature since that time. From the policy perspective, a number of prominent economists have commented on implementing negative interest rates in the United States, including Mankiw (2009), Blinder (2010), Bernanke (2016), and Kocherlakota (2016).

However, this transmission channel may be complicated by the effect of negative interest rates on bank profitability.[3] Bank profits are determined, in part, by the net interest margin—the difference between interest income and interest expenses. When the policy rate goes negative, a common concern is that banks might not be willing to pass this cost on to their deposit base. In this case, incomplete pass-through to deposit rates leads to compression of the net interest margin, which erodes bank profits. In turn, reduced profitability makes it more difficult to raise capital from retained earnings, thereby dampening monetary transmission through the bank lending channel. Kishan and Opiela (2000) and Gambacorta and Mistrulli (2004) present empirical evidence suggesting that banks' willingness to supply new loans is importantly influenced by bank capital. Even if banks do allow full pass-through to deposit rates, a negative interest rate policy can still pose complications because retail and wholesale depositors might not be willing to pay to hold deposits and may themselves substitute into other assets (i.e., cash). This potential for deposit flight can undermine financial stability by increasing liquidity risk in the banking sector.

The impact on the strength of monetary transmission, as well as on financial stability more generally, makes it clear that a more complete understanding of how bank profitability might evolve in a negative interest rate environment is an important component of the effectiveness of negative rates as a policy instrument. However, experience with negative rate episodes is limited. We can look to a short period of recent history for a subset of European and Japanese banks, but when it comes to understanding the U.S. banking system we are severely limited by lack of historical experience.

This paper is uniquely positioned to shed light on how U.S. banks view themselves as being exposed to negative interest rates. We

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[3]Concerns regarding negative interest rates extend beyond bank profitability. Bernanke (2016) points to potential adverse effects on money market funds as well as legal and operational constraints on the implementation by the Federal Reserve. Hannoun (2015) raises additional concerns regarding the potential to influence risk-taking behavior via the search for yield in a low rate environment as well as the adverse impact on nonbank financial institutions which offer long-term liabilities at fixed nominal rates, such as life insurance contracts. See also McAndrews (2015) for additional discussion of the complications associated with negative interest rates.

use confidential supervisory data from the Comprehensive Capital Analysis and Review (CCAR) stress tests to empirically assess how individual banks view their own profitability—specifically through the lens of net interest margins (NIMs)—evolving in a hypothetical negative interest rate environment.[4] The data cover the 30 largest bank holding companies (BHCs) which, taken together, constitute roughly 75 percent of total assets in the U.S. banking system over five consecutive years (2014 through 2018) of stress-test vintages.

Our identification strategy exploits the fact that negative rates were introduced by the Federal Reserve as an explicit scenario design feature in the supervisory severely adverse scenario of the 2016 vintage of CCAR. This design feature allows us to isolate how individual banks view their NIMs as evolving in a negative rate environment, even after controlling for underlying macroeconomic developments and bank-specific characteristics.

The main results reveal considerable differences across the BHCs in our sample. All banks anticipate reduced profitability in response to the macroeconomic conditions that give rise to the negative rate environment in the first place. After controlling for these effects, we find that roughly one-third of the banks are exposed to lower profits through NIM compression due to negative policy rates per se. In contrast, an additional one-third project expanded NIMs as negative rates lead to lower short-term funding costs. The remaining banks in our sample do not believe that negative rates will have a material impact on profitability beyond what can be explained by the underlying macroeconomic environment.

To explain these cross-bank differences, we present a simple decomposition of the NIM and use it to highlight some potential nonlinearities that may arise as the policy rate turns negative. We examine three hypothesized channels of exposure. The *retail deposit channel* suggests that imperfect pass-through to deposit rates will amplify NIM compression. Drawing on Kashyap, Rajan, and Stein

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[4]Negative interest rates can potentially affect bank profitability through a number of different channels beyond net interest margins. For example, negative rates could boost earnings through increased lending volumes or through stronger demand for capital management and investment banking services due to a low rate environment. Alternatively, negative interest rates may boost profits through asset-valuation changes. Our specific focus in this paper on net interest margins is due to data availability, as will be described in greater detail in section 3 below.

(2002), we also examine a *liquidity-management channel* whereby exposure to negative interest rates is driven by short-term assets on the balance sheet relative to short-term liabilities. In contrast with the deposit margin channel, the liquidity-management channel relies on unimpeded pass-through to interest rates on a wide variety of short-duration assets and liabilities. Finally, we examine the *yield curve compression channel*, which suggests that as the level of the policy rate moves lower and eventually turns negative, the yield curve becomes progressively flatter, thereby amplifying NIM compression.

The decomposition is done in a way that allows a test of the empirical relevance of each channel using publicly available balance sheet data. The results suggest that U.S. banks do not face significant exposure through either the retail deposit or the yield curve compression channel. There is, however, much stronger support for exposure through liquidity-management practices. On the asset side of the balance sheet, banks with a high proportion of reserves are highly exposed to amplified NIM compression as rates turn negative. On the liability side, banks that rely more heavily on short-term wholesale funding anticipate a boost to NIMs through a reduction in funding costs in a negative rate environment.

Banks also face significant exposure through their net repo position, but this exposure differs importantly between global systemically important banks (G-SIBs) and non–G-SIBs. The more active a non–G-SIB bank is in providing liquidity to borrowers via the repo market, the larger the expected NIM compression. But, this effect is ameliorated for G-SIBs due to the fact that they have large broker-dealer subsidiaries which rely heavily on repo financing. Hence, at the holding company level, the parent G-SIB anticipates a reduction in the funding costs of their dealer-related activity which largely offsets the negative exposure faced by non–G-SIB bank holding companies.

An implication of these results is that the impact of negative rates on the U.S. banking system is largely distributional and bank-specific exposure is determined by the structure of the individual balance sheet. Some banks will experience lower profits through NIM compression, while others will see their NIMs expand. However, at the aggregate level, it is reasonable to think that these distributional effects would wash out. There is sufficient diversity

in liquidity provision services across the banking sector as a whole such that, on average, the reduction in interest income from short-maturity assets is offset by lower funding costs on short-maturity liabilities.

From a policy perspective, one interpretation is that, rather than concentrating on the potential adverse consequences for the profitability of the aggregate banking sector, policymakers might be better served by placing greater emphasis on microprudential monitoring—that is, the safety and soundness of those institutions most heavily exposed to amplified losses in a negative interest rate environment. To this end, the liquidity coverage ratio (LCR)— a newly implemented regulation which encourages banks to hold a larger proportion of high-quality liquid assets on their balance sheet—could interact with a negative rate policy in an important way. The LCR is intended to reduce run risk in times of stress, but the results of this paper suggest that compliance with the LCR in a negative interest rate environment may have the unintended consequence of making it more difficult for these banks to raise capital.

We should emphasize that the results presented here are not based on *actual data*; instead, they are based on *projections* provided by the BHCs themselves *conditional on hypothetical macroeconomic scenarios*. The CCAR process is designed to ensure that the bank-provided stress-test projections are a reasonably accurate representation of how an individual bank views itself as faring in a particular macroeconomic scenario. As part of the stress-testing regime, regulators place considerable scrutiny on assessing the quality of the scenarios as well as the bank models used to produce the stress projections. In fact, at least through the 2018 stress-test vintage, banks could fail the stress tests for either quantitative or qualitative reasons, and the penalties for failure can be quite severe.[5] In addition, from an academic standpoint, there is a small body of empirical research which points favorably to the

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[5]The cost of failing the stress tests is very high for the participating banks. In the past, failure has played a role in the firing of a CEO (Vikram Pandit at Citibank in 2012), has led to significant declines in the stock prices of failing banks, and has led to restrictions being placed on planned dividend payouts for shareholders.

information content of the exercises, both in the United States and the European experience.[6]

In terms of related literature, in the broadest sense, this paper builds on a wide body of existing research seeking to understand bank exposure to interest rate risk.[7] More narrowly, a few papers have empirically examined the impact of low levels of interest rates on bank profitability, but this paper is most closely related to a small but emerging body of research on negative interest rates.[8]

The theoretical literature on negative rates is limited, but two recent contributions are Rognlie (2016) and Brunnermeier and Koby (2019), both of which develop microfounded models which show that the effective lower bound for monetary policy is not necessarily zero. From an empirical perspective, a handful of studies, including Basten and Mariathasan (2018), Bottero et al. (2019), and Heider, Saidi, and Schepens (2019), use a difference-in-differences methodology to identify the affects of negative interest rates on bank behavior, mainly using European data.[9] A key point of differentiation amongst these three papers is the way in which bank exposure is measured. For example, Heider, Saidi, and Schepens (2019) rely

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[6]Morgan, Peristiani, and Savino (2014), Fernandez, Igan, and Pinheiro (2017), and Flannery, Hirtle, and Kovner (2017) all present evidence arguing in favor of the information content of the U.S. stress tests, while Petrella and Resti (2013) and Camara, Pessarossi, and Philippon (2017) present evidence for the European stress tests.

[7]Flannery and James (1984) is an early paper in this literature. More recently, see Landier, Sraer, and Thesmar (2013), Begenau, Piazzesi, and Schneider (2015), and English, van den Huevel, and Zakrajsek (2018).

[8]Borio, Gambacorta, and Hofmann (2017) and Claessens, Coleman, and Donnelly (2018) find evidence of nonlinear effects of low interest rates on net interest margins. In addition, Saunders (2000), Genay and Podjasek (2014), and Busch and Memmel (2017) consider the impact of low interest rates on profitability through net interest margins.

[9]There are a couple of additional papers that study negative rates but do not use a difference-in-differences approach. Nucera et al. (2017) find evidence that market perceptions of bank-specific risk increase in a negative rate environment for institutions that rely predominately on deposit funding. Demiralp, Eisenschmidt, and Vlassopoulos (2017) measure exposure of European banks through excess liquidity and find that the way banks draw down this excess liquidity in a negative rate environment depends on their particular business model. Finally, Hong and Kondrac (2018) take a completely different approach by using stock price reactions to the Bank of Japan's unexpected announcement of its negative interest rate policy to measure exposure of Japanese banks.

on cross-bank heterogeneity in the reliance on deposit funding for identification. Basten and Mariathasan (2018) measure exposure of Swiss banks to negative rates as implemented by the Swiss National Bank using excess reserves. Finally, Bottero et al. (2019) exploit heterogeneity in the net interbank position to gauge the exposure of Italian banks to negative rates using Italian credit registry data. Each one of these papers uses its respective proxy for exposure to identify changes in bank behavior following the implementation of negative interest rates. The broad conclusion of these papers is that bank risk-taking tends to increase in a negative interest rate environment.

This paper differs from these empirical studies in two important dimensions, both of which directly relate to the use of stress-test data. First, the stress-test data are what allow this paper to focus on the exposure of U.S. banks, whereas previous studies concentrate on the actual experience of European or Japanese banks. Second, whereas previous studies identify the impact of negative rates through a single channel of exposure, an advantage of stress-test data is that they allow for many different hypothesized channels—including the ones at the heart of identification in each of the papers discussed above—in a single data set. Our results suggest U.S. banks face exposure through a variety of different channels and these channels may be importantly different from those found to be relevant for European banks. For example, the evidence here suggests the largest U.S. banks do not face significant exposure through retail deposits, whereas this has been found elsewhere to be important for European banks. Instead, U.S. banks are more concerned about direct exposure through pass-through of negative rates to short-term liquid assets held on the balance sheet. That said, the use of stress-test data also introduces some limitations. Because the structure of the balance sheet is assumed to be constant, this paper has nothing to say about how banks alter their behavior in response to negative interest rates. It cannot therefore address changes in risk-taking or portfolio rebalancing, both of which feature prominently in the analysis of the papers discussed above.

The remainder of this paper is organized as follows. The next section discusses how scenario design fits in with the broader objectives of stress testing. Section 3 describes the data and methodology. Section 4 presents the main results and section 5 examines some

explanations for the heterogeneity of outcomes in our main results. Finally, section 6 concludes.

2.　The Role of Scenario Analysis in Stress Testing

The Federal Reserve conducts stress tests of the largest bank holding companies in an annual exercise called the Comprehensive Capital Analysis and Review.[10] The CCAR is a supervisory exercise with both a quantitative component—to evaluate the adequacy of firms' capital buffers under a macroeconomic scenario specified by the Federal Reserve—and a qualitative component—to evaluate their capital planning processes.

The use of forward-looking scenarios is a critical component of assessing capital adequacy in CCAR. A forward-looking scenario consists of a set of variables that, taken together, detail a macroeconomic and/or financial event that forms the basis of the stress test. More specifically, a macroeconomic stress scenario consists of hypothetical paths for different macroeconomic variables (for example, gross domestic product (GDP), unemployment, etc.), various interest rates (short- and long-term Treasury rates, corporate yields, etc.) and other financial variables (equity prices, the VIX, etc.).[11] Each bank is required to project net income over a nine-quarter forward horizon conditional on the macroeconomic and financial market conditions assumed in the scenario. These net income projections, along with assumptions about dividends, share repurchases, and other capital actions, are combined to assess equity capital and regulatory capital adequacy.

All told, participating BHCs project their capital ratios under five scenarios: three are provided by the Federal Reserve, and the remaining two are provided by the banks themselves. Specifically, each participating BHC is required to develop two scenarios: a BHC baseline and a BHC severely adverse scenario. BHC-provided

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[10]A detailed overview of stress testing can be found in Hirtle and Lehnert (2015).

[11]The CCAR stress test also has a market shock as well as a counterparty default component for a subset of the largest participating firms. The set of variables and assumptions that comprise these aspects of the stress test are different from those underlying the macroeconomic scenarios.

scenarios are developed internally within the bank using models augmented by expert judgment and designed to comprehensively stress the bank given its unique business model and idiosyncratic risk profile. In addition, the Dodd-Frank Act calls for the Federal Reserve to evaluate participating firms under three additional scenarios: a supervisory baseline scenario; a supervisory adverse scenario; and a supervisory severely adverse scenario. All three of these supervisory scenarios are provided by the Federal Reserve, and each typically consists of a set of roughly 30 macroeconomic and financial variables accompanied by a narrative that describes how the variable paths are plausibly tied together by a common macrofinancial shock. Supervisory scenarios, as well as the underlying narrative, are made available to the public at the start of the CCAR process, typically about a month before the bank submissions are due.

This paper exploits the fact that the Federal Reserve varies the supervisory stress scenarios in response to changing macroeconomic conditions and risks. Scenario design can be motivated by a desire to stress risks seen as being particularly salient for the health of the banking sector. Alternatively, even if the risk is deemed unlikely to actually materialize, building a particular feature into a scenario can be informative in learning about exposures within the regulated banking system.

Design features introduced into scenarios in previous years include, for example, different configurations for the yield curve. In some scenarios, an adverse macroeconomic event is assumed to lead to a flatter yield curve. In others it is assumed to lead to a steepening yield curve as short rates decline while long rates either stay flat or increase. Figure 1 shows the distribution of interest rate configurations in all scenarios over the period 2014–18. Stress loss projections under different yield curve configurations reveal information to regulators about how individual BHCs view their idiosyncratic exposure to interest rate risk. Alternatively, in other instances scenarios have featured disproportionate stress playing out in certain markets in order to address potentially worrisome exposures in the banking system. For instance, the supervisory severely adverse scenario in 2015 featured a sharp widening of spreads on high-yield corporate debt, leveraged loans, or collateralized debt obligations to assess the exposure of the banking system to risky corporate lending.

**Figure 1. Frequency of Qualitative Yield Curve
Configurations in CCAR Scenarios, 2014–18**
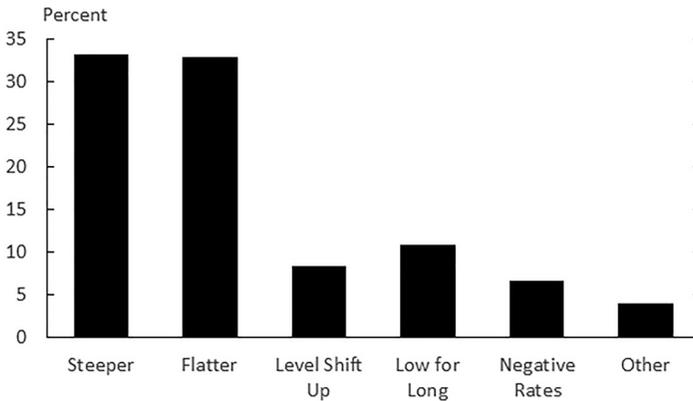
Source: Federal Reserve Y-14, author's calculations.
Notes: A steeper yield curve is one in which the spread between short and long
rates is consistently larger over the projection period than it is at the jumping-
off point. A flatter yield curve is one in which the spread is consistently smaller,
provided the levels of both long and short interest rates are both above 1 percent.
A level shift up in the yield curve captures a change in long and short rates that
preserves the spread at the jumping-off point. "Low for Long" is a flattening at a
level of interest rates below 1 percent. A negative rate scenario features the short
rate falling below zero. "Other" includes everything else, including yield curve
inversions and scenarios with no change.

