Volume 20, Number 2

April 2024

IJCB INTERNATIONAL JOURNAL OF CENTRAL BANKING Volume 20, Number 2 April 2024

# IJCB

# INTERNATIONAL JOURNAL OF CENTRAL BANKING

IJCB International Journal of Central Banking

Volume 20, Number 2 April 2024



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

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

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



ISSN: 1815-4654

# Perspectives on U.S. Monetary Policy and the Return to Price Stability

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September 2018–January 2022

Keynote Address Prepared for the
IJCB Annual Research Conference
Dublin
June 22–23, 2023

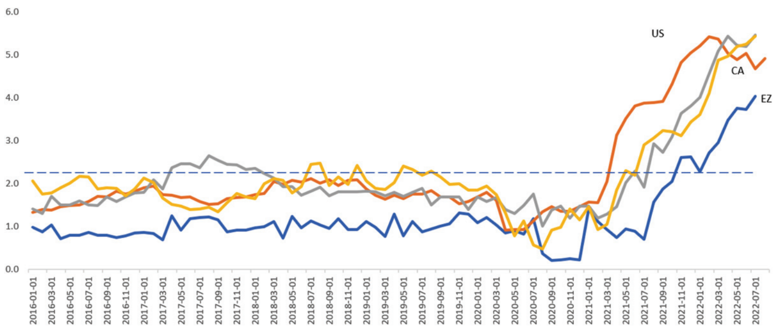
> "Starting in mid-2021, as inflation started to rise globally, many central banks went through similar sequences of responses. First they looked through the shocks in the sense of not reacting to rising inflation. This inert response was typically defended by pointing to the supply-side origins of the inflation as well as the likelihood that high inflation would prove to be temporary. However, when inflation shocks kept materializing, central banks pivoted to a much more aggressive policy stance. Policymakers then spent considerable effort defending the pivot as being necessary to anchor expectations in order to avoid igniting a wage-price spiral."
>
> Beaudry, Carter, and Lahiri (2022)

The COVID pandemic and the mitigation efforts put in place to contain it delivered the most severe blow to the U.S. and global economy since the Great Depression. In the United States more than 22 million jobs were lost in the two months of March and April of 2020, and in the second quarter of that year GDP collapsed at a 33 percent annualized rate, an even steeper pace of decline than recorded in the early months of the Great Depression. Monetary policy was all in—the Federal Reserve cut rates to zero and ramped up an unlimited quantitative easing program on Sunday, March 15; launched the week of March 16 several facilities (similar to those developed and deployed by the Fed during the global financial crisis) to provide liquidity to the commercial paper market and to money market mutual funds; and then the very next week of March 23, announced plans to stand up temporary programs to support lending and market access in the corporate and municipal bond markets.[1] That same week, Congress passed the $2.5 trillion CARES Act, which would turn out to be the first of three major COVID relief fiscal packages totaling nearly $6 trillion that would be approved by two Congresses and signed into law by two Presidents over the next 12 months. Of note, the CARES Act included $450 billion in appropriations to fund first-loss equity investments in the aforementioned Fed credit facilities. These facilities were set up to be temporary backstops—and have long since been unwound after limited take-up—that were priced "out of the money" so as to encourage the resumption of private credit intermediation in the midst of an economic shutdown of unknown duration. In the event, just the existence of facilities with the potential to lend up to or purchase in the secondary market more than $4 trillion of corporate and municipal bonds was, in short order, enough to restore market functioning.

But if 2020 was the year of the pandemic, economic collapse, and the "all-in" policy response, then 2021 was the year of vaccines, re-opening, and a surge in inflation flowing in no small part from that "all-in" policy response; 2022 was the year of an unprecedented and global hawkish monetary policy pivot as central banks around the world scrambled to get ahead of an inflation curve steepened even further by the energy supply shock emanating from Russia's invasion of Ukraine (Figure 1); and 2023 is shaping up to be the year in which central banks calibrate at what level policy rates need to peak to put inflation on a credible trajectory to reach their inflation targets over the medium term. In 2021, the real side of the economic recovery in the United States was about as good as it gets, with the strongest GDP growth in nearly 40 years and robust gains in payroll employment that totaled nearly 7 million jobs for the year. And in

[1]See Clarida, Duygan-Bump, and Scotti (2021) for an overview of Fed monetary policy actions taken and facilities launched—and since unwound—in response to the 2020 global pandemic collapse.

**Figure 1. Core Inflation: United States, United Kingdom, Euro Zone, Canada**




the first half of the year—although this point is often forgotten—this rapid return to the economy's potential was accompanied by indicators of underlying inflation that remained broadly consistent with the Fed's 2 percent objective. But in the second half of 2021, and continuing since, a surge in inflation emerged that was and continues to be (almost) as bad as it gets, not only in the United States but also in many other countries.[2] It was certainly not moderate, nor was it foreseen initially in the Fed's SEP projections, and it is turning out to be distressingly persistent and remains broad based, as evidenced in both price and wage data.

I came into the year 2021 as a Fed official with a Bayesian prior (yes, we did use that term and respected that concept in the halls of the Eccles building) that inflation expectations were well

[2]My focus in these remarks is on U.S. inflation since 2021 and the Fed's policy response. However, a persistent surge in underlying inflation in advanced economies is a distressing feature of the post-pandemic *global* economy. As discussed in detail in Clarida (2023), no advanced-economy central bank began to raise rates until headline inflation had exceeded target, and almost all AE central banks (except Norway and Switzerland) deferred lift-off until core inflation had moved above target. Thus if the persistent post-pandemic surge in AE inflation and the delayed monetary policy reaction represents a failure of monetary policy frameworks, it represents a failure of inflation targeting in most AE inflation-targeting countries, not simply a failure of flexible average inflation targeting in the United States. But I do not believe this is the case, as I argue in detail below and in Clarida (2023). Rather, these delayed policy reactions to what turned out to be persistent inflationary pressures I attribute to tactical misjudgments in the fog of war.