In this paper, we focus on a design feature introduced into the
2016 supervisory severely adverse scenario at a time when sovereign
bond yields around the world were turning negative. This scenario
assumed a severe global recession which resulted in short-term Trea-
sury rates falling to negative 0.5 percent shortly after the onset of the
initial shock and staying at that negative level over the remainder
of the nine-quarter horizon. The adjustment to negative short-term
rates was assumed to proceed without additional financial market
disruption.

The grey shaded region in figure 2 shows the distribution of sce-
nario paths for the three-month Treasury rate for all but one sce-
nario across five consecutive years of CCAR (2014 through 2018)
for all participating BHCs. The solid black line plots the path of the

Figure 2. Projected Short-Term Interest Rates in CCAR Scenarios, 2014–18
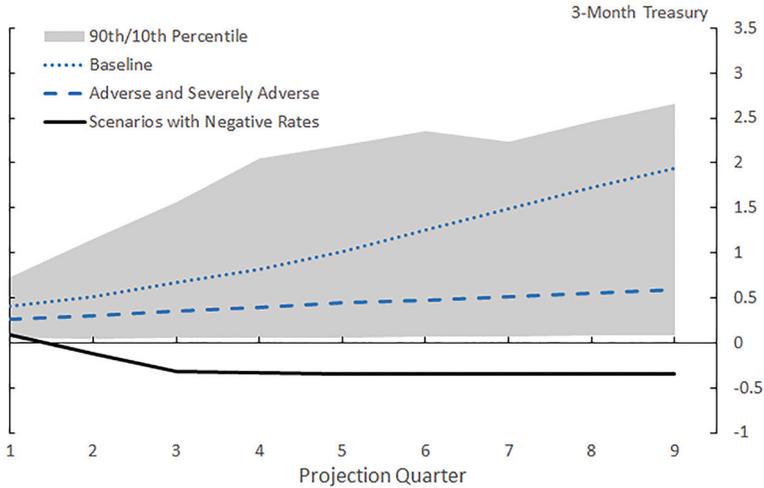
Notes: The shaded area represents the distribution of short-term interest rate projections for all CCAR scenarios submitted by all participating BHCs from 2014 through 2018. The dotted line is the average for the baseline (supervisory and BHC). The dashed line is the average for the adverse and severely adverse scenarios (supervisory and BHC). The solid black line plots the negative interest rate scenario.

three-month Treasury for the 2016 supervisory severely adverse scenario (which is excluded from the distribution in the grey shaded area). The lower edge of the distribution never goes below zero, suggesting that up until the 2016 supervisory severely adverse scenario, the banks operated under the implicit assumption that the zero lower bound would a binding constraint for interest rates. In this sense, negative interest rates—and the fact that the zero lower bound might not be a binding constraint for policy—appears to have come as a surprise to the banks.

The analysis that follows centers on empirically identifying the degree to which BHCs altered their net interest margin projections, either favorably or unfavorably, in response to potential nonlinear effects of negative interest rates.

3.   Methodology

3.1   Data

The analysis uses confidential supervisory data from five consecutive years (henceforth, "vintages") of CCAR stress-test exercises. A vintage consists of five different scenarios for every BHC: (i) the supervisory baseline (SB); (ii) the supervisory adverse scenario (SA); (iii) the supervisory severely adverse scenario (SSA); (iv) the BHC baseline (BHC-B); and (v) the BHC severely adverse scenario (BHC-SA). As discussed above, supervisory scenarios are designed and published by the Federal Reserve.[12] The BHC baseline is typically similar to the supervisory baseline, largely because both are based on the consensus view of economic forecasters. In contrast, banks are given explicit instructions to tailor the BHC-SA to their own risk profiles and unique vulnerabilities.[13] The motivation behind tailoring stems from the recognition of considerable diversity among the CCAR banks. Hence, a generic macroeconomic downturn as captured by the supervisory severely adverse scenario is unlikely to deliver comprehensive stress to all banks participating in the exercise. Tailoring of the bank-generated macroeconomic scenario helps alleviate this problem. To ensure compliance in scenario tailoring, the Federal Reserve has increased its scrutiny of the appropriateness of the BHC-SA through the qualitative reviews of the annual CCAR exercise. As noted in the introduction, the penalty of failure in the stress test is severe, hence banks have a strong incentive to tailor to idiosyncratic risk appropriately.

For every scenario vintage, each BHC is required to provide a nine-quarter projection for its NIM conditional on the

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[12]The SB is based on surveys of economic forecasters and is chosen to be representative of economic outcomes under normal conditions. The SA is typically a moderate downturn, potentially coupled with some other feature that sets it apart from the SSA. Finally, the SSA is characterized by a severe recession in the United States which propagates globally and is coupled with large declines in asset prices and increases in risk premiums.

[13]The preamble to the Capital Plan Rule (see 77 Fed. Reg. 74631, 74636 (December 1, 2011)) states that "the bank holding company-designed stress scenario should reflect an individual company's unique vulnerabilities to factors that affect its firm-wide activities and risk exposures, including macroeconomic, market-wide, and firm-specific events."

underlying macroeconomic environment that defines the scenario. In what follows let $i \in [1, I]$ index bank; let $j \in [SB, SA, SSA, BHC\text{-}B, BHC\text{-}SA]$ index scenario; and, let $k \in [2014, 2015, 2016, 2017, 2018]$ index CCAR vintage. Finally, let t index time over the nine-quarter projection period for each bank scenario vintage.

For each scenario vintage, bank i submits a nine-quarter horizon NIM projection, where each quarterly observation is denoted $\widetilde{NIM}_{i,j,k,t}$. The BHC-provided projection is derived from models—statistical, judgmental, or otherwise—that are internal to the bank. While we do not observe these models, we do observe the underlying macroeconomic data (which are submitted to the Federal Reserve as a requirement of CCAR) upon which the BHC's projection is conditioned. This information is critical because it allows us to construct a *model-based projection* for bank i's NIM, denoted $\widehat{NIM}_{i,j,k,t}$, which can be used to purge the *BHC-provided projection* of its dependence on macroeconomic and bank-specific factors.[14]

We do this in three steps. The first step is to estimate individually for every bank in our sample the following empirical model:

$$NIM_{i,t} = \beta_0^i + \beta_1^i NIM_{i,t-1} + \beta_2^i 3MT_{t-1} + \beta_3^i SPREAD_{t-1} \quad (1)$$
$$+ \beta_4^i \Delta GDP_t + \beta_5^{\mathbf{i}} \mathbf{X}_{i,t-1} + \varepsilon_{i,t},$$

where $NIM_{i,t}$ is the net interest margin for bank i; $3MT_{t-l}$ is the three-month Treasury rate; $SPREAD_{t-l}$ is the spread between the 10-year and three-month Treasury; ΔGDP_t is quarterly GDP growth; and $\mathbf{X}_{i,t}$ is a vector of bank-specific controls found in the literature to be important in explaining bank NIMs. Specifically, following Claessens, Coleman, and Donnelly (2018), $\mathbf{X}_{i,t}$ includes total securities over total assets, deposits over total liabilities, and total equity capital over total assets. The model is estimated using quarterly data over the period 1996:Q4 to 2017:Q4, implying a maximum of 84 quarterly observations for each bank (excluding one lag)

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[14]In our notation, a $\widehat{hat}$ denotes a model-based projection estimated specifically for bank i, whereas a $\widetilde{tilde}$ denotes a projection taken from a BHC-provided scenario vintage. So, to be clear, $\widehat{NIM}$ is a model-based projection, the construction of which is described on the next page. In contrast, $\widetilde{NIM}$ is an observable projection provided by the bank in its CCAR submission.

to get a set of eight bank-specific estimated coefficients conditioned on the general macroeconomy (captured by interest rates and output growth, which is obviously common to all banks) as well as bank-specific characteristics and bank i's own historic NIM data.

Macro data are taken from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis, and the bank-specific historic NIMs are obtained from the Call Report data, merger-adjusted and aggregated up to the bank holding company level. Summary statistics for all the data are presented in table A.1 in the supplementary appendix (available at http://www.ijcb.org), and the model output on a bank-by-bank basis is presented in table B.1.

Once we have these bank-specific coefficients, the second step is to use the bank-specific estimated model along with the bank-provided paths for the macrovariables in a given scenario vintage ($\widetilde{3MT}_{i,j,k,t}$, $\widetilde{SPREAD}_{i,j,k,t}$, and $\widetilde{\Delta GDP}_{i,j,k,t}$) to project the model-based NIM path, $\widehat{NIM}_{i,j,k,t}$. In generating this conditional model-based projection, we assume that bank's balance sheet stays constant, so that $\mathbf{X}_{i,t}$ is held constant at the last observed value over the entire projection period.[15]

The final step is to construct the difference between the model-based and the BHC-provided projections:

$$\xi_{i,j,k,t} = \widetilde{NIM}_{i,j,k,t} - \widehat{NIM}_{i,j,k,t}. \tag{2}$$

The model-based projection, $\widehat{NIM}_{i,j,k,t}$, as well as the BHC-provided projection, $\widetilde{NIM}_{i,j,k,t}$, both internalize the same underlying macroeconomic environment and, at least to some degree, the same broad bank-specific characteristics. Thus, the difference between the two should be purged of these effects. However, this does not necessarily mean that $E[\xi_{i,j,k,t}] = 0$. One reason is that bank i might have an understanding of how its particular business model might amplify or dampen the impact of a given macroeconomic environment on its net interest margins in a way that is not

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[15]As discussed in the introduction, this assumption is consistent with the implementation of the stress tests. It also necessarily precludes using these data to address portfolio rebalancing or changes in risk-taking behavior as is commonly the focus of other empirical papers studying negative interest rates.

easy to quantify through the simple linear empirical model as given by equation (1) above. For example, if $\xi_{i,j,k,t} > 0$ the bank projection is more optimistic with regard to how its NIMs will evolve in a particular macroeconomic environment relative to what the simple linear model would predict. The opposite is true if $\xi_{i,j,k,t} < 0$.

The analysis that follows builds on this in the sense that negative interest rates have a potentially nonlinear effect on NIMs that will not be captured in our simple linear model-based projection. In contrast, the banks themselves understand the nuances of their own business model and balance sheet exposures and, as such, the BHC-provided projections should internalize these nonlinear effects. In other words, the identification relies on the fact that the banks themselves are better equipped to forecast their own NIMs relative to our simple statistical model. This crucial difference suggests that we can identify the impact of negative interest rates on NIMs by using the qualitative feature of negative interest rates as a scenario design element to explain systematic projection differences for a given bank across different scenario-vintages.

3.2 Empirical Model

The final step of the analysis centers on the following regression, which tests the sensitivity of the earnings of bank i to potential nonlinear effects of negative interest rates:

$$\xi_{i,j,k,t} = \alpha_i + \beta_i Z_{i,j,k,t} + \gamma_i D_{k=2016} + \epsilon_{i,j,k,t}, \tag{3}$$

where $Z_{i,j,k,t}$ is an indicator function that takes on the value of one if negative short-term interest rates are a qualitative feature of the given bank scenario-vintage in quarter t and zero otherwise. Negative rates feature prominently in the 2016 vintage, so to ensure that $Z_{i,j,k,t}$ is not inadvertently capturing a vintage-specific effect, we include $D_{k=2016}$, which is an indictor that takes on the value of one if the scenario is from the 2016 vintage. The equation also allows for bank-specific fixed effects, α_i, to control for time-invariant differences in the NIM projections for a given bank. Finally, $\epsilon_{i,j,k,t}$ is an error term.

Our main results focus on the parameter of interest, β_i, which gauges how bank i views its profitability being influenced through the impact of negative interest rates on its NIM. Specifically, we

are interested in whether or not the scenario design feature of negative interest rates leads bank i to adjust its internal NIM projection beyond that which can already be explained through our linear model conditional on the general macroeconomic environment and bank-specific characteristics.

If we find that β_i is not statistically different from zero, then bank i does not have a strong view on how negative rates affect profitability. On the other hand, if we find $\beta_i \neq 0$, this suggests bank i has some internal view on potential nonlinear effects not picked up by the linear model. Conditional on finding evidence of nonlinearities, we remain agonistic at this point in the paper on whether the effects are expected to be positive or negative for the profitability of a given bank. We will return to this question later in the paper in section 5.

The model is estimated using ordinary least squares with robust standard errors clustered at the bank scenario-vintage level. The final data set is an unbalanced panel that includes 30 banks. All told, there are 4,986 total observations.[16] As shown in figure 1, negative interest rates feature in 7.5 percent of the sample, or 378 total observations.

4.   Main Results

The main results are presented in figure 3, which presents the estimated coefficient, $\widehat{\beta}_i$, for each bank along with 90 percent confidence intervals. The results are shown for a total of 30 banks, increasing in the magnitude of the point estimate going from left to right.

Starting on the left, 10 banks have coefficient estimates that are negative and statistically significant. These banks believe that negative interest rates would lead to a compression of their NIM above and beyond what would otherwise be explained by the underlying macroeconomic environment, even taking into account bank-level

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[16]If the panel were balanced, we would have 6,750 observations (that is, 30 banks, five vintages, five scenarios per vintage, with each scenario having nine quarterly observations). The unbalanced nature of the panel reflects that fact that the number of banks participating in each CCAR vintage has changed over time. The peak occurred in 2016 when 33 BHCs participated. But even in that year some data had to be dropped from firms that only became BHCs recently and, hence, had no record of historic NIMs data with which to derive a model-based estimate for $\widehat{NIM}$.

Figure 3. Estimated Effect of Negative Interest Rates on NIM Projections for CCAR BHCs
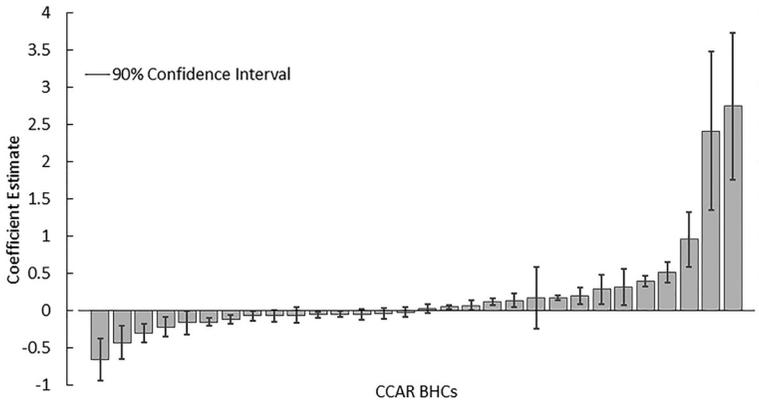
Notes: Each bar represents the coefficient estimate for β_i from equation (3) for a given CCAR BHC. The whiskers around each coefficient estimate show the 90 percent confidence interval based on cluster-robust standard errors.

controls. The point estimates range from −0.07 to −0.65, implying that the NIM is permanently lower over the nine-quarter projection period by between 7 and 65 basis points. On the far right, there are 12 banks that have coefficients that are positive and statistically significant. These banks anticipate improved profitability through an expansion in the NIM by between 5 and 275 basis points. Finally, the remaining roughly one-third of banks in the middle of the figure all have coefficients that are not statistically different from zero. Our interpretation is that these banks do not have strong views on how negative rates might affect their profitability.

There are two ways to give some economic context. First, as in Genay and Podjasek (2014), it is informative to express the estimated coefficient for each bank as a ratio of the volatility of that bank's historic NIMs data. This gives a sense of the size of the negative rate shock relative to typical quarter-to-quarter variation in the data. To preserve anonymity of the banks in the sample, the results in table 1 are reported as averaged across banks that fall within one of three bins depending on whether negative rates increase, decrease, or have no impact on NIMs.

Table 1. Economic Significance

	Estimated Coefficient	Estimated Coefficient Relative to Volatility of Historic NIMs	Observations
NIM Compression	−0.25	−0.55	8
NIM Expansion	0.66	0.78	13
No Effect	−0.03	−0.07	9

Source: Federal Reserve Y-14, author's calculations.

For the 13 banks that anticipate that negative rates will lead to higher NIMs, the average estimate, shown in the first column, is 66 basis points. When expressed relative to historic NIM volatility, the resulting ratio averages 0.78 across the 13 banks. This means that, on average, these banks expect negative rates to result in a positive shock that is in line with just under a one-standard-deviation shock, given the historical distribution of their respective NIMs data. Moreover, the shock is anticipated to persist over all nine quarters of the scenario horizon. Viewed in this light, the overall effect is economically sizable. Similarly, the average coefficient estimate for the nine banks that anticipate NIM compression is −25 basis points and the average ratio of the point estimate to observed volatility is 0.55—somewhat smaller, but still sizable.