anchored, that in the aggregate there remained substantial slack in the economy—recall that inflation had fallen sharply in 2020 and the unemployment rate in December of that year remained elevated at 6.7 percent—and that also there were some significant sectoral imbalances between supply and demand that would likely require sizable relative price adjustments—for example, the relative prices of durable goods versus contact-intensive services. As a starting point, with well-anchored inflation expectations, the textbook monetary policy response would be to look through such relative price changes caused by supply shocks so long as inflation expectations stayed well anchored and economic slack remained available.[3] That was certainly my view in the spring of 2021; it was not inconsistent with the available data on price and wage inflation that we had at the time—for example, as is shown in Figures 2 and 3, the real-time data on trimmed mean measures of inflation and the employment costs—and it was also the view of virtually all private-sector forecasters. On this latter point, I suspect, future scholars may be interested to explore the extent to which what turned out to be an epic forecast miss can be attributed to "group think" among policymakers and professional forecasters, many of whom are former Fed staffers themselves.[4]

My Bayesian prior of course proved to be wrong, and beginning in the summer of 2021, my posterior distribution shifted up sharply as the incoming data began to reveal, certainly to me, that the inflation surge was becoming broad based in both goods and labor markets and that, moreover, the balance of risks to the inflation outlook were skewed decidedly to the upside.[5] Certainly by the fall of 2021, as is shown in Figures 4 and 5, time-series plots of the above-mentioned inflation indicators along with many other inflation readings "went parabolic," indicating clearly that, already

[3]For recent discussion of adverse supply shocks and optimal monetary policy, see Guerrieri et al. (2021) and Caballero and Simsek (2022).

[4]For example, in April 2021 after the American Rescue Plan had already passed, the *Wall Street Journal* surveyed 77 private-sector economists on their outlook for 2021. The panel's median projection for core PCE inflation in 2021 was 2.1 percent, and the most pessimistic forecaster in the sample projected core PCE inflation to reach 2.8 percent. Realized core PCE inflation in 2021 was 5 percent.

[5]And I indicated as much in remarks delivered at a Petersen Institute event in August of that year (Clarida 2021c).

**Figure 2. Federal Reserve Bank of Dallas Trimmed Mean PCE through July 2021**

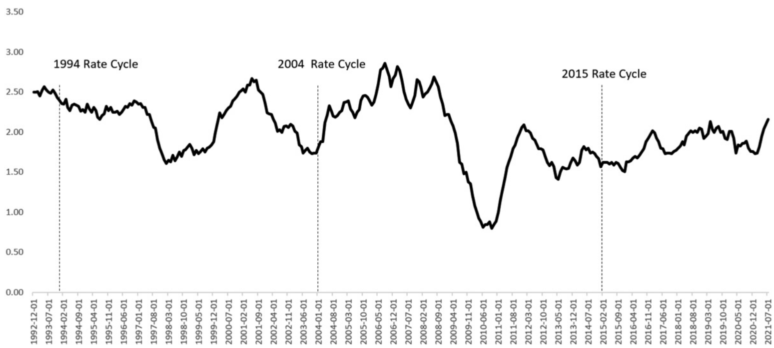
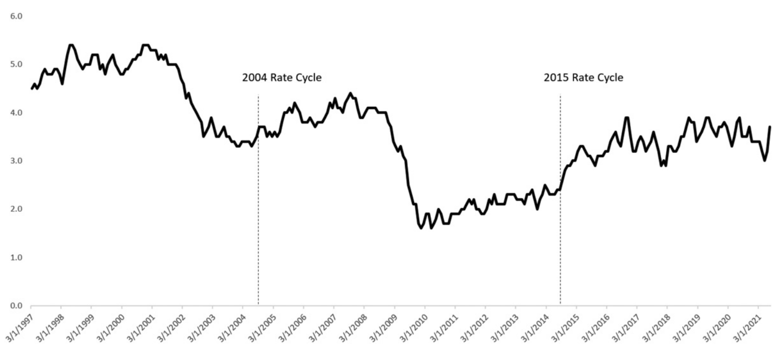



**Figure 3. Federal Reserve Bank of Atlanta Wage Tracker through July 2021**




by that time, the level of nominal aggregate demand in the economy exceeded available aggregate supply forthcoming at the Fed's 2 percent inflation target, even though the data then available—as shown in Figures 6, 7, and 8—indicated that the level of real GDP remained some 2 percentage points below the Congressional Budget Office's contemporaneous estimate of potential,[6] that the unemployment rate, at 5.2 percent, remained well above contemporary estimates of NAIRU, and that the prime-age labor force participation

[6]Figure 6 presents the real GDP data as originally released and thus as available to the Fed in real time.

**Figure 4. Federal Reserve Bank of Dallas Trimmed Mean PCE Full Sample**

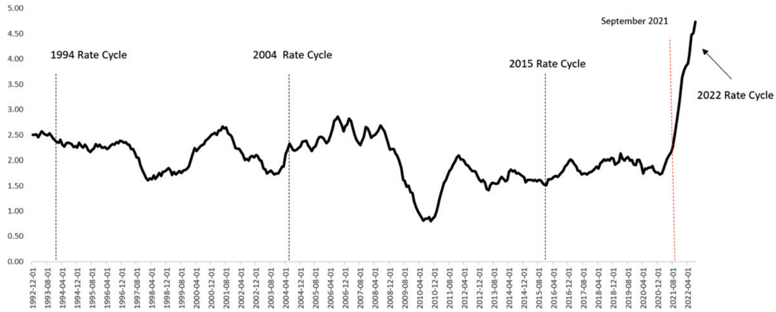
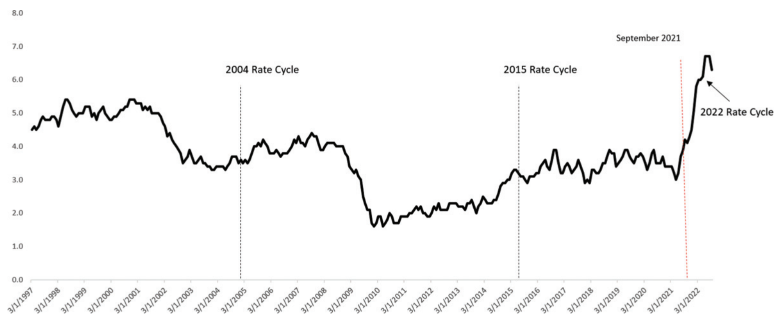



**Figure 5. Federal Reserve Bank of Atlanta Wage Tracker Full Sample**




remained 1.3 percentage points below its pre-pandemic peak. Simply put, the Fed in 2021 got aggregate supply wrong,[7] and, in so doing, it kept in place an exceptionally accommodative monetary policy longer than it would have had it not overestimated the economy's potential, especially given the robust demand support delivered by the December 2020 Consolidated Appropriations Act, the March

[7]Interestingly, the minutes to the September 2022 FOMC meeting state that (page 6) "the staff's estimate of potential output in recent history was revised down significantly in response to continued disappointing productivity growth and the sluggish gains in labor force participation seen so far this year; moreover, this lower trajectory for potential output was expected to persist throughout the forecast period. As a result, the staff's estimate of the output gap was revised up considerably this year."

**Figure 6. Real GDP vs. CBO Potential GDP**

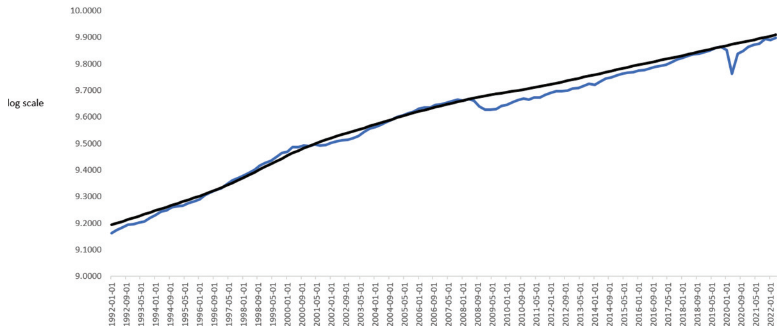
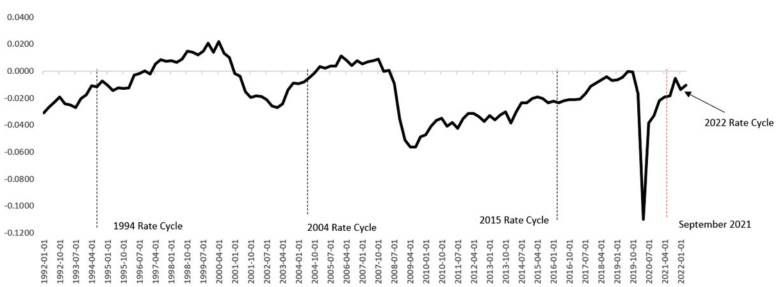


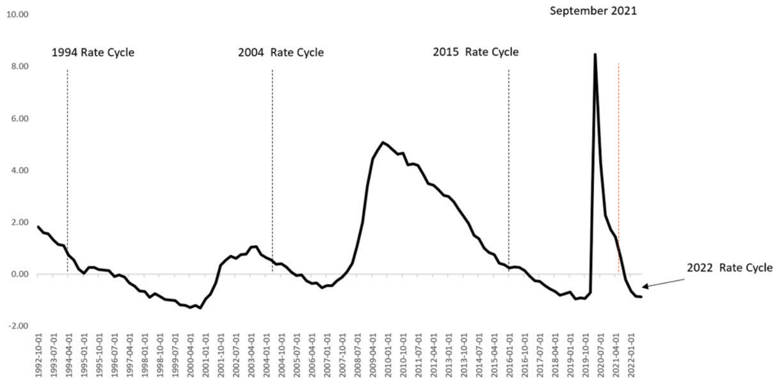

**Figure 7. Output Gap: Actual minus CBO Potential**




2021 American Rescue Plan, as well as the more than $1 trillion of accumulated "excess saving" then remaining from the March 2020 CARES Act transfers.[8] I also note that in its July 2021 "Update to the Budget and Economic Outlook"—with only six months remaining in the calendar year—the CBO projected that real GDP for 2021 on a fourth-over-fourth-quarter basis would grow at 7.4 percent, that nominal aggregate demand would rise by 10.7 percent, and that core PCE inflation would rise by 2.4 percent. In the event, real GDP grew by 5.7 percent in 2021, nominal GDP rose by 12.2

[8]As of this writing, there remains roughly $500 billion of accumulated household "excess saving" relative to the counterfactual accumulation that would have resulted with the pre-pandemic saving rate applied to actual household disposable income since March 2020. That said, the household saving rate has over the past two years declined substantially—and is now well below its pre-pandemic rate—as households have in aggregate cut back on saving to finance consumption growth notwithstanding absolute decline in real disposable income since July 2021.

**Figure 8. Unemployment Gap: Actual minus CBO NAIRU**

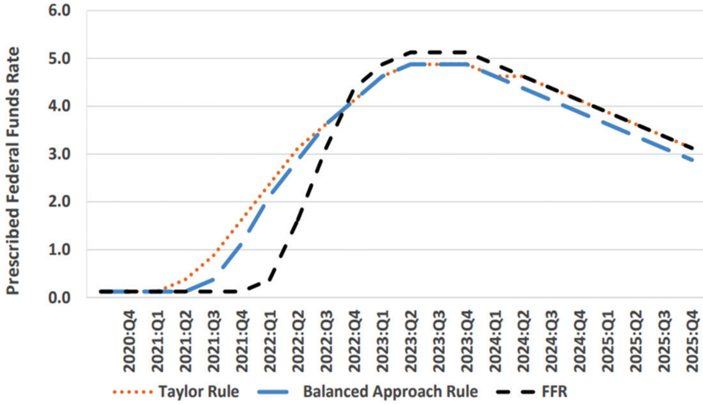



percent, and core PCE inflation rose by 5 percent. The Fed's June 2021 SEP projections were similar and, as with the CBO, indicate that not only did the Fed in 2021 get aggregate supply wrong, it also got nominal aggregate demand growth wrong (Furman 2022; Summers 2022). That said, the 1.7 percentage point undershoot of real GDP growth in 2021 relative to the CBO's mid-year forecast was not due to insufficient aggregate demand growth!