An alternative way of gauging the economic effect is to compare the results found here with those found elsewhere the literature. No other papers study the effect of negative interest rates on NIMs, so we do not have a direct comparison, but there are a handful of papers that report empirical estimates of the impact of movements in short-term interest rates.[17] Here, the estimates typically fall on the order of tens of basis points, with Borio, Gambacorta, and Hofmann (2017) finding the largest effects—as much as 50 basis points over a year time frame when monetary tightening brings the interest rate from 0 percent to 1 percent. Another point of reference is Claessens,

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[17]See Genay and Podjasek (2014), Altavilla, Boucinha, and Peydró (2017), Borio, Gambacorta, and Hofmann (2017), Busch and Memmel (2017), and Claessens, Coleman, and Donnelly (2018).

Coleman, and Donnelly (2018), which finds that "low-for-long" interest rates imply an initial decline of up to 20 basis points in the NIM, with the effect growing by 10 basis points for every additional year of "low for long." Compared with these estimates (which, admittedly, are for a different type of shock, but are nonetheless informative as a benchmark), the findings presented here are sizable.

4.1   Robustness

The results are based on a bank-specific NIMs model motivated by Claessens, Coleman, and Donnelly (2018). Other studies have found additional macroeconomic and financial variables, beyond those already included in equation (1), that also have explanatory power for net interest margins. We test the sensitivity of the results presented above to the inclusion of these other variables by reestimating the bank-specific NIMs model while controlling for the unemployment rate, the level of the VIX, changes in residential home prices, changes in commercial real estate prices, and changes in stock prices as measured by the S&P 500. For each alternative specification of equation (1), a new model-based NIM prediction, $\widehat{NIM}_{i,j,k,t}$, is generated and used to recalculate $\xi_{i,j,k,t} = \widetilde{NIM}_{i,j,k,t} - \widehat{NIM}_{i,j,k,t}$. This new measure of $\xi_{i,j,k,t}$ is then used to reestimate equation (3) and we can compare the output with the main results presented in figure 1.

   We find that introducing these additional variables to the bank-specific NIM model makes very little difference. For this reason, we do not present the results in the main text and instead put them in table C.1 in the online appendix.

   Another robustness test tries to further isolate the effect of negative interest rates by controlling for alternative interest rate configurations. Using the estimate for $\xi_{i,j,k,t}$ from the baseline model, we reestimate equation (3) introducing a dummy variable to control for a so-called "low-for-long" interest rate configuration interpreted as a scenario in which the yield curve flattens out with both short- and long-term interest rates settling in at under 1 percent for the duration of the projection. This dummy variable should help isolate how negative interest rates are different from a "low-for-long" configuration, which accounts for roughly 10 percent of the sample

(see figure 1). The results are robust to controlling for "low-for-long" scenarios, further emphasizing the special nature of negative interest rates. Additionally, we also control for either a steeper yield curve or a higher, flatter yield curve. Neither make much of a difference.

Finally, we examine whether or not regulatory ratios affect the NIMs projections for different banks. For example, banks with low regulatory capital ratios may have an incentive to report higher NIMs paths in the stress-test submissions. To address this, we use the baseline estimate for $\xi_{i,j,k,t}$ and reestimate equation (3) controlling for, separately, the common equity tier 1 (CET1) capital ratio, the leverage ratio, and high-quality liquid assets (HQLA) as a fraction of total assets. The results, reported in table C.1 in the online appendix, are robust to controlling for either regulatory capital or liquidity ratios.

5.   What Explains the Cross-Bank Differences?

The results reveal considerable heterogeneity in bank-specific exposure to negative interest rates. This section presents a simple decomposition of the net interest margin to help explain these cross-bank differences using publicly available balance sheet data.

5.1   Potential Nonlinearities in NIMs Associated with Negative Rates

The definition of net interest margin is given by

$$NIM = \frac{Interest\ Income - Interest\ Expense}{Interest\ Earning\ Assets}.$$

For simplicity, assume that banks hold only two types of assets.[18] Short-duration assets, denoted A^s, deliver a gross return R^s, and long-duration assets, A^l, deliver a return $R^l \geq R^s$. Total interest income can be expressed as $R^s A^s + R^l A^l$. On the liability side of the

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[18]By assuming a simplified balance sheet, this approach abstracts from some important aspects of the duration mix of interest-bearing products and the way interest rates on these products are linked to market rates. Busch and Memmel (2017) show this is important for how the level of interest rates affects NIMs using data on German banks.

balance sheet, assume that banks fund themselves through deposits or other sources of short-term funding, denoted L^s, and long-term liabilities, denoted L^l. The deposit rate paid by the bank is given by R^d. For simplicity, assume that the cost of funding for long-term liabilities is similar to the return on long-term assets and, hence, is also given by R^l. Total interest expenses can be expressed as $R^d L^s + R^l L^l$. Finally, total interest-earning assets are given by $A^s + A^l$ and total interest-bearing liabilities are $L^s + L^l$.

Define the share of long-duration assets in total interest earning assets, $\chi = \frac{A^l}{A^s + A^l}$, which is a measure of the duration sensitivity of interest-earning income. Similarly, define $\eta = \frac{L^l}{L^s + L^l}$ as a measure of the duration sensitivity of interest expenses. Finally, let $\lambda = \frac{L^s + L^l}{A^s + A^l}$ denote total interest-bearing liabilities as a share of total interest-earning assets.

With these share definitions, we can rewrite the net interest margin as

$$NIM = R^s - \lambda R^d + \chi(R^l - R^s) - \lambda\eta(R^l - R^d).$$

Written this way, the net interest margin is made up of three components. The first, $R^s - \lambda R^d$, captures the idea that, all else equal, net interest margins are higher as the short-term lending rate exceeds the short-term cost of funding. The second term, $\chi(R^l - R^s)$, captures the idea that it is profitable for the bank to engage in maturity transformation as the returns on long-term assets exceed those on short-term assets. Finally, the third term, $-\lambda\eta(R^l - R^d)$, highlights the fact that short-term funding is cheap relative to long-term funding.

To address potential nonlinearities associated with negative rates, we need to make some additional assumptions about both the policy rate itself and how the policy rate is passed through to interest rates on assets and liabilities on the bank balance sheet.

The *unconstrained policy rate*, denoted $\hat{R}(\epsilon)$, is assumed to fluctuate around a target level, $\bar{R}$, in response to an underlying shock, ϵ. The shock takes a value of $\epsilon > 0$ with probability $1/2$, or, alternatively, a value of $-\epsilon$ with probability $1/2$. The unconstrained policy rate fluctuates around its target as follows:

$$\hat{R}(\epsilon) = \begin{cases} \bar{R} + \epsilon & with\ probability\ \ 1/2 \\ \bar{R} - \epsilon & with\ probability\ \ 1/2. \end{cases}$$

For simplicity, assume the target rate is sufficiently low so we just consider the case of $\bar{R} = 0$. In this low interest rate environment, a bank forming expectations of the policy response to an underlying shock must take into account not only the realization of the shock but also whether or not the zero lower bound (ZLB) is expected to bind for monetary policy. If banks anticipate that the ZLB is a binding constraint, the *actual policy* rate will be given by $R^*(\epsilon) = max(0, \hat{R}(\epsilon))$. In contrast, if banks believe the monetary authority is willing to implement negative interest rates, the actual policy rate is unconstrained, so that $R^*(\epsilon) = \hat{R}(\epsilon)$. The motivation for including expectations over whether or not the ZLB is a binding constraint for policy comes from figure 1. In all of the CCAR scenarios over the three years from 2014 to 2016, the lower end of the distribution of short-term interest rate projections was always bounded below by zero. The exception is the 2016 SSA as well as a few instances of the 2016 BHC-SA scenarios.[19] The interpretation is that negative interest rates came as a surprise to these banks and therefore the surprise itself may explain the nonlinear results found in section 4.

The next set of assumptions relate the policy rate to interest rates on short-duration assets and short-duration liabilities held by the bank. The interest rate on short-duration assets is assumed to be a fixed markup, $\mu > 1$, over the policy rate, so that $R^s = \mu R^*(\epsilon)$. In contrast, the interest rate paid on short-duration liabilities is given by

$$R^d = \Omega R^*(\epsilon) \text{ where } \Omega = \begin{cases} 1 & if\ R^*(\epsilon) \geq 0 \\ \omega & if\ R^*(\epsilon) < 0. \end{cases}$$

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[19]The banks observe the supervisory scenarios roughly a month prior to submitting their CCAR submissions. Hence, it is reasonable to think that banks were surprised after observing the supervisory scenarios when they were released publicly and this surprise informed the construction of the BHC scenario for that same vintage.

In this expression, $\omega \in (0,1)$ captures the possibility of imperfect pass-through from the policy rate into interest rates on short-duration liabilities, including the retail deposit rate. If $\omega = 1$, as is assumed when interest rates are positive, pass-through is complete and the policy rate flows through one-for-one into the interest paid on short-term liabilities. However, when the policy rate turns negative, values of $\omega < 1$ allow for incomplete pass-through. For example, in the case of retail deposit rates, a bank might not want to pass on the cost of holding deposits on to its customer base out of concern of deposit flight—that is, depositors may look to move their funds elsewhere to avoid paying the fee or they may simply hold cash instead. In the extreme, $\omega = 0$ sets a floor such that $R^d = 0$ when $R^*(\epsilon) < 0$.

Finally, moving up the yield curve, we assume long-term interest rates are a function of short-term rates, so that $R^l = \phi(R^*(\epsilon))$, where $\phi(R^*(\epsilon))$ is a sufficiently general function that captures a wide variety of alternative assumptions regarding the response of the yield curve to a decline in short rates. For example, $\phi(R^*) = \bar{\phi}R^*$ where $\bar{\phi} \geq 1$ implies that the yield curve shifts down in parallel as short-term rates decline. Alternatively, $\phi(R^*)$ could be parameterized to have properties that imply that short-term interest rates are an increasing proportion of long rates as the level of the policy rate declines (and potentially turns negative). This has the implication that the yield curve becomes progressively flatter as the level of the policy rate declines. Claessens, Coleman, and Donnelly (2018) find that such a relationship is important for describing NIMs in a low interest rate environment.

Substituting these interest rate assumptions into the expression for NIMs and rearranging yields

$$NIM = [(1-\chi)\mu - (1-\eta)\lambda\Omega] R^*(\epsilon) + (\chi - \lambda\eta)\phi(R^*(\epsilon)).$$

This expression allows us to highlight three potential sources of nonlinearities associated with negative interest rates, each operating through three distinct channels described below.

5.1.1   The Retail Deposit Channel

According to this channel of exposure, what differentiates an interest rate cut into negative territory from a similar cut at a low, but ultimately positive, level of interest rates is the idea that banks want

to avoid passing negative interest rates through to their deposit base and they are willing to change their behavior in order to do this. In other words, it is the change in behavior of the banks that makes negative interest rates special from the perspective of net interest margins.

We can isolate the retail deposit channel by assuming that $\phi(R^*) = \bar{\phi}R^*$, so that long-term interest rates on assets and liabilities move one-for-one with the policy rate. Under this assumption, the expected change in the NIM with respect to the underlying shock becomes

$$\frac{\partial NIM}{\partial \epsilon} = \left[(1-\chi)\mu - (1-\eta)\lambda\Omega + (\chi - \lambda\eta)\bar{\phi}\right] E[\partial R^*(\epsilon)/\partial \epsilon].$$

As the policy rate moves into negative territory, the shift in the degree of pass-through that banks chose to allow introduces a non-linearity as $\Omega = 1$ changes to $\Omega = \omega < 1$. With incomplete pass-through, the decline in the policy rate does not fully translate into lower deposit funding costs. All else equal, this should compress NIMs relative to the alternative of complete pass-through.

This channel is summarized with the following hypothesis:

HYPOTHESIS 1. *If banks are hesitant to let negative rates flow through to their deposit base, imperfect pass-through implies additional nonlinear NIM compression as the policy rate moves below zero.*

To test this hypothesis, we can proxy for the strength of the deposit margin channel using balance sheet data to measure the share of retail deposits in total interest-bearing liabilities, $(1 - \eta)\lambda$. A bank that has greater dependence on retail deposit funding likely values its deposit base more relative to a bank that can easily substitute into other funding short-term sources. As a result, these banks should be more reluctant to pass negative rates through to deposit rates and, hence, more likely to suffer NIM compression in a negative rate environment.

5.1.2   The Liquidity-Management Channel

In contrast to the retail deposit channel, exposure through the liquidity-management channel assumes that pass-through to interest

rates on short-duration assets and liabilities is not impeded and, as a result, generates potential gains and losses depending on a given banks' liquidity-management practice. An important aspect of the identification of this channel stems from the fact that the violation of the zero lower bound comes as a surprise.[20] In other words, what makes a cut into negative territory special is the fact that it reveals that a constraint on monetary policy that was previously thought to be binding, in fact, no longer binds.

To understand the importance of the ZLB in identifying this channel of exposure, consider that when the policy rate is positive, $R^*(\epsilon) \geq 0$, our assumptions on pass-through imply $\Omega = 1$. As long as the bank believes that the ZLB is a binding constraint, we have $E[R^*(\epsilon)|ZLB] = \frac{1}{2}\epsilon$. These expectations reflect the fact that the policy rate is assumed to respond only asymmetrically to shocks. This asymmetry carries over to the expected evolution of the NIM as the ZLB effectively dampens anticipated losses (gains) on interest income (expenses) from short-duration assets (liabilities) in the event of an adverse shock. However, if the monetary authority pushes the policy rate into negative territory, this insulating effect no longer applies. In this case, we have $E[R^*(\epsilon)|No\ ZLB] = 0$, and because $E[R^*(\epsilon)|No\ ZLB] \leq E[R^*(\epsilon)|ZLB]$, any bank with a large share of short-duration assets will suffer amplified NIM compression through losses on interest income. In contrast, a bank with a large share of short-duration liabilities will experience an unanticipated expansion of its NIM through a reduction in funding costs. Hence, it is the liquidity-management practice (short-term assets relative to short-term liabilities on the balance sheet) that determines the response of NIMs when the movement of the policy rate into negative territory comes as a surprise.

This leads to the following testable hypothesis:

HYPOTHESIS 2. *When the policy rate unexpectedly moves into negative territory, relaxing the zero lower bound amplifies exposure via unanticipated pass-through to short-term interest rates.*

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[20]Hong and Kondrac (2018) also use the surprise announcement of a negative interest policy to identify the exposure of Japanese banks to negative interest rates.

We can proxy for the strength of this channel of exposure using balance sheet data to measure the share of short-duration assets in total interest-earning assets, $(1 - \chi)\mu$, and the share of short-duration interest-bearing liabilities in total interest-bearing liabilities, $(1 - \eta)\lambda$. Banks that have a large exposure to short-duration assets will suffer amplified NIM compression as the policy rate turns negative. The opposite is true of banks that have a large exposure to short-duration liabilities.

5.1.3 The Yield Curve Compression Channel

The yield curve compression channel captures the idea that the yield curve becomes progressively flatter as the level of short-term interest rates decline.

This exposure channel can be highlighted by assuming full pass-through to deposit rates, $\Omega = 1$. Additionally, rather than assuming $\phi(R^*) = \bar{\phi}$ as above, assume the yield curve flattens (non-linearly) as the level of the policy rate moves lower and eventually turns negative. To capture this we assume $\phi(R^*)$ is convex, so $\partial\phi(R^*)/\partial R^* \geq 0$ and $\partial^2\phi(R^*)/\partial R^{*2} > 0$. We also allow for an effective lower bound to the (gross) policy rate, $\underline{R}^*$ (which is less than one to accommodate a negative net policy rate) and further assume $\lim_{R^* \to \underline{R}^*} \phi(R^*) = \gamma > 0$ and $\lim_{R^* \to \underline{R}^*} \partial\phi(R^*)/\partial R^* = 0$.

With these assumptions in mind, consider the change in NIMs with respect to the policy rate

$$\frac{\partial NIM}{\partial R^*} = (1 - \chi)\mu - (1 - \eta)\lambda + (\chi - \lambda\eta)\frac{\partial\phi(R^*)}{\partial R^*}.$$

The first two terms capture the deposit margin and liquidity-management channels discussed above; absent shocks to the economy, these two channels are linear in the policy rate. In contrast, the third term captures a potential nonlinearity that occurs through a flattening of the yield curve that gets more pronounced as the level of the policy rate declines and eventually turns negative. For most banks, the share of long-term assets in total interest interest-earning assets exceeds that of long-term liabilities, so that $\chi > \lambda\eta$, implying that the flattening of the yield curve will increasingly depress NIMs as the level of the policy rate declines.