By the time of the September 2021 Federal Open Market Committee meeting, the monetary policy rules I consult, including those based on my research with Mark Gertler and Jordi Galí as well as the "shortfalls" version of the balanced-approach Taylor rule featured in the Fed's recent Monetary Policy Reports, were signaling that liftoff from the zero lower bound was by then warranted (Figure 9).[9] In

[9]Under the Fed's new framework ratified in August 2020, the FOMC's Statement on Longer-Run Goals and Monetary Policy Strategy has referred to "shortfalls of employment" from the Committee's assessment of its maximum level rather than the "deviations of employment" used in the previous statement. According to the March 2023 MPR, "the balanced-approach (shortfalls) rule reflects this change [in the framework] by responding asymmetrically to unemployment rates above or below their estimated longer-run value: When unemployment is above that value, the policy rates are identical to those prescribed by the balanced-approach rule, whereas when unemployment is below that value, policy rates do not rise because of further declines in the unemployment rate." Thus had the Fed chosen to implement its new framework with a framework-consistent balanced-approach policy rule, it would have lifted off in September 2021 just as would have been the case if it followed a traditional Taylor rule

**Figure 9. Inertial Policy Rules from Papell and Prodan (2023), "The Fed is Following a Taylor Rule"**




**Note:** Between September 2020 and December 2022, authors use real-time inflation and unemployment data that were available at the time of the FOMC meetings. Between March 2023 and December 2025, they use inflation, unemployment, and real FFR in the longer-run projections from the December 2022 SEP.

the event, the FOMC did begin to pivot in November 2021, first with the taper that would end quantitative easing earlier than had been expected, followed in March 2022 by the lift-off itself, followed in May 2022 by the announcement that a muscular quantitative tightening program would commence in the summer, and followed, beginning the next month, by a sharp increase in the pace of policy normalization to 75 basis points per meeting at each of the June, July, September, and November 2022 FOMC meetings. The pace of rate hikes downshifted to 50 basis points at the December 2021 meeting, at which time the SEP projections indicated that the median

(Figure 10). The Fed in its September 2020 FOMC statement (with two "hawkish" dissents) had offered more robust forward guidance than required by its August 2020 framework statement. It committed (subject to inflation expectations remaining well anchored) to delay lift-off until "labor market conditions have reached levels consistent with . . . maximum employment and inflation has risen to 2 percent." While this stronger commitment was consistent with the new framework, it was not required by it, as is evidenced by the fact that Presidents Kaplan and Kashkari supported the new framework but did not support the September 2020 forward guidance.

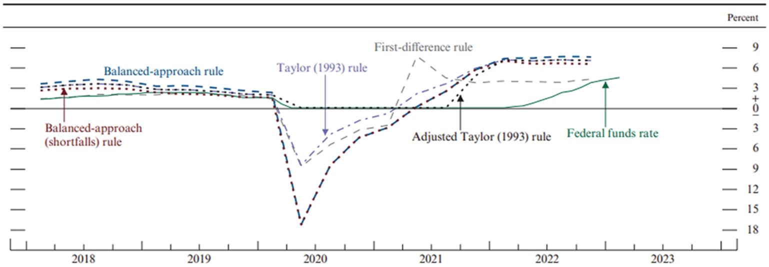
participant believed that a peak policy rate of 5.25 percent would be sufficiently restrictive, if maintained for some time, to eventually return inflation to the 2 percent longer-run goal, although not until 2025. Also of note, the December 2022 SEP projected a second consecutive year of below-trend GDP growth in 2023 accompanied by a 1 percentage point rise in the unemployment rate. Such a rise, historically, has never occurred outside of an NBER recession, although Fed officials, perhaps understandably, have been reluctant to predict a recession in their public remarks.[10,11]

As Chair Powell indicated at Jackson Hole in August 2022, policies required to disinflate the U.S. economy and bring aggregate demand into balance with aggregate supply will almost certainly cause "some pain" as growth slows sharply and unemployment rises as much as or more than indicated in the SEP projections. But even if through some combination of good policy and good luck—and I suspect both will be required—inflation does return to 2 percent over the next several years, inflation will have averaged well north of 2 percent from March 2020 through the end of the Fed's customary three-year projection window. And that was a point I made in August 2021 remarks at the Peterson Institute: the conditions *on inflation* for lift-off that the FOMC set out in its September 2020 threshold guidance had already been met by the summer of 2021, and at almost exactly the same time that a conventional Taylor-type rule was also signaling lift-off (Figure 10). As I argued in presentations I delivered at a Brookings conference in November 2020 (Clarida 2020), at a Hoover Institution seminar in January 2021 (Clarida 2021a), and at a Shadow Open Market Committee meeting in April 2021 (Clarida 2021b), the Fed's August 2020 Revised Statement of Longer-Run Goals and Monetary Policy Strategy is, in my reading and interpretation, fully consistent with and could, if a future FOMC chose to, be implemented and communicated in a

[10]However, the minutes of the March 2023 FOMC meeting reported that the Fed staff was, as of that meeting, forecasting a recession would commence in 2023.

[11]The FOMC at the February, March, and May 2023 meetings raised the target range for the federal funds in 25 basis point increments to 5.25 percent, and it indicated in the March 2023 projections that the median participant thought at that time that this would represent the peak rate for this cycle.