This leads to the following testable hypothesis:

HYPOTHESIS 3. *As the level of interest rates moves into negative territory, a progressive flattening of the yield curve leads to amplified NIM compression.*

We can proxy for the strength of the yield curve compression channel using balance sheet data that assess the duration sensitivity of the bank, $\chi - \lambda\eta$. Banks that face the greatest exposure to yield curve compression are those that have considerably longer maturities and repricing times on the asset side of their balance sheet relative to the liability side.

5.2   Empirical Model

We test our three hypothesized nonlinearities using the following regression framework:

$$y_i = \alpha + \beta X_i + \lambda D_i + \theta Size_i + \varepsilon_i, \tag{4}$$

where y_i is a measure of bank-specific sensitivity to negative interest rates, which we proxy with the estimated coefficient from equation (3), normalized by its standard error.[21] To explain this bank-specific sensitivity, we include a set of two dummy variables, denoted D_i, to proxy for bank business models. The first dummy takes on the value of one if the BHC is a custodial bank. Custodial banks are unique in that they do not follow a traditional banking business model but instead take on custodial functions in transactions between third parties. These banks tend to hold a larger share of assets in cash and securities than other banks in our sample. We also include a second dummy variable for BHCs that are considered global systemically important banks. The G-SIB dummy captures the systemic nature and complexity of the largest banking organizations. Finally, we also include bank size, $Size_i$, measured as the log of total assets (in billions of dollars). This variable is included because banks' size generates differences in economies of both scale and scope

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[21]This approach to testing channels of exposure relies on previous output generated using equation (3). See Pagan (1984) for a discussion of complications that arise for statistical inference with a generated regressand.

that might help a bank deal with the nonlinear effects of negative interest rates. For example, large banks are more likely to have the expertise and personnel to more effectively hedge interest rate risk using derivatives.

The focus of the analysis is to uncover a systematic link between the sensitivity to negative rates and bank balance sheet character-istics, denoted generically as X_i. As touched upon above, the exact measurement of X_i is tailored to each hypothesis.

In order to test the *retail deposit channel,* we measure $1 - \eta$ using data on the share of retail deposits in total interest-bearing liabili-ties. Combining this with data on the share of interest-bearing liabil-ities in total interest-earning assets, our measure of λ, we construct $X_{L_d} = (1 - \eta)\lambda$ and include it in the regression above to proxy for the degree to which the bank is reliant on short-term retail deposit funding. Allowing $\hat{\beta}_{L_d}$ to denote the estimated coefficient on X_{L_d}, the following tests the empirical validity of this channel of exposure:

$$H1_0 : \hat{\beta}_{L_d} = 0.$$

Rejecting the null hypothesis in favor of the one-sided alterna-tive of $H1_1 : \hat{\beta}_{L_d} < 0$ supports exposure through the retail deposit channel.

To test the *liquidity-management channel,* we begin by examin-ing the short-term asset and liability side of the balance sheet sep-arately. First, we use data on the share of reserves in total interest-earning assets to measure $1 - \xi$. Letting $X_{A_s} = 1 - \xi$, this enters into the regression framework above to proxy for the exposure of NIMs to short-term interest rates through the asset side of the balance sheet. On the liability side, we use data on the share of short-term wholesale funding in total interest-bearing liabilities to measure $1 - \eta$. Combin-ing this with the measure of λ described above, we let $X_{L_s} = (1-\eta)\lambda$ proxy for the exposure of NIMs to interest rates through short-term liabilities.

Allowing $\hat{\beta}_{A_s}$ and $\hat{\beta}_{L_s}$ to denote the estimated coefficients on X_{A_s} and X_{L_s}, respectively, we can test the following null hypotheses to assess the empirical validity of this transmission channel:

$$H2_0 : \hat{\beta}_{A_s} = 0; \hat{\beta}_{L_s} = 0.$$

Rejecting the null hypothesis in favor of the one-sided alternative of $H2_1 : \hat{\beta}_{A_s} < 0; \hat{\beta}_{L_s} > 0$ is evidence of exposure through liquidity management.

In addition, we also examine separately exposure through the net repo position—that is, securities purchased under agreement to resell (on the asset side of the balance sheet) net of securities sold under agreement to repurchase (on the liability side). A larger net repo position implies that a bank is more actively engaged in liquidity provision through the repo market relative to its reliance on the repo market for short-term funding. The coefficient on the net position is expected to be negative in sign so that liquidity provision (for example, through the interbank market) exposes the bank to greater losses in a negative interest rate environment. One complicating factor owes to the fact that G-SIBs tend to be much more active in the repo market relative to other banks in the sample. The reason is that G-SIBs have large broker-dealer subsidiaries which rely heavily on short-term funding obtained through the repo market.[22] In light of this, we treat the G-SIBs differently by interacting the G-SIB dummy with the net repo position.

Finally, to test the *yield curve compression channel*, we measure $\chi - \lambda\eta$ using the maturity gap measure developed in English, van den Huevel, and Zakrajsek (2018). While we leave the details regarding the construction of this metric to that paper, the authors use granular balance sheet data on U.S. banks to construct a metric that captures the degree of mismatch between the maturity and repricing time of a bank's assets relative to those of its liabilities. If the yield curve flattens disproportionately as the level of interest rates declines below zero, we would expect banks with a larger maturity gap—that is, banks that have a higher proportion of assets with longer maturities and repricing times relative to liabilities—to be most exposed to a decline in its NIM as the yield curve progressively flattens.

Letting $X_{MGAP} = \chi - \lambda\eta$, this enters into the regression framework above to proxy for the exposure of NIMs to the progressive flattening of the yield curve in a negative interest rate environment. Allowing $\hat{\beta}_{MGAP}$ to denote the estimated coefficient on X_{MGAP},

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[22]See, for example, Kirk et al. (2014).

the following tests the empirical validity of this transmission channel:

$$H3_0 : \hat{\beta}_{MGAP} = 0.$$

Rejecting the null hypothesis in favor of the one-sided alternative of $H3_1 : \hat{\beta}_{MGAP} < 0$ is evidence in favor of the yield curve compression channel.

Summary statistics for all the variables used in this part of the analysis are shown in table A.2 in the online appendix.

5.3   Results

Results are presented in table 2, with robust standard errors reported in parentheses below each coefficient estimate.[23]

Column 1 examines exposure through the retail deposit channel. If banks were hesitant to pass negative rates through to their depositor base, we would expect those with the highest share of retail deposits to be the most exposed to the adverse effects of negative interest rates. The estimated coefficient is negative in sign, so the results are broadly consistent with this view. However, it is not statistically significant and the effect is small in economic magnitude, especially when compared with the other channels of exposure shown elsewhere in the table (see columns 2 through 4). A 1 percent increase in the share of retail deposits increases exposure, leading to a roughly 10 basis point reduction in NIMs as a result of negative interest rates.[24] The size of this effect is only about one-fifth of the historical standard deviation of NIMs averaged across all the banks in the sample (0.62). All told, these results suggest that large U.S. banks do not face significant exposure through the retail deposit channel.

This finding contrasts sharply with Heider, Saidi, and Schepens (2019), which finds strong evidence of the exposure of European

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[23]We reiterate the caveat of footnote 21 regarding statistical inference on a generated regressand.

[24]The proxy for the sensitivity to negative rates is the estimated coefficient on the indicator variable for negative rates in equation (3) normalized by its standard error. Hence, to arrive at a 10 basis point reduction in NIMs, we multiply the coefficient reported in column 1 of table 2 (-0.87) by the average standard deviation (0.11) obtained from the estimated coefficients across all banks in equation (3).

Table 2. Tests of Hypothesized Channels of Exposure of U.S. Banks to Negative Interest Rates

	$H1_0: \hat{\beta}_{L_d} = 0$ Imperfect Pass-Through to Deposit Rates	$H2_0: \hat{\beta}_{A_s} = 0; \ \hat{\beta}_{L_s} = 0$ Direct Exposure via Short-Term Assets and Liabilities			$H3_0: \hat{\beta}_{MGAP} = 0$ Yield Curve Compression
	(1)	(2)	(3)	(4)	(5)
Constant	0.36 (20.14)	7.76 (18.54)	0.25 (20.51)	12.28 (20.10)	10.59 (19.74)
Retail Deposits	−0.87 (3.16)				
Reserves		−14.74* (6.28)			
Short-Term Wholesale Funding			10.19*** (3.13)		
Net Repo Position				−25.43*** (7.39)	
Net Repo Position × G-SIB				20.60** (7.45)	
Duration Gap					−6.52 (7.89)
Ln (Size)	0.10 (1.09)	−0.29 (0.96)	0.06 (1.07)	−0.56 (1.05)	−0.35 (1.05)
Processing Bank Dummy	−2.27 (1.79)	−1.61 (1.26)	−2.01 (1.64)	−2.85 (1.56)	−3.51 (1.86)
G-SIB Dummy	−2.81 (2.68)	−1.61 (2.23)	−2.41 (2.40)	−1.00 (2.50)	−1.25 (2.39)
Adj. R²	0.15	0.22	0.17	0.23	0.21
Obs.	30	30	30	30	29

Source: Author's calculations.
Notes: Robust standard errors are reported in parentheses below each coefficient estimate. *** denotes significance at the 0.01 level; ** denotes significance at the 0.025 level; and * is significance at the 0.05 level.

banks to negative rates through retail deposits. One interpretation is that the results presented here highlight that the U.S. banking system may face very different exposures to the effects of negative interest rates relative to European banks.

The next three columns present results for exposure through the liquidity-management channel. If the negative policy rate is passed through to interest rates on short-duration assets and liabilities (beyond retail deposits), we would expect this to affect profitability through reduced interest income (expenses) on these short-term assets (liabilities). Asset- and liability-side exposure are tested separately, followed by a test of exposure through net activity in the repo market.

Column 2 shows that banks with a higher share of reserves are heavily exposed to amplified losses in a negative interest rate environment. The estimated coefficient is negative in sign, statistically significant at the 5 percent level, and quantitatively large. For every additional percentage point increase in exposure through reserves, NIMs decline by roughly 160 basis points. Based on the average historical volatility of NIMs for all the banks in the sample, this is roughly a 2.5-standard-deviation shock that persists over a nine-quarter horizon. Turning to column 3, banks that rely more heavily on short-term wholesale funding anticipate a boost to their NIMs through a reduction in funding costs. The estimated coefficient is positive, statistically significant at the 1 percent level, and quantitatively about as large (in absolute value) as exposure through reserves. Increasing reliance on short-term wholesale funding boosts NIMs by about 110 basis points, a nearly two-standard-deviation shock that persists over nine quarters.

Results on exposure through the net repo position are presented in column 4. For the average CCAR bank, an increase in the net repo position lowers NIMs in a negative rate environment by about 275 basis points, a shock that is four-and-a-half times the average historical standard deviation for the banks in the sample. Economically, this is a very large shock and the coefficient is statistically significant at the 1 percent level. It is worth keeping in mind, however, that non–G-SIB banks tend to have relatively small net exposure to the repo market. The average net position for these banks is only about 2.5 percent of total assets. Nevertheless, these results suggest that U.S. banks face significant exposure via pass-through of the

negative policy rate into the repo market. The more active a bank is in providing liquidity to borrowers via repo, the larger the expected NIM compression in a negative rate environment.

However, the effect for G-SIBs is much smaller, likely due to the importance of their broker-dealer subsidiaries. In a negative interest rate environment, G-SIBs anticipate benefiting from lower funding costs through these subsidiaries as the negative policy rate passes through to repo rates. The difference in exposure of G-SIBs versus non–G-SIBs through the net repo position is further evidence of the heterogeneous nature of bank exposure to negative rates.

Finally, the last column presents results for exposure through the yield curve compression channel. If the primary transmission comes through a progressive flattening of the yield curve as the policy rate turns negative, we would expect banks to suffer compressed NIMs as the policy rate turns negative. In this case, we would expect the estimated coefficient on the measure of the duration gap to be negative and statistically significant. As can be seen from the table, it is negative in sign, but the estimate is insignificant and economically small. Claessens, Coleman, and Donnelly (2018) showed that the sensitivity of net interest margins tends to increase as the level of interest rates declines. The results here suggest this sensitivity is not further amplified when rates turn negative.

5.4   Robustness

The baseline results presented in table 2 control for size and bank business model through the inclusion of two dummy variables indicating if the bank is either a processing bank or a G-SIB. Hence, our results are not driven simply by size, a basic indicator for bank business model, or by the systemic importance of the bank.

Additionally, we did a wider set of robustness tests for each hypothesized transmission channel. The results can instead be found in the online appendix in tables C.2–C.6. In short, the baseline results are robust to controlling for the intensity of trading activity (measured as the share of held-for-sale plus held-to-maturity assets over total assets) as well as two different measures of foreign exposure (foreign deposits over total liabilities and C&I (commercial and industrial) loans to borrowers with foreign addresses over

total assets). They are also robust to controlling for regulatory capital holdings, including both the CET1 capital ratio (a risk-weighted measure) and the tier 1 leverage ratio (which is not risk weighted) for each bank. The results are largely robust to liquidity regulation with the exception of the statistical significance of exposure through reserves. This can be explained by the fact that reserves make up a large fraction of HQLA, so the two are highly correlated.

A final robustness check extends the analysis in section 4.1. Specifically, we replaced our baseline estimates used to measure bank-specific exposure to negative rates (the dependent variable in equation (4) and that which is being explained in table 2) with the alternative estimates detailed in section 4.1 (that is, the robustness estimates obtained from the alternative NIM models, as well as those obtained from the alternative specifications for equation (3)). Using these alternative estimates, we reestimated equation (4) to see whether there is any impact on the statistical or economic relevance of each hypothesized transmission channel. The results can be found in the online appendix in table C.7. In short, the main qualitative results of the paper are largely robust to these many alternative specifications of the models in each step of the analysis.

6. Conclusion

There is no historical experience from which to draw upon to understand how U.S. banks would fare in a negative interest rate environment. In light of this, the contribution of this paper is to exploit a unique new data source to empirically examine expectations of the banks themselves regarding how they believe they would fare in a negative rate environment.

The results reveal a significant degree of heterogeneity in bank exposure through the lens of net interest margins. The most significant channel of adverse exposure comes from the pass-through of negative rates to short-term liquid assets held on the balance sheet. At the same time, on the liability side, banks that rely more heavily on short-term wholesale funding, including financing through the repo market, may benefit from negative rates through a reduction in funding costs. This is especially relevant for G-SIBs, which have large broker-dealer subsidiaries that rely heavily on repo financing. While the results point to a variety of idiosyncratic exposures for

individual U.S. banks, these effects likely wash out at the aggregate level as liquidity provision is sufficiently well diversified across the banking sector.

There are some important policy implications. First, absent any available historical experience upon which to draw, this paper offers the only empirical evidence that can inform the policy debate on the potential effects of a negative rate policy on the U.S. banking sector. Additionally, the finding that negative interests have largely distributional effects suggests that policymakers should focus their attention on the safety and soundness of those specific institutions which are most exposed to elevated losses in a negative interest rate environment. Finally, these results also potentially suggest that liquidity regulation could interact with a negative interest rate policy in an important way. By forcing banks to hold more liquid assets on their balance sheet, compliance with the liquidity coverage ratio may amplify losses in a negative interest rate environment.

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Anchoring Inflation Expectations in Unconventional Times: Micro Evidence for the Euro Area[*]

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We exploit micro data from professional forecasters to examine the stability of the distribution of long-term inflation expectations in the euro area following the Great Recession. Although mean expectations declined somewhat, we find no evidence that the central tendency of the long-run distribution became unanchored. Also, the degree of co-movement of expectations with other variables did not increase noticeably. In contrast, long-term inflation uncertainty increased and expectations became negatively skewed. Such findings are in line with the predictions of theoretical models emphasizing the impact of the lower bound on policy rates and uncertainty about the transmission of unconventional monetary policies.

JEL Codes: E31, E58.

1.   Introduction

A tight anchoring of medium- to long-term inflation expectations around the central bank's target is commonly seen as crucial for

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steering inflation toward this target without suffering substantial economic costs. However, during recent years, large macroeconomic and financial shocks associated with the Great Recession and the fact that policy rates reached their effective lower bound (ELB) have led to concerns about a possible de-anchoring of long-term inflation expectations in the major currency areas. In the case of the euro area, concerns have focused on persistently too-low inflation or even deflationary risks and an associated departure of inflation expectations from levels consistent with the objective of the European Central Bank (ECB). For example, Draghi (2014) highlights "the risk that a too prolonged period of low inflation becomes embedded in inflation expectations." Indeed, recent unconventional monetary policies are often motivated as addressing such risks.

In this paper we examine empirically this central policy question: How well anchored did euro-area inflation expectations remain in the wake of the Great Recession and euro-area sovereign debt crisis? By the anchoring of long-term inflation expectations, we refer to their stability over time and their consistency with the objectives of a central bank. In principle, a necessary and sufficient condition for long-term expectations to be perfectly anchored is that they are constant and equal to the central bank's target. However, a direct test of these conditions is complicated by uncertainty about what constitutes "well" in practice and also about the precise target and/or the horizon over which the central bank aims to achieve it.[1] A situation in which expectations become unanchored would imply a significant and substantial movement in the level of long-term inflation expectations away from the level implied by the central bank's objective. Clearly, the concept of anchoring is also a matter of *degree* in the sense that it is insightful to consider how tightly or firmly expectations may be anchored at a given level. For example, even in a situation where the level of inflation expectations remains aligned with the central bank's objective, economic agents may become less confident about this outcome and may therefore attach a lower probability or likelihood that this objective will be

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[1]For example, in the case of the euro area, while price stability is clearly defined to be an increase in the Harmonised Index of Consumer Prices that is below, but close to, 2.0 percent, the ECB indicates that it aims to achieve this "over the medium term," which retains some degree of vagueness.

achieved and, at the same time, may attach higher probabilities to more extreme inflation outcomes. Such an analysis of changes in the degree to which expectations are anchored requires information extracted from the probability distribution surrounding long-term inflation expectations.[2]

Much of the recent economic literature attempting to quantify the evidence and risks of such a de-anchoring—both in the euro area and elsewhere—has focused only on the *mean* or first moment of the distribution of long-term inflation expectations (Demertzis, Marcellino, and Viegi 2009, 2012; Gürkaynak, Levin, and Swanson 2010; Beechey, Johannsen, and Levin 2011; van der Cruijsen and Demertzis 2011; Dräger and Lamla 2013; Mehrotra and Yetman 2014).[3] In this paper, we provide new micro evidence about the anchoring of inflation expectations in the euro area considering the *full subjective forecast distribution*. Strong theoretical arguments justify the need to study the properties of the full distribution and not simply focus on mean expectations. In particular, shifts in the variance of this distribution, its skewness, or tail risk can offer additional evidence of change in agents' beliefs about future inflation over the longer term and the factors that may be shaping them. For example, the model of imperfect credibility in Bodenstein, Hebden, and Nunes (2012) suggests that achieving the central bank's inflation objective may become more challenging following a period such as the Great

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[2]Mehrotra and Yetman (2014) highlight the importance of the full probability distribution, noting that "there are at least two dimensions to anchoring: both the level at which expectations are anchored . . . and how tightly expectations are anchored at that level."

[3]In particular, such studies have focused on possible changes in the mean or in the strength of its co-movement with other economic variables. Most evidence emerging from this literature suggests that long-term inflation expectations were affected by the Great Recession. For the U.S. economy, Galati, Poelhekke, and Zhou (2011), Autrup and Grothe (2014), Ciccarelli and García (2015), and Nautz and Strohsal (2015) all suggest that inflation expectations in the United States started to react more strongly to macroeconomic news. Ehrmann (2015) also reports evidence of a similar increased sensitivity during periods of low inflation. For the euro area, Galati, Poelhekke, and Zhou (2011) identify a structural break in the responsiveness of European inflation expectations to macroeconomic news and Lyziac and Paloviita (2017) conclude that there are "some signs of de-anchoring." However, Autrup and Grothe (2014), Strohsal and Winkelmann (2015), and Speck (2016) have argued that the degree of anchoring did not change around that time.

Recession, as central bank credibility becomes more relevant than in "normal" times. In a similar vein, Beechey, Johannsen, and Levin (2011) demonstrate how imperfect information and potential time variation in the central bank's objective can be associated with a sizable increase in long-term inflation uncertainty as measured by the variance of the distribution for long-term expected inflation.[4] However, it is the incidence of the ELB that makes the strongest case for studying the full distribution. Under the ELB, models of the business cycle exhibit multiple equilibriums, implying that the distribution of long-term inflation expectations may change and attach non-negligible probabilities to quite distinctive outcomes.[5] Clearly, the risks of such bad equilibriums will tend to first show up in increased long-term inflation uncertainty or tail risks, i.e., in the second and fourth moments of the distribution. In addition, models which take into account the ELB also emphasize that limitations in the central bank's ability to respond to deflationary shocks lead to a negatively skewed distribution for long-term expectations (see, for example, Coenen and Warne 2014; Hills, Nakata, and Schmidt 2016).

To address our central question, we proceed in three steps. In a first, we test for possible structural change in the distribution of the long-term subjective forecast distribution, exploiting the methods of Andrews and Ploberger (1994), Bai and Perron (1998, 2003),

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[4]Regarding possible changes in the central bank's objective, there has been considerable discussion in the wake of the financial crisis about the need for central banks to consider adjusting upward their inflation objectives, and the euro area has not been immune to these discussions. For example, Ball et al. (2016) recently make this recommendation as a means to avoid the incidence, severity, and costs of hitting the ELB constraint. This discussion is conceptually distinct from other recommendations which have emphasized increasing short-run inflation expectations as a demand-management device at the ELB.

[5]For instance, Benhabib, Schmitt-Grohé, and Uribe (2001) highlight the existence of a deflationary equilibrium where the ELB is binding and inflation is stuck below target. More recently, Aruoba and Schorfheide (2015) construct a two-regime stochastic general equilibrium model in which the economy may alternate between a "targeted inflation regime" and a "deflation regime." Busetti et al. (2014) also study the risks of such a regime in a model with learning and show that it may imply considerable risks of a de-anchoring of long-term inflation expectations and may give rise to a period of sustained low real output growth.

and Inoue (2001) to shed light on possible shifts, their magnitude, and timing. This provides direct evidence about whether or not the Great Recession and its aftermath resulted in any significant changes in key features of that distribution.

In a second step, we exploit the available micro data in a panel setting and explain changes in long-term inflation expectations by studying their co-movement with other macroeconomic variables. Our use of micro data contrasts with most other recent studies mentioned above which have focused on average measures of expectations or representative proxies extracted from asset prices. Although we do not claim a causal interpretation, the analysis of such co-movements sheds light on possible changes in the degree to which the distribution is anchored. For example, allowing for uncertainty about the central bank's objective, and learning on the part of private agents about its ability to hit that objective, we can expect some positive co-movement between short-term macroeconomic news and long-term inflation expectations (e.g., as in Beechey, Johannsen, and Levin 2011). In the spirit of Levin, Natalucci, and Piger (2004), we also consider the co-movement of long-term expectations with an ex post measure of central bank performance to assess whether agents partly update their future long-term expectations by taking into account the rate of inflation that the central bank has actually delivered. In line with recent discussions about secular stagnation and deflationary equilibriums with simultaneously weak trend growth and excessively low inflation expectations, e.g., as discussed in Eggertson and Mehrotra (2014) and Summers (2014), we also examine the co-movement between long-term inflation expectations and corresponding long-term expectations about the real economy. Using matched individual-level expectations, our panel data allow us to study these interrelationships while also controlling for other sources of variation that are common to all forecasters, such as observed inflation rates. In addition, we provide direct tests of whether these interrelationships have changed following the Great Recession and during the more recent period when the ELB has been binding and the ECB has employed nonstandard monetary policy.

In a third and final step, using a similar set of appropriately transformed covariates, we extend the above micro-level analysis to shed light on the factors which co-move with changes in long-term inflation uncertainty which we measure by the individual variance of

the subjective forecast distributions.[6] Again, such an analysis speaks directly to the question of anchoring because higher uncertainty about long-term inflation prospects implies that the distribution is less tightly anchored even if overall mean expectations remain unchanged.

The layout of the remainder of the paper is as follows. In section 2, we briefly describe our data set and the manner in which we estimate key moments of the subjective long-term forecast distributions. Section 3 presents the empirical evidence for changes in the distribution. In section 4, we turn to the analysis of the variables which co-move with changes in long-term mean expectations and uncertainty and analyze whether the strength of this co-movement has changed following the Great Recession. Section 5 concludes by discussing the economic significance of our findings and their implications for monetary policy.

2.   Data and Estimation of Moments

We base our analysis on the individual density forecasts provided by the ECB's Survey of Professional Forecasters (SPF), which has been conducted and published by the ECB at a quarterly frequency since the beginning of 1999. Since we are interested in long-term inflation expectations, we primarily focus on those forecasts that have a forecast horizon of roughly five years (i.e., 20 quarters or $h = 20$). Our sample period ranges from 1999:Q1 to 2017:Q1.[7] Online appendix A (available at http://www.ijcb.org) provides detailed information about the SPF histograms and other data sources used in the study. Reflecting its survey origins, the SPF data set is heavily unbalanced because forecasters leave the panel or enter later and because they

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[6]In the remainder of this paper we will use the two terms "variance" and "uncertainty" interchangeably. For an overview of other definitions and measures of uncertainty see, for instance, Rossi, Sekhposyan, and Soupre (2016).

[7]Note that during the first two years of the SPF long-term forecasts were only surveyed on an annual basis in 1999:Q1 and 2000:Q1. We make use of these observations whenever possible. However, we have to drop them from our econometric estimation whenever we relate long-term expectations to lagged information from the SPF.

are not required to report their forecasts in every survey round. The number of individual respondents therefore varies from one quarter to the next. We focus on the analysis of this unbalanced panel and, in particular, do not attempt to interpolate any missing observations. The number of respondents providing the histograms depicting the probabilities they assign to a range of future inflation outcomes averages 39.1 in our sample. Although this is slightly lower than the number of respondents who report point forecasts for inflation (44.6 on average), it nonetheless provides a rich cross-sectional basis for econometric analysis. Moreover, when considering co-movement with other variables, we are able to match the estimated moments for inflation at the individual level with corresponding individual moments estimated from equivalent histograms for gross domestic product (GDP) growth and the unemployment rate.

Before attempting to study the properties of the full distribution, it is necessary to estimate the key moments summarizing its location, spread, symmetry, and tail risks. The density forecasts are provided as histograms for which every forecaster reports probability forecasts that reflect their assessment of the likelihood that future inflation will fall within certain intervals. Formally, denote with $p_{i,t+h|t}^{j}$ the probability that forecaster i ($i = 1, \ldots, N$) in survey period t attaches to the event that the inflation rate in period $t + h$ falls into a particular interval j ($j = 1, \ldots, J$).[8] To compute mean long-term expectations, the corresponding inflation uncertainty, and higher moments of the density forecasts, we adopt the most common approach as our baseline estimates and we then consider robustness with respect to alternative approaches. The baseline approach is non-parametric and assumes that all the probability mass in a particular interval j is compressed at the midpoint of this interval, which we denote by μ_j. We assume that the open intervals at both ends of the distribution have the same width as all other intervals and accordingly compute the midpoints of these intervals in the same way. The

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[8]Note that J, which represents the total number of surveyed intervals, changes over time, as the survey design was changed at several points in time (see online appendix A). As the probabilities must sum to 100 percent, it can be reasonably assumed that a probability of 0 is assigned by agents to intervals that were not included in a particular survey round.

mean $\pi_{i,t+h|t}$ is, for instance, computed as the probability-weighted sum of each midpoint (equation (1)). The first four moments are computed as follows:

$$\text{Mean:} \qquad \pi_{i,t+h|t} = \sum_{j=1}^{J} p_{i,t+h|t}^{j} \mu_j \qquad\qquad (1)$$

$$\text{Variance:} \quad \sigma^2_{i,t+h|t} = \sum_{j=1}^{J} p_{i,t+h|t}^{j} (\mu_j - \pi_{i,t+h|t})^2 \qquad\qquad (2)$$

$$\text{Skewness:} \quad S_{i,t+h|t} = \sum_{j=1}^{J} p_{i,t+h|t}^{j} (\mu_j - \pi_{i,t+h|t})^3 / \sigma^3_{i,t+h|t} \qquad (3)$$

$$\text{Kurtosis:} \quad k_{i,t+h|t} = \sum_{j=1}^{J} p_{i,t+h|t}^{j} (\mu_j - \pi_{i,t+h|t})^4 / \sigma^4_{i,t+h|t} - 3 \quad (4)$$

As highlighted in Engelberg, Manski, and Williams (2009), it must be acknowledged that our moment estimates are subject to measurement and estimation error. In our case, the assumptions we make regarding the allocation of probability mass to the midpoints of the surveyed intervals may be a particularly important source of such error, and it is therefore of interest to test the overall robustness of our conclusions with respect to the above nonparametric approach. Therefore, we present alternative results based on different assumptions and parametric methods below and, in more detail, in online appendix B. These are based on (i) the assumption that the probability mass is distributed uniformly within bins, (ii) the assumption that the true underlying distribution is normal, and (iii) the approach of Engelberg, Manski, and Williams (2009) that assumes a beta distribution for cases with more than two used bins and a triangular distribution for cases with fewer used bins.[9] Furthermore,

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[9]For the standard deviation, we find very close correspondence across all methods considered (see online appendix B for further details). For the skewness and the kurtosis, also both discrete approximations are highly correlated, while the correlations with the moment estimates produced by the beta function tend to

rounding on the part of respondents[10] may be an important source of measurement error and, as highlighted in online appendix C, it may be associated with bias in particular affecting the estimation of the second and fourth moments.

To summarize the common pattern across individual SPF respondents, from the individual moments computed according to equations (1) to (4), we can construct the cross-sectional averages by summing each of the individual moments and dividing by the number of density forecast available at each point in time. One reason to focus on the average moments rather than the individual moments when testing for structural breaks in the next session is that measurement error is likely to affect more strongly the estimation of moments at the individual level. When averaging across individuals, idiosyncratic individual-specific approximation errors tend to offset each other, resulting in an overall smaller measurement error (see online appendix C for further details on this).

Note that an estimate of the central tendency of expectations is also available directly from the reported point forecasts that are collected in the SPF. We refrain from using this information in the computation of moments for two main reasons. First, it is not clear whether panelists report their expected mean, mode, or median as their point forecasts and whether density forecasts and point

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be lower. These lower correlations suggest that a key possible source of measurement error may link to the assumption of a discrete versus a continuous distribution function. We have opted for the discrete approach because it is in line with the discrete nature of the survey design (i.e., the discrete bins used in the survey questionnaire) and does not attribute a specific continuous functional form to the respondents' subjective densities. Nonetheless, the analysis points to a potentially important role for measurement error in influencing the third and fourth moment estimates.

[10]There is empirical evidence that a large fraction of reported interval probabilities are integers or multiples of 5 or even 10 (Manski and Molinari 2010; Glas and Hartmann 2018; online appendix C) which, on the one hand, suggests that forecasters tend to round the raw probabilities derived from a model for the density of the continuous random variable to be forecast. On the other hand, many forecasters state that they use judgment (instead of formal models) when producing the density forecasts (ECB 2014). This could imply that the reported probabilities are the (raw) outcome of a more intuitive heuristic process rather than representing the rounding of an underlying continuous distribution. This latter view suggests that rounding per se may not be a source of measurement error in the reported probabilities.

Figure 1. Different Measures of Central Tendency of Long-Term Inflation Expectations
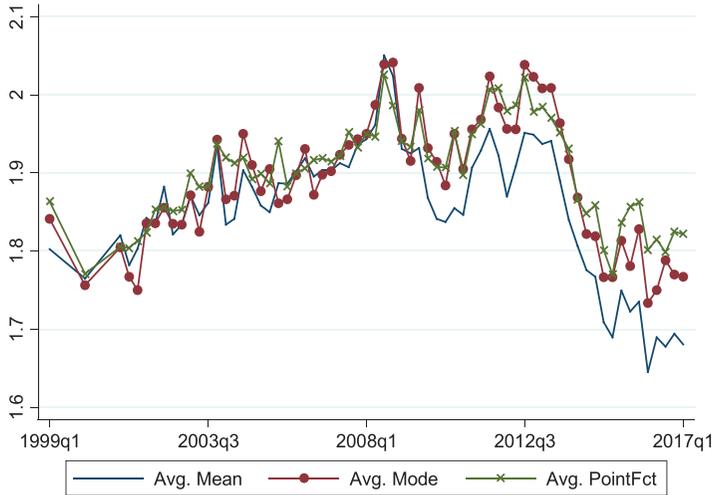
Notes: Average (Avg.) mean expectations and average modal expectations are computed based on the reported density forecasts. The average point forecasts are computed based on the reported individual point forecasts.

forecasts are consistent.[11] Second, a focus on mean expectations from equation (1) is also justified because it draws on all the probabilities collected from respondents. As such, it may contain more information than the long-term point forecasts. Figure 1 plots the mean estimated according to equation (1) together with two other measures of central tendency taken from the survey. The first is the

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[11] The SPF survey itself does not offer any information concerning what part of the distribution the point forecasts capture, e.g., whether panelists report a most likely or modal outcome or a conditional expectation (e.g., based on specific assumptions about policy or other exogenous variables) or whether density forecasts and point forecasts are even consistent. Engelberg, Manski, and Williams (2009) study the consistency between density and point forecasts and García and Manzanares (2007) provide evidence that the density forecasts from the SPF are more reliable than the point forecasts. In a separate (unreported) robustness analysis we also compute our moment estimates under the assumption that the point forecasts equate with the mean of the distribution. As expected, we do find that this assumption can change significantly our moment estimates, especially the estimated skewness.

mode computed as the midpoint of the interval which is assigned the maximum probability, again averaged across the responding forecasters in a given round. The second alternative measure is simply the average point forecast. Overall, one observes a very clear co-movement and similarity between these three measures of central tendency. In particular, the average point forecast and the estimated mode are very closely related, suggesting that when they give their point forecasts survey respondents may be giving a modal prediction rather than an estimate of their mean expectations. In the period since the financial crisis mean expectations dropped slightly below both the estimated average mode and the reported point forecasts. Given this divergent pattern, we also include the estimated mode of the probability distributions in our empirical analysis of potential shifts in the distribution's location.