**Figure 10. Historical Federal Funds Rate Prescriptions from Simple Policy Rules**




**Source:** Federal Reserve Bank of Philadelphia; Wolters Kluwer, Blue Chip Economic Indicators; Federal Reserve Board staff estimates.
**Note:** The rules use historical values of core personal consumption expenditures inflation, the unemployment rate, and, where applicable, historical values of the midpoint of the target range for the federal funds rate. Quarterly projections of longer-run values for the federal funds rate and the unemployment rate used in the computation of the rules' prescriptions are derived through interpolations of biannual projections from Blue Chip Economic Indicators. The longer-run value for inflation is set to 2 percent. The rules prescriptions are quarterly, and the federal funds rate data are the monthly average of the daily midpoint of the target range for the federal funds rate and extend through February 2023.

straightforward manner according to the temporary price-level targeting proposal outlined in Bernanke, Kiley, and Roberts (2019) and Bernanke (2020). Under TPLT, when finding itself at the effective lower bound with inflation running below 2 percent, the Fed would commit itself to delay lift-off until inflation over a trailing 12-month window had reached 2 percent. After lift-off, the policy would revert to traditional inflation targeting which could, for example, be implemented with an inertial Taylor-type reaction function as is in the simulations reported in Bernanke, Kiley, and Roberts (2019).

Thus it was not the goal that inflation average 2 percent over time, as was endorsed in the Fed's August 2020 framework revision that precluded the FOMC in 2021 from lifting off from the effective lower bound and beginning to shrink its balance sheet. It was instead the Committee's additional commitment to honor its September 2020 threshold guidance as well as its communication that it would follow a "taper–hike–shrink" sequence of policy normalization similar to the practice it implemented following the global financial crisis, in tandem with a reluctance even to commence the taper until a majority of the Committee deemed that "substantial further progress" towards its maximum employment mandate had been achieved, the threshold standard for tapering quantitative easing the FOMC had laid out in its December 2020 FOMC statement. Let me be clear that committing—and honoring the commitment—to follow a "taper–hike–shrink" sequence and to the delay the taper itself until "considerable progress" had been made towards the maximum employment goal—decisions I did support in real time—were FOMC decisions with regards to how best to *execute* policy to achieve the Fed's dual mandate goals of maximum employment and inflation that averaged 2 percent over time, but were not, in my judgment, decisions compelled by (nor were they necessary to honor) either the spirit or the letter of the August 2020 framework statement. This also applies to the September 2020 threshold guidance on the conditions for lift-off: this stronger commitment was consistent with the new framework, but it was not required by it, as is evidenced by the fact that the shortfalls version of the balanced-approach policy rule did signal lift-off before those conditions were met.[12,13]

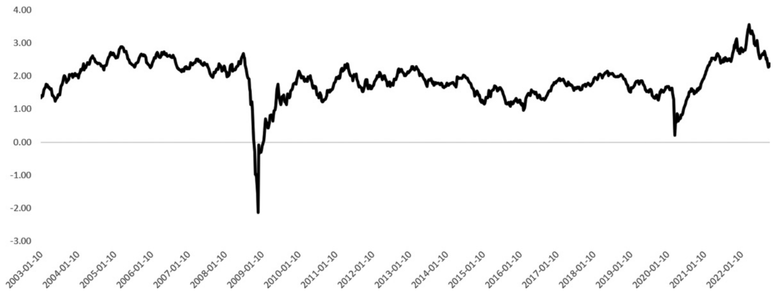
Engineering a soft or even a softish landing under present circumstances will be challenging: the Fed's instruments are blunt, the mission is complex, and difficult trade-offs lie ahead.[14] Underlying

[12]For a thoughtful discussion of this point, see Quarles (2022).

[13]In retrospect, the take-off in broad-based wage inflation depicted in Figure 5 is consistent with an assessment that, in fact, the level of "maximum employment" in the 2021 U.S. labor market consistent with price stability had already been attained by the third quarter of 2021. At that time, not only did wage inflation "go parabolic," but the vacancy/unemployment ratio as well as the Federal Reserve Bank of Kansas City's broad Labor Market Conditions Index had by then returned to their respective pre-pandemic peaks, even though at the time of the September FOMC meeting, the unemployment rate, at 5.2 percent, was more than a percentage point above the Committee's estimate of full employment.

[14]In March and April 2023, four commercial banks—Silvergate, Silicon Valley Bank (SVB), Signature, and First Republic—collapsed in part because of substantial unrealized losses on their security and mortgage holdings that triggered sizable deposit outflows. In response to the SVB and Signature failures, the Fed launched a Bank Term Funding Program on March 12, 2023 to provide term liquidity against Treasury and MBS collateral on favorable terms. The March and May 2023 rate hikes were approved by the FOMC after the SVB and Signature failures, and reflected the Fed's desire to meet its monetary policy goals

**Figure 11. Five-Year Breakeven Inflation**



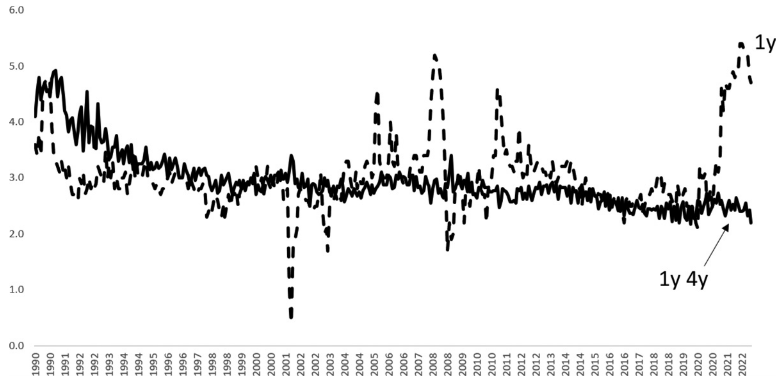

inflation appears to be running at least 1 percentage point faster than its pre-pandemic pace, and compensation gains, unit labor costs pressures, and the recently popularized "jobs–workers" gap metric are all indicative of a labor market in which the rate of unemployment consistent with price stability may now and for some time to come be higher than the Fed's current median longer-run projection of 4 percent indicates.[15] That said, it does appear to be the case that medium- and longer-term inflation expectations—measured either by household surveys or from breakeven inflation rates implied by TIPS yields—remain well anchored at levels consistent with the Fed's 2 percent inflation target (Figures 11 and 12). Thus the FOMC's task, while daunting, is less onerous than it would be were it aiming also to reduce medium-term inflation expectations, a challenge that confronted Paul Volcker in 1979 and Alan Greenspan in 1987. But of course inflation expectations—whether they are formed rationally, adaptively, or diagnostically—are endogenous, and the longer inflation remains above 2 percent, the greater is the risk that inflation expectations eventually ratchet up to levels inconsistent with the FOMC's price stability objective.

As Chair Powell indicated at Jackson Hole in 2022, he and the FOMC are determined to insure that the hard-won battles under Paul Volcker and Alan Greenspan to achieve price stability are not

using the federal funds rate tool, and to support financial stability objectives using other macroprudential tools, including in this case liquidity facilities.

[15] Please see Ball, Leigh, and Mishra (2022) and Clarida (2023) for an econometric analysis that models the 2021–22 inflation surge as a function of the V/U ratio and the pass-through from headline to core inflation.

**Figure 12. Michigan Inflation Survey**




squandered, and in that speech he stated—twice—that the Fed will "keep at it until the job is done." I have every confidence that they will indeed keep at it until the job is done, although I am under no illusion that "the job" will be easy. Thank you very much for your time and attention and the invitation to address this esteemed group. I look forward to the question-and-answer session.

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# A New Supply Bottlenecks Index Based on Newspaper Data*

Pablo Burriel, Iván Kataryniuk, Carlos Moreno Pérez, and Francesca Viani
Banco de España

We develop a new monthly indicator of supply bottlenecks using newspaper articles. The supply bottlenecks index (SBI) provides a consistent narrative of supply issues related to wars, natural disasters, strikes, and, most recently, the COVID-19 pandemic. Innovations in the SBI have important macroeconomic implications: an increase in the SBI works as a cost-push shock, decreasing industrial production and employment and pushing prices up, making monetary policy face important trade-offs.

JEL Codes: F40, E23, E31.

## 1. Introduction

Since the beginning of the COVID-19 pandemic, supply bottlenecks have been one of the key determinants of the global outlook. The global lockdown adopted to fight the health crisis produced severe supply chain disruptions, which hampered the trade of goods within and across borders. The subsequent reopening led to a strong rebound in the global demand for manufacturing goods, unmatched by supply, which worsened disruptions further. In addition, several sectors, such as the semiconductor industry, could not accommodate the increase in demand for electronic products. On top of that, maritime transport, especially in the case of containers, also suffered from supply bottlenecks, due to port congestion caused

*We thank Corinna Ghirelli, Antonio Millaruelo, Florens Odendahl, and Hervé Le Bihan for their help in drafting the list of words in the different languages. We also thank conference participants at the Central Bank of Ireland, Universidad de Alcalá, and Banco de España for their useful comments. The analyses and opinions included in this paper are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Bank of Spain or the Eurosystem.

by local lockdowns. Finally, in 2022, when the disruptions produced by the COVID were subsiding, the invasion of Ukraine heightened those risks—in particular, in the case of energy supplies and derived products, like fertilizers, and food.

From an economic point of view, the globalization of supply disruptions can severely affect inflation, as supply problems transmit through the production chain, creating upward price pressures. In the words of the European Central Bank president, Christine Lagarde, when explaining the 50 basis point interest rate increase implemented in July 2022: "Persistent supply bottlenecks for industrial goods and recovering demand, especially in the services sector, are also contributing to the current high rates of inflation."[1] At the same time, supply disruptions can also strongly depress economic activity, since their impact can have long-lasting and sizable effects on production processes. A survey of supply chain experts by the McKinsey Global Institute (2020) found that supply disruptions may reduce firms' annual profits by more than 40 percent over a period of 10 years. In this sense, these linkages have been thoroughly studied by the theoretical literature on the importance of input-output networks (Acemoglu and Tahbaz-Salehi 2020, Bonadio et al. 2021, Baqaee and Farhi 2022).

Supply (or, alternatively, supply chain) disruptions, however, are not new. They occurred before the COVID-19 pandemic, although they were of a more local nature, and were usually caused by wars, strikes, or natural disasters. An example of this is the Great Tôhoku Earthquake of 2011 in Japan, which created supply chain problems that spilled over the whole Japanese economy (Carvalho et al. 2021). Other examples are Hurricane Katrina, which affected port infrastructures, diverting all freight transport to alternative ports (Friedt 2021), or the supply chain uncertainty created by Brexit (Chung, Dai, and Elliott 2022).

However, the empirical evidence on the macroeconomic impact of supply bottlenecks is very limited. In this paper, we contribute to closing this gap by developing a high-frequency measure of supply disruptions and studying its impact on inflation and output through a vector autoregression (VAR). In particular, we construct a supply

[1]ECB press conference, July 21, 2022. Available at https://www.ecb.europa.eu/press/pressconf/2022/html/ecb.is220721~51ef267c68.en.html.

bottlenecks index (SBI), based on newspaper data, for the United States (starting in 1990), United Kingdom, Germany, France, Italy, Spain, and China.

We define supply disruption as a negative event related to supply provision or the functioning of supply chains. We follow the methodology developed by Baker, Bloom, and Davis (2016) to construct text indices of economic policy uncertainty for different countries and other topics such as geopolitical risk (Caldara and Iacoviello 2022) or trade policy uncertainty (Caldara et al. 2020). Our strategy relies on counting the relative frequency of the number of articles that contain some chosen words, belonging to two semantic groups. In English, the first group contains words related to the topic of supply chains, such as “supply chain, supply chains, supply, supplies.” The second group of words includes terms reflecting a negative tone or the existence of problems or disruptions, such as “bottleneck, bottlenecks, shortage, shortages, woe, woes, disruption, disruptions, problem, problems, scarcity, scarcities, lack, delay, delays, backlog, backlogs.” For the article to be identified as reflecting supply concerns, a word from each one of the two groups must be present within a range of 10 words. In the case of the euro-area economies, we rely on natives to translate the words to national languages, while the Chinese index is based on news from international and domestic sources in English.