3.   Evidence of Change in the Distribution of Long-Term Inflation Expectations

In this section we report our empirical analysis of possible structural breaks in the distribution of long-term inflation expectations. We first discuss the result of a general test for distributional change due to Inoue (2001). This test provides nonparametric prima facie evidence about possible structural change in the whole distribution. We then present the methods used to estimate the timing and magnitude of possible breaks in the first four moments of the distribution before reporting the main findings. Also, to complement the proposed tests of stability in the estimated moments, we apply these breakpoint tests to selected interval probabilities taken directly from the surveyed histograms. The advantage of this complementary approach is that it offers more direct evidence for change in the distribution that does not require the assumptions needed for the estimation of distributional moments.

3.1   Testing for Distributional Change

Before proceeding to tests for change in the moments, it is of interest to examine the prima facie evidence for changes in the distribution as a whole. To do this, Inoue (2001) suggests a nonparametric test

which is particularly useful in situations where the correct specification of the underlying datagenerating process is unknown.[12] Inoue (2001) proposes a test of change in the distribution function of a time series x_t that is observed over a total sample of n periods. The test is based on the difference, $(T(s, \tau))$, between the empirical distribution functions for two subsamples defined by a candidate change date $s < n$:

$$T(s, \tau) = \left| \frac{1}{s} \sum_{t=1}^{s} I(x_t \leq \tau) - \frac{1}{n-s} \sum_{t=s+1}^{n} I(x_t \leq \tau) \right|. \quad (5)$$

In equation (5), the measured distance between the two distribution functions is based on an observed time series and uses the indicator function, $I(\cdot)$, to estimate the relevant probabilities from the time-series observations.

Our data, however, contain a sequence of reported distribution functions in the form of the SPF histograms. We construct a modified test statistic by replacing the empirical distribution functions with subsample averages of the observed distribution functions. Denoting the probability that inflation will be below τ in the long run as reported in period t by $CDF_t^{SPF}(\tau)$, we obtain the modified expression

$$T(s, \tau) = \left| \frac{1}{s} \sum_{t=1}^{s} CDF_t^{SPF}(\tau) - \frac{1}{n-s} \sum_{t=s+1}^{n} CDF_t^{SPF}(\tau) \right|. \quad (6)$$

Note that in the case of the application to the SPF, the grid for τ is determined by the bins defined in the survey questionnaire. Using the distance measure in equation (6), a weighted Kolmogorov-Smirnov test statistic can be computed as

$$T_1 = \sup_{1 \leq s < n} \sup_{\tau \in \mathbb{R}} \left| \frac{s}{n} \left(1 - \frac{s}{n}\right) n^{1/2} \times T(s, \tau) \right|. \quad (7)$$

To determine critical values for this modified test, we use the bootstrap that Inoue (2001) proposes.[13] We obtain a test statistic of

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[12]We would like to thank the editor Barbara Rossi for pointing us to this test, which is very useful in our context.

[13]For the bootstrap we set the number of iterations to 1,000 and use a window size of nine, following the rule of thumb suggested in Inoue (2001).

$T_1 = 0.174$, which is marginally larger than the 10 percent critical value of 0.173 (the 5 percent and 1 percent critical values are 0.192 and 0.225, respectively).[14] This means that we can reject the null hypothesis that there is no structural break at the 10 percent level. The test statistic is maximized for $s = 2009$:Q4, indicating that the distribution of long-term inflation expectations most likely changed during the Great Recession. Although certainly not definitive, this result motivates a further investigation of how the distribution may have changed following the Great Recession. Motivated by this result, we explore the data for further evidence of distributional change by testing for evidence of structural breaks. Below we first describe the implementation of these structural break tests in general and then apply them to the specific interval probabilities collected in the SPF survey and also to the distributional moments.

3.2   Testing for Structural Breaks

One condition for long-term inflation expectations to be well anchored is that their distribution is relatively stable around the central bank's inflation target. To examine this, we test for evidence of any breaks in the probabilities assigned to certain intervals and, subsequently, in the first four moments. Since a priori we know neither the number of breaks nor their timing, we employ the method of Bai and Perron (1998, 2003), who consider the linear regression model with a finite number of possible regimes defined by unknown breaks in the model parameters. Their method yields estimates of the unknown regression coefficients associated with each regime together with estimates of the unknown breakpoints. To select the number of significant breaks and to date their occurrence, we apply these methods by regressing a given interval probability or moment on its first lag and an intercept term. The inclusion of the former term is intended to account for the strong persistence in such long-horizon moments and probability forecasts which would

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[14]All data used in this paper and codes for replicating all results can be downloaded from https://www.dropbox.com/s/ue9pyq0cv03mffq/Replication_Files_Dovern_Kenny_2019.zip?dl=0.

otherwise cause substantial residual autocorrelation in our regressions.[15] Formally, the considered model is

$$\bar{m}_{t+h|t} = \alpha_{m,r} + \beta_{m,r}\bar{m}_{t+h|t} + \varepsilon^m_{t+h|t}, \tag{8}$$

where $\alpha_{m,r}$ and $\beta_{m,r}$ are regime-specific parameters (with $r = 1, \ldots, R$), $\varepsilon^m_{t+h|t}$ is an iid error term, and $\bar{m}_{t+h|t}$ represents the cross-sectional average of individual interval probabilities or moments. For the case of mean long-term expectations ($m = \pi$), for instance, $\alpha_{\pi,r}/(1 - \beta_{\pi,r})$ yields an estimate of the average expected rate of long-term inflation in a given regime. Under the assumption that forecasters believe that, in general, the central bank is able to achieve its inflation target in the absence of further shocks, such an estimate provides a regime-specific measure of the perceived inflation objective. In the absence of any structural breaks, we have $\alpha_{\pi,r} = \alpha_{\pi}$ and $\beta_{\pi,r} = \beta_{\pi}$, which implies that the long-term expectation for inflation is constant. In a similar way, for each of the three higher-order moments and the interval probabilities, $\alpha_{m,r}/(1 - \beta_{m,r})$ provides an estimate for the average perceived future variance, skewness, tail risk, or interval probability embodied in the distribution in any given regime. Breaks of these moments and probabilities may signal changes in the degree to which the distribution of long-term inflation expectations is anchored.

In implementing the Bai-Perron (BP) procedure, it is necessary to specify a *minimum* required distance between any two potential break dates. We set this minimum distance between breaks at a relatively conservative level of eight quarters in order to avoid overfitting and possibly finding an implausibly large number of spurious breaks for each moment. In Bai and Perron's jargon, given our sample size, this implies a "trimming parameter" of $8/72 \approx 0.11$. We determine the number of structural breaks by looking at a modified Schwarz criterion (LWZ) which is suggested for the case of models

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[15]According to the Ljung-Box test, we cannot reject the null hypothesis of no residual autocorrelation at the 5 percent level for both the specification without structural breaks and the one with breaks for all moments with one exception: In the case of inflation uncertainty, the large structural break causes mild negative autocorrelation in the residuals of the specification that does not allow for this break.

that include a lagged dependent variable and the sequential SupF-test which is the overall preferred test according to Bai and Perron (2003).[16] Because it turns out that we find evidence for at most one break in all the moments that we consider, we run robustness checks using the test proposed by Andrews and Ploberger (1994). This tests the null hypothesis of no break against the alternative of exactly one break (at an unknown point in time) and is more powerful as well as robust to heteroskedasticity and residual autocorrelation.

Clearly, an important practical consideration for all of the tests discussed above is whether they are sufficiently powerful to identify actual breaks in the data, particularly in the presence of measurement error. To investigate this issue, online appendix C reports the results of two simulation exercises which analyze how the size and power of the breakpoint tests we employ might be affected by measurement error. Overall, the results of these simulations suggest that the tests have reasonable power in samples of the size we are using even in the presence of measurement error. At the same time, the simulations indicate that the power for detecting breaks in higher moments may be lower the more rounding is applied when forming the interval probabilities. Thus, any results on the number of breaks reported below should be considered a "lower bound."[17]

3.3   Breaks in Selected Interval Probabilities

In this section, we apply the above breakpoint analysis to test for breaks in selected interval probabilities over time. In particular, we consider the average probabilities attributed by forecasters to the following five long-term inflation scenarios: (i) outright deflation (long-term inflation outcome below 0 percent), (ii) relatively low inflation of between 0 percent and 1.5 percent (i.e., low compared with the ECB mandate of below but close to 2.0 percent),

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[16]The sequential test is based on the idea of sequentially testing the null hypothesis of no l breaks versus $l + 1$ breaks until the null hypothesis can no longer be rejected. In each step of this sequence and given a set of l breakpoints, Bai and Perron (1998) suggest applying $l + 1$ tests of the null hypothesis of no structural break against the alternative hypothesis of a single structural break to the $l + 1$ segments of a time series defined by the l breaks.

[17]However, given that only a fraction of probability statements in the SPF is rounded while in our simulations we assume all of the probabilities are rounded, the issue should certainly not be overrated.

## Figure 2. Breakpoints for Selected Interval Probabilities
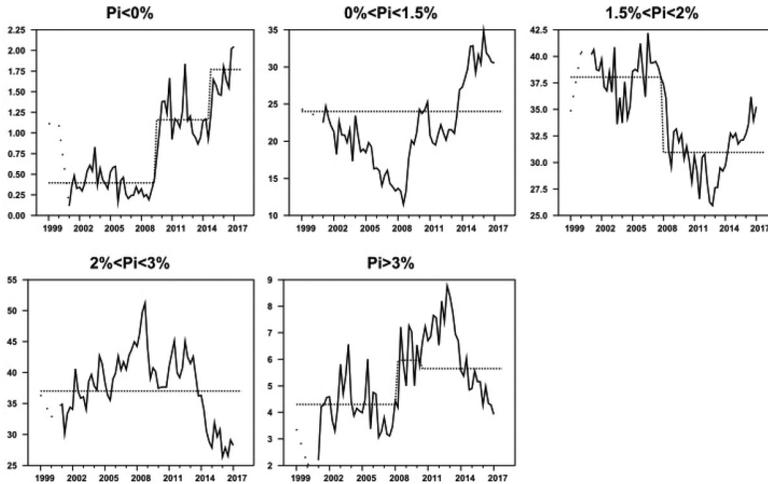
Notes: Selection of breakpoints based on Bai and Perron (2003). The solid black lines refer to the average probability (across forecasters) assigned to the intervals. The dotted lines show the implied unconditional means for different subperiods, with breaks in AR(1) models for the average moments selected using the LWZ statistic. The minimum distance between two breakpoints was set to eight quarters.

(iii) inflation broadly consistent with the ECB's mandate (between 1.5 percent and 2.0 percent), (iv) inflation moderately above target (between 2 percent and 3 percent), and (v) relatively high long-term inflation (above 3 percent). These selected intervals provide an economic narrative relative to the ECB's definition of price stability. For example, a reduced probability mass assigned to the interval between 1.5 percent and 2.0 percent may signal a deterioration in the degree to which long-term expectations are anchored at a level that is below but close to 2.0 percent. In selecting these intervals, we also avoided having to interpolate probabilities within intervals, as this would require the use of auxiliary assumptions that would be hard to justify.

Figure 2 shows the evolution of these probabilities across survey rounds together with their estimated means for which we select significant breaks based on Bai and Perron (1998, 2003) using the LWZ statistic. Overall we find evidence for significant breaks in three of the five intervals examined. On the one hand, we find no significant

breaks in the probabilities assigned to the low inflation outcomes (0.0 percent to 1.5 percent) and outcomes moderately above the target (2.0 percent to 3.0 percent). Despite the lack of evidence of a break in these interval probabilities, on the other hand, the sizable movements in the probabilities of these two events are certainly of interest from a policy perspective. In particular, following the Great Recession, there was a large rise in the probability of low inflation, from less than 15 percent to more than 30 percent. Also, the chances of moderately higher inflation dropped from a peak of over 50 percent to below 30 percent toward the end of the sample period. These relative shifts in probabilities are also suggestive of a possible shift toward a more negatively skewed distribution. In contrast, the tests do indicate one downward break for the probability associated with inflation being broadly in line with the target (1.5 percent to 2.0 percent) and two breaks for each of the two outer intervals (deflation and relatively high inflation above 3.0 percent). The direction of the breaks indicate that following the Great Recession forecasters have reduced their assessment of the likelihood that long-term inflation falls between 1.5 percent and 2.0 percent from above 37.5 percent before the Great Recession to below 32.5 percent in the second half of the sample. The lower probability assigned to this outcome range, which is the most consistent with the ECB definition of price stability of below but close to 2.0 percent, can be taken to imply a reduction of the *degree* to which long-term inflation expectations were anchored following the Great Recession. Such a result is suggestive of a more spread-out long-run distribution that has a lower concentration of probability mass in the area surrounding mean expectations and the central bank's target. It may therefore also imply higher long-run inflation uncertainty. There also seem to be (ongoing) shifts toward lower and more negative inflation outcomes, as indicated by the persistent increase in the probabilities associated with negative inflation. In this case, however, it is important to note the considerably smaller shift in the probabilities from below 0.5 percent in the first part of the sample to around 1.75 percent in the more recent period. Overall, therefore, these direct tests of stability in the reported interval probabilities tend to provide empirical support for possible changes in the long-run distribution. In the following sections, we offer further evidence on the nature of these changes based on the estimated moments.

Figure 3. Breakpoints for Moments of Density Forecasts
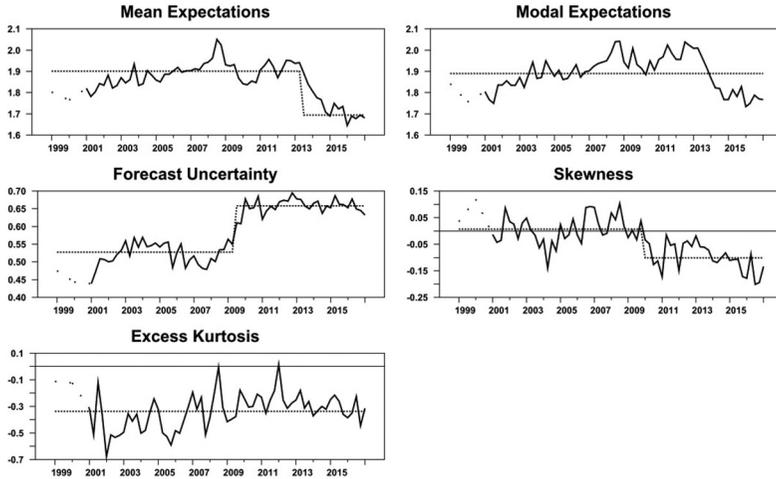
Notes: Selection of breakpoints based on Bai and Perron (2003). The solid black lines refer to the average moments of the density forecasts of the individual SPF participants. The dotted lines show the implied unconditional means for different subperiods, with breaks in AR(1) models for the average moments selected using the LWZ statistic. The minimum distance between two breakpoints was set to eight quarters.

3.4   Breaks in the Mean

We now turn to the analysis of breaks in the estimated moments to provide more formal evidence about which features of the predictive densities may have changed over time. Figure 3 shows the evolution of the modal expectation discussed above together with the first four moments given by equations (1) to (4). In each panel, the regime-specific moment estimates $\hat{\alpha}_{m,r}/(1 - \hat{\beta}_{m,r})$ are also plotted (as identified by the LWZ statistic). The breakpoint analysis of density moments is further detailed in table 1. In particular, we report a list of the estimated break dates and the corresponding F-statistics indicating the significance of each break as well as complementary results based on the sequential SupF-test.