This paper improves the existing measures of bottlenecks available on several dimensions. First, our text-based procedure guarantees the selection of only supply-side events. We confirm this through two exercises. On the one hand, we check that the news generating the main spikes of the index are related to supply-side news. Before the COVID pandemic, we find several spikes that correspond closely to identified supply disruptions, such as strikes, Hurricane Katrina, or the Gulf War. After the COVID pandemic, although our index explodes, the spikes are related to the lack of global supplies such as semiconductors, raw materials, medical equipment, and COVID vaccines. On the other hand, we use word embedding, an unsupervised machine learning technique, to show that our word selection only identifies supply chain pressures in the case of the *New York Times* for the United States. On the contrary, the widely used monthly Purchasing Managers’ Index (PMI) surveys on delivery times, backlogs, or purchased stocks react to both demand and supply issues, as shown by Benigno et al. (2022). Finally, we show that the index does not wrongly identify as bottlenecks an increase in newspaper news due to a reduction in disruptions.

Second, the high-frequency nature of the indicator, which can be retrieved daily, allows for a real-time analysis of bottlenecks and helps to better identify shocks to macro variables.[2] Survey-based indicators tend to be more lagging, like the monthly PMIs or the quarterly survey on restrictions of production by the European Commission. Moreover, we show that our index for the United States leads the monthly one developed by Benigno et al. (2022).

Third, our index spans a longer sample and covers the whole economy. In the U.S. case, the index is based on daily article searches from 11 nationwide newspapers since 1990, while the European indices start in the early or mid-2000s. Other supply bottlenecks indices based on text, such as Young et al. (2021), using the quarterly Standard & Poor's (S&P) earnings calls as a source of information, are available for a more limited period.

In addition, we provide VAR evidence showing that the news-based index has a relevant impact on production, unemployment, and prices, in the United States and in a panel of six economies (United States, United Kingdom, Germany, France, Italy, and Spain). We use a recursive identification, which relies on the interpretation of the index as a proxy (or an instrument, in the sense of Plagborg-Møller and Wolf 2021) for supply problems. Our results suggest that a shock of one standard deviation in the index raises both unemployment and prices, and decreases industrial production. This evidence confirms the macroeconomic importance of supply chain disruptions for inflation using the PMI-based indices, as in di Giovanni et al. (2022), Blanchard and Bernanke (2023), Hall, Tavlas, and Wang (2023), or Kabaca and Tuzcuoglu (2023). In contrast, we provide evidence that our index captures this behavior both before and during the pandemic period and that it behaves as a true supply shock, affecting activity and inflation in an opposite way.

The paper is organized as follows. In the first section, we start by defining and measuring supply disruptions. Section 2 shows a

[2] Other high-frequency indicators, such as the Baltic Dry Index or the Harpex Index for maritime transport, only cover particular sectors and thus are more related to trade dynamics.

variety of checks that verify the plausibility of the SBI and compare it with existing supply chain indicators. Section 3 presents VAR evidence on the macro impact of supply bottlenecks. Finally, Section 4 concludes.

## 2. The Supply Bottlenecks Index

### *2.1 Definition of Supply Disruptions*

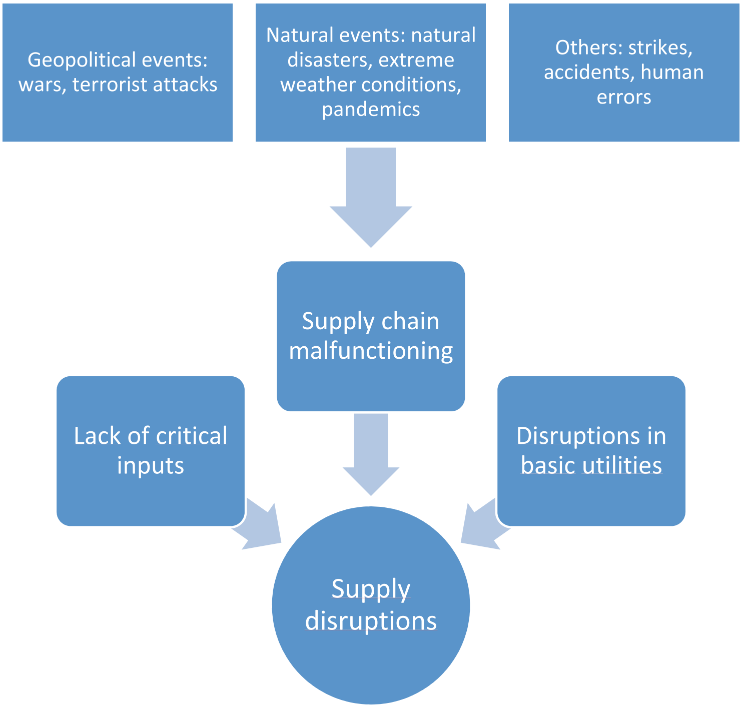
In line with the literature, we define a supply disruption as a negative event related to supply provision or the functioning of supply chains (see also Young et al. 2021). These events might be anticipatory (for example, the possibility of a supply shortage due to port congestion at the source of imports) or realized (such as energy shortages after a blackout). Figure 1 shows the main sources of supply disruptions we are considering. They include geopolitical events, such as wars and terrorist attacks; natural phenomena, like natural disasters, extreme weather conditions, or pandemics; and a variety of other human-related events, such as strikes, accidents, or human errors, which can give rise, for instance, to transportation issues or power outages. These events may lead to supply chain disruptions or lack of critical inputs when happening in foreign economies (such as the ones reported during the COVID crisis or the invasion of Ukraine) and to the destruction of capital and lack of provision of basic utilities in the directly affected country.

### *2.2 Constructing a Newspaper Supply Bottlenecks Index*

The methodology followed in this article to construct the supply bottlenecks index using newspaper articles from Factiva is the following. First, in line with Baker, Bloom, and Davis (2016) or Young et al. (2021), we set two groups of words, one with the terms "supply" and "supply chain," that aim to capture the nature of the article, and then we search if within 10 words,[3] before or after each of the terms of the first group, there appears a word of the second group, which is related to negative sentiment words such as "bottleneck," "shortage," etc. In particular, the words in English used for the United

[3]We present robustness exercises around this window in Appendix D.