    For mean expectations, we find one significant break in 2013:Q2 according to both the LWZ statistic and the Andrews and Ploberger (AP) test reported in table 1. The break is downward and occurs in

Table 1. Breakpoints for Average Moments of Density Forecasts

	LWZ			Sequential SupF			Andrews-Ploberger		
	Period	F-test	Mean	Period	F-test	Mean	Period	F-test	Mean
A. Mean Expectations									
	1999:Q1–2013:Q2	7.89***	1.90	1999:Q1–2017:Q1		1.83	1999:Q1–2013:Q2	7.89***	1.90
	2013:Q3–2017:Q1		1.69				2013:Q3–2017:Q1		1.69
B. Model Expectations									
	1999:Q1–2017:Q1		1.89	1999:Q1–2017:Q1		1.89	1999:Q1–2017:Q1		1.89
C. Inflation Uncertainty									
	1999:Q1–2009:Q2	16.56***	0.53	1999:Q1–2009:Q2	16.56***	0.53	1999:Q1–2009:Q2	16.56***	0.53
	2009:Q3–2017:Q1		0.66	2009:Q3–2017:Q1		0.66	2009:Q3–2017:Q1		0.66
D. Skewness									
	1999:Q1–2009:Q4	8.05***	0.01	1999:Q1–2017:Q1		−0.05	1999:Q1–2009:Q4	8.05***	0.01
	2010:Q1–2017:Q1		−0.10				2010:Q1–2017:Q1		−0.10
E. Excess Kurtosis									
	1999:Q1–2017:Q1		−0.34	1999:Q1–2017:Q1		−0.34	1999:Q1–2006:Q2	5.95***	−0.45
							2006:Q3–2017:Q1		−0.29

Notes: The number of breaks and their location is selected based on the modified Schwarz criterion (LWZ) and the sequential SupF-test proposed by Bai and Perron (2003). The minimum distance between two breaks is set to eight quarters. The third test is taken from Andrews and Ploberger (1994) and tests against the alternative of only one break at an unknown point in time. Dependent variables are the average moments of the density forecasts of the individual SPF participants. Dates refer to periods in which we observe a significant change in the parameters of an AR(1) model for the respective moment. Implied unconditional means are computed for every break segment based on the estimated coefficients. *** indicates that breaks in the model parameters are jointly different from 0 at a 1 percent significance level.

the wake of the Great Recession and euro-area sovereign debt crisis. Although quantitatively modest, the break is noteworthy, with the regime-specific mean falling to 1.69 percent from 1.90 percent prior to the break, and points to growing beliefs that long-term inflation outcomes could be "below" but "not so close to" 2.0 percent. The drop in mean expectations is found to be statistically significant given the low overall volatility of the time series. Importantly, this break in the mean is detected across three of the four moment estimation methods presented in online appendix B. However, when one fits a beta distribution to the survey histograms, a break in the mean is not detected by both the LWZ-based BP test and the AP test. The case for a significant downward shift of long-term inflation expectations is also weakened by two additional results reported in table 1. First, the sequential SupF-test does not identify any breaks in the dynamics of mean expectations and, as a result, the estimate for the average over the full sample is constant at 1.83 percent. Second, none of the tests identifies any breaks in the case of modal expectations, which average 1.89 percent over the full sample. A finding of a downward break in the mean combined with a stable modal value is consistent with a shift toward a more negatively skewed distribution, and we examine this hypothesis directly below by applying the same test to the estimated third moment.

Overall, our results for mean expectations provide at most only weak evidence for a quantitatively modest decline in long-term inflation expectations toward the end of our sample. Mean inflation expectations also remain in a range that can be considered consistent with price stability as defined by the ECB's price stability objective of "below but close to 2.0 percent." Hence, our analysis provides no grounds to think that the central tendency of euro-area long-term inflation expectations became unanchored. This finding is in line with other recent studies that use market-based inflation expectations, as, for instance, Autrup and Grothe (2014), Strohsal and Winkelmann (2015), and Speck (2016).

3.5   Breaks in the Variance

Figure 3 and table 1 report equivalent results for higher moments. In the case of long-term inflation uncertainty, all three reported tests identify a break in 2009:Q3 that is associated with an increase in

uncertainty about long-term inflation. In relative terms, this shift is quantitatively more noticeable than the shift in mean expectations. After the break, i.e., in the immediate wake of the Great Recession, average uncertainty about the long-term inflation at 0.66 percentage points (pp) had increased by about 25 percent compared with its level in the pre-crisis regime (0.53 pp). Following this increase, long-term inflation uncertainty has been quite stable at the new level and has shown no tendency to decline. This pronounced and persistent increase in the variance of the distribution signals that forecasters perceive the long-term inflation outlook to be more uncertain now than before the Great Recession.[18] As a result, the distribution has become less concentrated around levels that are consistent with the definition of price stability. Interestingly, the increase correlates well with an increase of the historical variance of annual inflation rates in the euro area when computed recursively based on an expanding sample starting in 1997; the latter increases from about 0.2 in 2007 to a little below 0.6 in 2014. Thus, it seems as if forecasters anticipate that the increase in inflation volatility which emerged after the Great Recession will be highly persistent—or even permanent—rather than being relevant only to recent years or the short-term outlook for inflation.[19] As a caveat, it should be mentioned that the estimated level of long-term inflation uncertainty could be subject to bias reflecting the rounding behavior of forecasters when they respond to the survey (see online appendix C for further details).

Overall, the identified upward shift in the variance could be taken to imply that the *degree* to which long-term inflation expectations are anchored has diminished. The shift in the variance is consistent with macroeconomic theories highlighting the implications of uncertainty surrounding the central bank's objective (Beechey, Johannsen, and Levin 2011) and, in particular, the potential effects of the lower

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[18]It is noteworthy that the upward adjustment came quite soon after the Great Recession and the sovereign debt crisis was not associated with any further rise in long-term inflation uncertainty.

[19]The above-identified upward break in the variance appears to be relatively robust with respect to measurement error. For example, in online appendix B we show how, across four different ways to estimate the variance, we identify the same break in 2009:Q3 using both the LWZ test and the AP test.

bound on nominal interest rates (Benhabib, Schmitt-Grohé, and Uribe 2001). However, the higher variance is also consistent with the view that forecasters believe it may take longer for the central bank to achieve its price stability objective, e.g., as a result of more persistent and volatile shocks in the future or a perceived change in the transmission of monetary policy. It does not necessarily imply that they have reduced their belief in the ECB's ability to ultimately achieve that objective over a longer horizon than the five years to which the survey data relate. Nonetheless, our findings highlight an important challenge for monetary policy and its communication; namely to limit any further the rise in the uncertainty surrounding long-term inflation prospects.

3.6   Breaks in Symmetry and Tail Risk

Figure 3 and table 1 also report the results of the break analysis for the skewness and tail risk in the distribution of long-term expected inflation in the euro area. The time path of the average skewness provides insight on possible changes in the symmetry of the distribution and may thus signal concerns among forecasters about long-term inflation risks either to the upside or the downside. The analysis reveals that, since 2010:Q1, the forecast densities are negatively skewed, on average, whereas prior to this date they were broadly symmetric. This means that since the Great Recession forecasters have assigned a greater share of the overall probability mass to relatively low as opposed to relatively high inflation outcomes. This finding of a negatively skewed distribution is in line with our previous result of a possible downward break in mean expectations with a higher and more stable mode. It is also precisely what is predicted by macroeconomic models which incorporate a lower bound constraint on nominal interest rates (e.g., Coenen and Warne 2014; Hills, Nakata, and Schmidt 2016). Interestingly, according to both the LWZ and AP test results reported in table 1, the break in skewness occurred relatively soon after the Great Recession and prior to the break in mean expectations. The tendency toward a negatively skewed distribution has also been highly persistent and has lasted up to the end of our sample in 2017:Q1. At the same time, these results have to be taken with some caution because the alternative

SupF-test identifies no break in skewness.[20] For the kurtosis, only the AP test identifies a small increase in tail risk. However, the long-term inflation density is platykurtic, which means that forecasters believe that, relative to a normal distribution, less of the inflation uncertainty is associated with infrequent tail events. Overall, therefore, the survey data tend to give relatively small weight to tail risks for inflation.[21] Importantly, as we show in online appendix C, estimates of kurtosis appear to be the most uncertain and the most sensitive to approximation error, in particular linked to rounding behavior on the part of respondents. Using other moment estimation techniques, we find no clear evidence of a break in kurtosis (see online appendix B).

4.   Co-movement of Moments with other Variables

The previous section provided evidence that the distribution of long-term inflation expectations in the euro area changed in the period since the Great Recession. In particular, our analysis shows that the distribution experienced a modest downward shift in its mean, a more sizable and significant increase in its dispersion, and a persistent negative skewness. As discussed in the introduction, a second way to shed light on how well-anchored long-term inflation expectations have been is to examine the strength of their co-movement with other economic variables. In a perfect world with no uncertainty about monetary policy effectiveness, we might expect to observe no correlation between moments of the distribution of expectations and other macroeconomic developments. However, in a world with uncertainty and learning on the part of private agents, some co-movement even with short-term macroeconomic developments at business cycle frequencies can be expected. In such circumstances, an increased sensitivity of long-term inflation expectations to such factors would

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[20]In online appendix B we provide further information on the robustness of this break in skewness. We find that most moment estimation methods that allow for asymmetry do identify a break in the first half of 2010, in line with our baseline results.

[21]This is a well-known finding in the literature exploiting such data. It is a direct consequence of the fact that many participants in the SPF attach positive probability weights to only a very limited number of the bins in the survey questionnaire (see Kenny, Kostka, and Masera 2015).

be indicative of a change in the degree to which expectations are anchored.

In this section, we use panel regressions to examine the co-movement between the first two moments of the distribution of expected long-term inflation with other economic variables.[22] The proposed panel analysis offers a way to exploit the individual-level replies in order to assess the extent of *average* co-movement of mean long-term expectations and long-term inflation uncertainty with other variables. In particular, the regression coefficients represent the *average* co-movement that is derived from the micro data. Hence, these coefficients, and the co-movements that they identify, match very well the macroeconomic focus of the study. In particular, we exploit the individual expectations in a panel setting to address the following questions: Are there factors that co-move strongly with long-term inflation expectations and uncertainty? Did the role of such factors change after 2007, the year in which the financial crisis began to unfold? Can we identify any coincidences between recent monetary policy events—such as the hitting of the ELB on nominal interest rates or the introduction of nonstandard monetary policies—and changes in the first two moments of the distribution? We first present the results for the mean and then turn to the analysis of the variance.

4.1 Long-Term Mean Inflation Expectations

To examine the co-movement between mean expectations and other macroeconomic developments, we consider the following set of variables: First, we consider the change in forecaster-specific short-term (one-year-ahead) and medium-term (two-year-ahead) inflation expectations ($dE_i[\pi(1y)]_t$ and $dE_i[\pi(2y)]_t$). In addition, we look at the reaction of long-term expectations to past short- and medium-term forecast errors for inflation, again at the individual level ($\pi - E_i[\pi(1y)]_{t-4}$ and $\pi - E_i[\pi(2y)]_{t-8}$). To capture perceived

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[22]We focus on the first two moments because these are the ones for which we can readily identify a set of appropriate covariates. However, given the results of the break test analysis in section 3 above, the examination of co-movement with other higher moments or with the interval probabilities discussed in section 3 represents an interesting avenue for future empirical research.

structural changes linked to possible concerns about secular stagnation and deflationary equilibriums, we include the change in long-term expectations for GDP growth $(dE_i[GDP(5y)]_t)$ and the unemployment rate $(dE_i[U(5y)]_t)$ from the SPF. In the spirit of Levin, Natalucci, and Piger (2004), who show that long-term inflation expectations in the United States and the euro area were highly correlated with a slow moving average of inflation over the period 1994 to 2003, we also consider an inflation "performance gap" as the difference between recent long-term expectations and a (five-year) moving average of past inflation $(\text{MA}(\pi)_{t-1} - E_i[\pi(5y)]_{t-1})$. In addition to these forecaster-specific variables, we consider the possible co-movement with factors that are common across forecasters, such as shocks to the inflation process itself, as reflected in the recently observed change in the inflation rate $(d\pi_{t-1})$. Also, we consider the change in the volume of the ECB's balance sheet $(d\text{CBBS}_{t-1})$ as a monetary policy indicator that is associated with recent unconventional monetary policies and quantitative easing, with the expectation that an expansion of the balance sheet might potentially lead agents to change their expectation of the long-term inflation rate upward. To control for important monetary policy changes, we additionally include a dummy variable for quarters following the announcement of important nonstandard monetary policies (MPA_t)[23] and a dummy capturing the hitting of the effective lower bound (ELB_t).[24]

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[23]The events are the introduction of enhanced credit support on May 7, 2009; the introduction of the Security Market Program (SMP) on May 10, 2010; the introduction of the Outright Monetary Transaction (OMT) program on August 2, 2012; the introduction of forward guidance on July 4, 2013; the introduction of the enhanced asset purchase program (APP) on January 22, 2015; and the extension of the APP on March 10, 2016.

[24]There is some uncertainty concerning the precise date on which the effective lower bound became binding in the euro area. Our empirical analysis reflects this uncertainty, with the ELB dummy taking a value of one for the two survey rounds after July 11, 2012 and June 5, 2014, and zero otherwise. These dates correspond, respectively, to the policy meetings when the ECB deposit rate was cut to zero and the rate on the ECB's main financing operations was cut by 10 basis points to 0.15 percent. Our focus on the June meeting reflects the ECB communication at that time. In particular, when asked at the monetary policy press conference about future interest rate reductions, the president of the ECB stated, "I would say that for all the practical purposes, we have reached the lower bound. However, this doesn't exclude

We use an unbalanced panel regression with fixed effects to look at the co-movement discussed above and to test whether the correlation structure has changed since the Great Recession. Let $\Delta\pi_{i,t+20|t} = \pi_{i,t+20|t} - \pi_{i,t-1+20|t-1}$ denote the change in the long-term inflation expectation of an individual forecaster. We regress this change on forecaster-specific fixed effects and the set of proposed covariates. Collecting the forecaster-specific variables in a vector $X_{i,t}$ and the common covariates in Y_t, the linear panel regression is given by

$$\Delta\pi_{i,t+20|t} = \alpha_i + MPA_t\beta_{MPA} + ELB_t\beta_{ELB} + X_{i,t}\beta_X + Y_t\beta_Y + \varepsilon_{i,t}, \tag{9}$$

where $\varepsilon_{i,t}$ is an error term that we allow to exhibit both spatial and temporal correlation (Driscoll and Kraay 1998).[25] The parameters β_{MPA} and β_{ELB} and parameter vectors β_X and β_Y measure the extent to which long-term expectations co-move with the other variables. For perfectly anchored inflation expectations, we would expect the effect of the two dummy variables to be insignificant and also both $\beta_X = 0$ and $\beta_Y = 0$.

Table 2 lists the results of estimations of equation (9). The first column reports the coefficient estimates over the full sample and without allowing for any break in the parameter values. The second specification allows all parameters in the equation (except for the fixed effects and the constant) to break after 2007:Q3, which we chose because it represents the start of the Great Recession and the

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some little technical adjustments and which could lead to some lower interest rates in one or the other or both parts of the corridor. But from all practical purposes, I would consider having reached the lower bound today." See the "Introductory Statement to the Press Conference (with Q&A)" available at https://www.ecb.europa.eu/press/pressconf/2014/html/is140605.en.html.

[25]Driscoll and Kraay (1998) suggest a nonparametric way for estimating standard errors that are heteroskedasticity- and autocorrelation-consistent and robust to general forms of temporal and cross-sectional dependence. Their approach uses cross-section averages of regressors and residuals to compute a heteroskedasticity- and autocorrelation-consistent (HAC) estimator. Given that forecasters form their predictions simultaneously and that professional forecasts are usually found to be subject to information rigidities (Coibion and Gorodnichenko 2012; Dovern et al. 2015), which cause forecast revisions to be autocorrelated, both features are important. Ignoring them and assuming independently distributed error terms is likely to results in an underestimation of the true long-term covariance.

Table 2. Co-movement of Long-Term Inflation Expectations with Other Variables

	Without Break	With Break	
	Full-Sample Coefficients	Pre-2007:Q4 Coefficients	Change after 2007:Q4
$dE_i[\pi(1y)]_t$	0.011	0.006	0.010
	(0.02)	(0.04)	(0.04)
$dE_i[\pi(2y)]_t$	0.177***	0.205***	−0.052
	(0.02)	(0.05)	(0.06)
$(MA(\pi) - E_i[\pi(5y)])_{t-1}$	0.155***	0.187***	−0.026
	(0.02)	(0.04)	(0.05)
$\pi - E_i[\pi(1y)]_{t-4}$	−0.006	0.003	−0.010
	(0.01)	(0.02)	(0.03)
$\pi - E_i[\pi(2y)]_{t-8}$	0.007	0.017	−0.013
	(0.01)	(0.03)	(0.03)
$dE_i[GDP(5y)]_t$	0.007	0.019	−0.017
	(0.03)	(0.03)	(0.06)
$dE_i[U(5y)]_t$	−0.013	0.000	−0.019
	(0.01)	(0.02)	(0.02)
$d\pi_{t-1}$	0.031**	0.032	0.001
	(0.01)	(0.02)	(0.03)
dCBBS$_{t-1}$	−0.160**	−0.882***	0.764**
	(0.06)	(0.34)	(0.34)
MPA Dummy	0.018	—	0.016
	(0.02)	—	(0.02)
ELB Dummy	0.011	—	0.012
	(0.01)	—	(0.01)
Constant	−0.000	−0.004	—
	(0.01)	(0.01)	—
Observations	1,180	1,180	
R^2	0.195	0.204	

Notes: Dependent variable is the change in long-term inflation expectations. Both models include fixed effects for each forecaster. The constant is identified by restricting the average of the fixed effects to equal 0. We report the within R^2. Standard errors are computed using the method of Driscoll and Kraay (1998) and are robust against general forms of spatial and temporal dependence. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

launch of monetary policy measures aimed at mitigating turbulences in financial markets. The table reports the coefficients for the sample period prior to the Great Recession (second column) as well as the estimated change in the coefficients after the Great Recession, i.e., from 2007:Q4 onward (third column).

Looking first at the full-sample results, we observe that only a few of the marginal correlations are significantly different from zero. In particular, those are the correlations with the change in two-year inflation expectations and with the inflation performance gap. For example, long-term inflation expectations are revised by roughly 0.18 pp, on average, when two-year-ahead expectations move by 1 pp. Thus, the co-movement is relatively strong, supporting evidence from U.S. household expectations provided by Dräger and Lambla (2013). Also, according to the estimated parameter values on the inflation performance gap indicator, a 1 pp deviation of the past inflation trend above the announced price stability objective is associated with an upward revision in long-term inflation expectations of just above 0.15 pp. This co-movement potentially highlights the importance of the central bank actually hitting the inflation target in the medium run if long-term inflation expectations are to be stabilized. The observed co-movement is in line with macroeconomic theories which allow for uncertainty about the central bank objective. For example, if private agents are uncertain about the true inflation objective held by the central bank, they may adjust their long-term inflation expectations upward in response to past inflation trends (see, for example, Beechey, Johannsen, and Levin 2011).

In our panel regression results, we also find some quantitatively less important but significant co-movement with the change in actual inflation.[26] The only other significant parameter estimate corresponds to the change in the size of the ECB's balance sheet. The negative sign appears counterintuitive at first and demonstrates that the estimates should not be interpreted causally. A valid interpretation is not that expanding the balance sheet causes inflation expectations to decline. Instead, reverse causality is the most plausible explanation and, also, possible omitted-variable bias. For example, a plausible explanation of the negative co-movement is that the ECB anticipated a decline in inflation expectations and responded with expansionary measures that were associated with an expansion of the balance sheet. On the other hand, both the ECB and the forecasters

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[26]This is in contrast to Beechey, Johannsen, and Levin (2011), who find a response of long-term inflation expectations to inflation news for the United States but not for the euro area. However, the sample period used in their study did not cover the period associated with the aftermath of the Great Recession.

included in our panel could simply respond to other macroeconomic news that we do not capture with our variable selection.

Concerning the two monetary policy dummies, we find no evidence for any co-movement with our measure of mean long-term expectations. This implies that the hitting of the ELB and the announcement of nonstandard measures were not immediately followed by a change in inflation expectations. This result is not so surprising given the other controls and co-movement that we have captured in the regressions. For example, it is entirely plausible that the effects of the ELB and the announcement of nonstandard measures are captured via the co-movement with two-year-ahead expectations. The result may also be due to the low frequency of the SPF data, which makes it harder to connect changes in expectations to specific events. Based on higher-frequency data, Karadi (2017) finds that nonstandard measures helped to prevent long-term inflation expectations in the euro area from becoming unanchored after 2013.

The reported changes in the coefficients after 2007:Q4 suggest that the estimated co-movement did not change much after the Great Recession. An F-test of the joint hypothesis that none of the model's coefficients exhibits a structural break in 2007 does not reject this hypothesis. The only coefficient that changes significantly is the one corresponding to the ECB's balance sheet variable.[27] The pre-2007:Q4 estimate is strongly negative and highly significant, suggesting that this period also drives the full-sample results. In contrast, the overall estimate for the sample since 2007:Q4 is much smaller in absolute value and only significant at the 10 percent level.

In summary, the panel regressions suggest that the process governing the means of the subjective forecast distributions is far away from a simple stylized case where the inflation objective is a universal constant and where there is "blind faith" in the ability of the central bank to achieve this objective. Instead, this process is more in line with theories emphasizing uncertainty about the monetary policy transmission mechanism in which agents update their beliefs about long-term inflation in response to relevant shocks. However, there is

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[27]These results are clearly a reflection of the major structural break in the balance sheet data after the onset of the financial crisis. Changes in the balance sheet size were very small and regular before 2007 and larger and also more volatile afterward.

no evidence of a substantially higher sensitivity to the main covariates following the Great Recession. This result is also in line with previous results in section 3, where we identified at most only weak evidence that mean inflation expectations had declined following the Great Recession. At the same time, the co-movement that we have identified highlights that the anchoring of the mean of this distribution can in no way be taken for granted. Online appendix B provides more detail on our empirical results and highlights how, although the values of some of the estimates can change slightly, they are generally very robust across different moment estimation strategies. In particular, the strong co-movement of both the medium-term inflation expectations and the central bank performance gap measure with long-term mean expectations as well as the relative stability of coefficients across both subsamples are confirmed for several different moment estimation techniques.

4.2   Long-Term Inflation Uncertainty

We now turn to the co-movement of long-term inflation uncertainty with other variables. We follow the same analytic approach but adjust the set of covariates to correspond to the change in the dependent variable. In particular, we now look into the co-movement with the change in short- and medium-term inflation uncertainty (instead of expectations), and with the *absolute values* of lagged forecast errors and the difference between recently held long-term expectations and the five-year moving average of past inflation. We also consider the co-movement with long-term uncertainty about growth and the unemployment rate (instead of expectations), and with the *absolute values* of changes in the inflation rate and the size of the ECB balance sheet size.

Table 3 reports the results of the panel estimation for long-term inflation uncertainty. Compared with mean expectations, the results suggest that a higher share of variation of long-term inflation uncertainty can be explained by movements in the covariates considered (R^2 of 0.39 for the full sample). The main findings are as follows: First, long-term inflation uncertainty co-moves strongly with inflation uncertainty at a two-year horizon. Second, absolute changes in the current inflation rate are positively correlated with long-term

Table 3. Co-movement of Long-Term Inflation Uncertainty with Other Variables

	Without Break	With Break	
	Full-Sample Coefficients	Pre-2007:Q4 Coefficients	Change after 2007:Q4
$dV_i[\pi(1y)]_t$	0.067	−0.012	0.134
	(0.05)	(0.08)	(0.09)
$dV_i[\pi(2y)]_t$	0.265***	0.417***	−0.231**
	(0.05)	(0.08)	(0.09)
$|(MA(\pi) - E_i[\pi(5y)])_{t-1}|$	0.005	−0.014	0.026
	(0.01)	(0.02)	(0.02)
$|\pi - E_i[\pi(1y)])_{t-4}|$	0.003	0.004	0.001
	(0.01)	(0.02)	(0.02)
$|\pi - E_i[\pi(2y)]_{t-8}|$	−0.003	−0.005	0.004
	(0.01)	(0.01)	(0.02)
$dV_i[GDP(5y)]_t$	0.250***	0.282***	−0.077
	(0.04)	(0.05)	(0.07)
$dV_i[U(5y)]_t$	0.101***	0.074**	0.048
	(0.02)	(0.03)	(0.04)
$|d\pi_{t-1}|$	0.021***	0.032**	−0.015
	(0.01)	(0.01)	(0.01)
$|dCBBS_{t-1}|$	−0.082*	−0.323**	0.296*
	(0.04)	(0.16)	(0.17)
MPA Dummy	0.020***	—	0.021***
	(0.01)	—	(0.01)
ELB Dummy	−0.004	—	−0.001
	(0.01)	—	(0.01)
Constant	−0.000	−0.003	—
	(0.00)	(0.00)	—
Observations	1,180	1,180	
R^2	0.388	0.402	

Notes: Dependent variable is the change in long-term inflation uncertainty. Both models include fixed effects for each forecaster. The constant is identified by restricting the average of the fixed effects to equal 0. We report the within R^2. Standard errors are computed using the method of Driscoll and Kraay (1998) and are robust against general forms of spatial and temporal dependence. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

inflation uncertainty. Thirdly, we find a strong and highly significant positive co-movement with the perceived uncertainty about long-term growth rates and the long-term unemployment outlook.

The panel regressions for uncertainty also reveal some important co-movement with the indicators linked to monetary policy. In the

full-sample estimation, a higher absolute change in the volume of the assets held by the ECB tends to be associated with, on average, a reduction in long-term inflation uncertainty. However, when one considers the persistent rise in long-term uncertainty highlighted in section 3, the changes in ECB balance sheet in absolute terms did not fully insulate long-term inflation uncertainty from the other factors discussed above. Looking at the coefficients corresponding to the monetary policy dummies, we find that the announcement dates for nonstandard measures were generally associated with an increase in inflation uncertainty in the subsequent survey round, although this correlation is quantitatively less important than the above-mentioned downward effects.[28] On the one hand, this might indicate that the announcement of these monetary policy measures, as a side effect, led to a slight increase in long-term inflation uncertainty because forecasters had no historical experience on which to assess their transmission and the long-term implications for inflation. However, the co-movement may also reflect factors that the regression fails to control for and which simultaneously led to an increase in uncertainty and to the monetary policy announcements.

Looking at the second and third columns of table 3, we observe that many of the estimated coefficients do not change significantly after 2007:Q4. Apart from the coefficient on nonstandard monetary policy announcements, which is zero by definition in the pre-2007:Q4 sample, there are only two other individual parameters that exhibit a statistically significant change. First, the correlation with medium-term inflation uncertainty drops significantly after 2007. Second, the negative correlation with the absolute change in the balance sheet volume increases and is no longer significantly different from zero at a 5 percent significance level after 2007. Thus, similar to our results for mean expectations, we do not find evidence of a de-anchoring of the distribution that would be associated with an increase in the co-movement of long-term inflation uncertainty with other variables after the Great Recession. Nonetheless, the co-movement that we

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[28]Coenen et al. (2017) have also recently studied the effectiveness of ECB communication during the period of unconventional policies. They show in particular how stock market uncertainty declined following several unconventional policy announcements but also that it rose following other announcements. These authors report evidence that the clarity and detail of the communication was an important factor for those occasions when it reduced uncertainty.

do identify highlights a number of potentially important forces that may be behind the rise in long-term inflation uncertainty that was highlighted in section 3.

Online appendix B analyzes in more detail how the chosen moment estimation technique may affect the inflation uncertainty regressions. It shows again that, with one or two exceptions, much of the significant co-movement is not dependent on a particular measure of the variance, although the value of estimates changes considerably in some cases (perhaps not surprisingly, given that many of the insignificant coefficients exhibit very large standard error). Across all moment estimation strategies considered, we observe significant co-movement with short-term inflation uncertainty and volatility in actual inflation, as well as with long-term growth uncertainty. Also, for all measures, we observe the positive effect on long-term inflation uncertainty associated with nonstandard policy announcements.[29]

5.   Discussion and Conclusions

In this paper we have studied the key properties of the distribution of long-term inflation expectations in the euro area and the co-movement of key moments of this distribution with other variables. Our primary purpose has been to assess the extent to which the Great Recession and its aftermath, including the onset of a period in which the effective lower bound on nominal interest rates started to bind, led to any perceptible changes in this distribution. A word of caution is warranted, however, due to the fact that (i) our post–Great Recession sample is small and (ii) the reported probabilistic forecasts are often rounded, which raises the possibility of distortions linked to measurement error. Both factors make it difficult to detect structural breaks and to determine, particularly toward the end of the sample, whether breaks are temporary or permanent. However, our results appear robust across a number of different testing procedures and moment estimation methods. Our main findings add to the recent evidence provided in Autrup and Grothe (2014), Strohsal

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[29]There are, however, some differences linked to the changes in the coefficients in the second half of the sample that are discussed further in online appendix B.

and Winkelmann (2015), and Speck (2016) and fall into three broad categories, which we discuss below.

First, and in contrast to most existing studies which have focused only on mean expectations or representative indicators extracted from financial markets, our analysis targets the entire subjective forecast distributions for long-term inflation by looking for breaks in the entire distribution, in interval probabilities, and in the first four moments. Hence, we can provide additional information about how long-term inflation uncertainty, the balance of long-term inflation risks, and the risk of extreme inflation events may have changed since the Great Recession. We find evidence for a change in the distribution around the time of the Great Recession as well as complementary evidence for significant breaks in each of the first three moments of the distribution. All of the latter evidence points toward a heightened risk of lower inflation outcomes. Importantly, we document a small downward shift in the mean long-term inflation expectations around 2013 soon after the intensification of the euro-area sovereign debt crisis. However, the most likely inflation outcome as represented by the mode of the distribution has been much more stable. Also, both the mean and the mode remain broadly aligned with the ECB's definition of its price stability objective of "below but close to 2.0 percent." In addition, however, our analysis of higher moments of the distribution points to a reduction in how tightly expectations are anchored at this level. For example, we document a substantial increase in uncertainty about long-term inflation prospects compared with the period prior to the Great Recession and also a tendency toward a negatively skewed long-term distribution with a higher probability mass attached to relatively low inflation outcomes. The finding of a negatively skewed distribution is precisely what is predicted by macroeconomic models which incorporate a lower bound constraint on nominal interest rates (see, for example, Coenen and Warne 2014 or Hills, Nakata, and Schmitt 2016).

Second, our study has uncovered substantial co-movement between the first two moments of the distribution of long-term inflation expectations and various macroeconomic indicators, including other expectations and indicators capturing the effects of monetary policy. Such co-movement implies that the process governing the distribution is far away from a simple stylized case where the inflation objective is a universal constant and where there is "blind faith" in

the ability of the central bank to achieve this objective. Instead, the co-movement that we identify is in line with theories in which agents update their beliefs about long-term inflation in response to certain shocks (Orphanides and Williams 2004, 2007). For example, we find that persistent periods of lower-than-expected inflation are associated with a downward revision in long-term inflation expectations. In this sense, our results suggest that long-term inflation expectations are not completely forward looking. Ultimately, they tend to be influenced by the ex post historical track record of the central bank relative to its announced objective. Such results provide strong support for recent concerns about inflation remaining "too low for too long" (e.g., Draghi 2014) and the motivation behind unconventional monetary policies aimed at avoiding a persistent undershooting of the price stability objective. Regarding our central question, however, these empirical relationships existed also prior to the Great Recession and, overall, they do not appear to have strengthened in its aftermath.

Third, our analysis sheds light on how forecasters update their assessment of long-term inflation uncertainty in response to macroeconomic developments. Factors which influence this assessment include the volatility in recent inflation rates and perceptions of increased inflation uncertainty at shorter horizons. Also, calling to mind the correlated long-term risks associated with the prospect of secular stagnation discussed in Eggertson and Mehrotra (2014) and Summers (2014), our results suggest that longer-term uncertainty about growth and unemployment can spill over into increased uncertainty about long-term inflation. This empirical relationship may help explain the large upward shift in long-term inflation uncertainty in the euro area following the Great Recession. Concerning the role of recent nonstandard monetary policies, our sample is such that we must limit ourselves to an assessment of how inflation uncertainty changed after key monetary policy announcements. Once we control for other factors, we find that the announcement dates for nonstandard measures were generally followed by a modest increase in inflation uncertainty. Although this result must be interpreted with caution, it may highlight how such measures led to a slight increase in long-term inflation uncertainty because forecasters had no historical experience on which to assess their transmission and the long-term implications for inflation.

In conclusion, by focusing on the full distribution and by exploiting individual-level data, we have been able to make an innovative contribution to the empirical literature trying to understand the process governing the formation of long-term inflation expectations. Many of our findings are well predicted by macroeconomic theory stressing the effects of uncertainty about monetary policy and the implications of constraints such as the lower bound on nominal interest rates. However, a number of open questions remain for future research. These include an analysis of whether expectations of other agents such as private households or financial market participants show similar tendencies to the ones that we have identified. Also, further work is needed to jointly model monetary policy, the business cycle, and the formation of inflation expectations in ways which can help identify the causal mechanisms that may be behind our empirical results.

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