**Figure 1. Diagram of Main Sources of Supply Disruptions**




States and the United Kingdom to compute our supply bottlenecks index are

1. supply chain, supply chains, supply, supplies;
2. bottleneck, bottlenecks, shortage, shortages, woe, woes, disruption, disruptions, problem, problems, scarcity, scarcities, lack, delay, delays, backlog, backlogs.

Second, we follow the approach of Baker, Bloom, and Davis (2016) to construct the index from the selected articles (see Appendix A for a detailed description of the procedure).[4] For each newspaper, we divide the number of articles that comply with our

[4]See also Ghirelli et al. (2021) for the case of Spain.

search by the total number of articles published. This ratio is then standardized by dividing it by the standard deviation of the subsample of that newspaper previous to 2022. The supply bottlenecks index (SBI) is calculated as the average value for all newspapers in each country. To make the indices comparable across countries, the SBI of each country is divided by the mean of its subsample previous to 2022 and multiplied by 100.[5] Finally, to avoid the impact of outliers at each date, only the newspapers with a significant number of articles for that month are included in the index.

Using this methodology, supply bottlenecks indices for seven different countries are constructed: United States, United Kingdom, Germany, France, Italy, China, and Spain. The list of words chosen is translated into the languages of the non-English-speaking countries by native speakers and adapted when necessary. For example, in the case of Germany, a new third group of words was added to account for the fact that the German language has words that by themselves mean “supply bottleneck,” such as “Versorgungsengpass.” Thus, in the German search, we count the article as 1 if we find the same search as for the other languages (groups 1 and 2) or any word of group 3.

In addition, we ensure that the newspaper articles refer to supply bottlenecks developments in a specific country by using a Factiva option that restricts the search to the articles related to that country.[6]

The list of newspapers and words used in the respective language to build each country index is described in Appendix A. For the case of the United States, these are the following: *USA Today*, the *Miami Herald*, the *Chicago Tribune*, the *Washington Post*, the *Los Angeles Times*, the *Boston Globe*, the *San Francisco Chronicle*, the *Dallas Morning News*, the *Houston Chronicle*, the *Wall Street Journal*, and the *New York Times*; and the time period goes from January 1, 1990 until today.[7]

[5]This standardization is done to avoid the problem that raw counts vary substantially across newspapers and time.

[6]Factiva allows to select the region that an article is about.

[7]For instance, for the United States there is only available data for all the sample for four newspapers: the *Los Angeles Times*, the *San Francisco Chronicle*, the *Houston Chronicle*, and the *New York Times*. The rest of the newspapers join the index when their data become available in Factiva (in parentheses is the

**Figure 2. U.S. Supply Bottlenecks Index (full sample)**


**Note:** U.S. SBI from 1990 until June 2023. U.S. SBI is normalized to 100 throughout the 1990–2021 period.

## *2.3 Results and Validation of the Index*

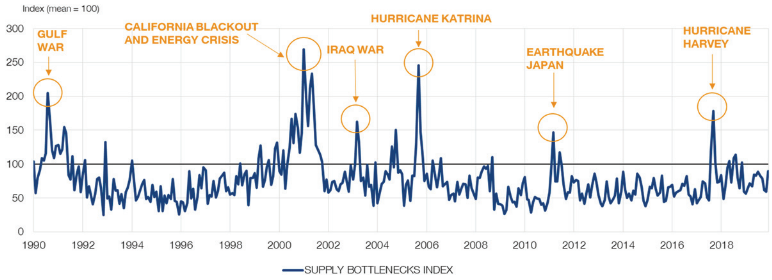
The evolution of the monthly SBI for the United States is shown in Figure 2. The index increased dramatically in 2020, as a result of the COVID-19-related supply disruptions, and has remained at this higher level until today. In Figures 3 and 4 we show the evolution of the SBI over, respectively, the pre-COVID and post-COVID subsamples. Similar dynamics are observed for all the countries considered, but for brevity's sake we concentrate in the main text on the results relative to the United States and provide the analysis for the other countries in Appendix B.

### *2.3.1 Checking the Historical Events Driving the Index*

To understand the evolution of the index and ensure that it is correctly capturing supply disruptions, we report in the charts the main events behind the spikes. This is achieved by reading the articles that comply with our search criteria on each date. In particular, we consider as spikes all the observations that are one standard deviation above the mean, using sample-specific mean and standard deviation for the pre-COVID and the post-COVID sample. We highlight in

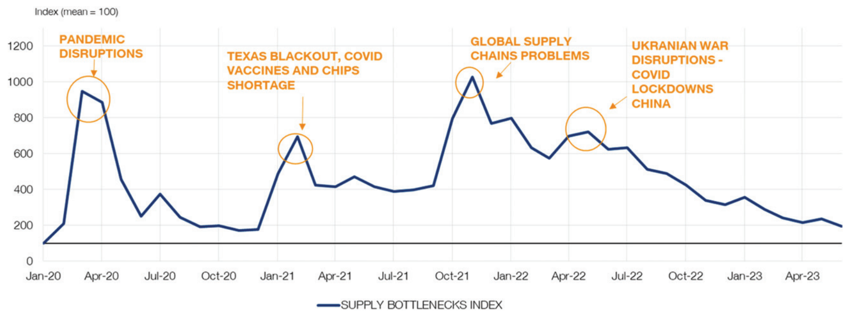
time they joined the index): the *Washington Post* (December 1997), the *Chicago Tribune* (January 2000), the *Wall Street Journal* (April 2001), the *Miami Herald* (June 2001), the *Boston Globe* (September 2001), *USA Today* (February 2002), and the *Dallas Morning News* (May 2003).

**Figure 3. U.S. Supply Bottlenecks Index (before COVID)**




**Note:** U.S. SBI from 1990 until the end of 2019. U.S. SBI is normalized to 100 throughout the 1990–2021 period. We describe in yellow the main events behind the spikes of the U.S. SBI.

**Figure 4. U.S. Supply Bottlenecks Index (after COVID)**




**Note:** U.S. SBI from 2020 until June 2023. U.S. SBI is normalized to 100 throughout the 1990–2021 period. We describe in yellow the main events behind the spikes of the U.S. SBI.

yellow in the charts below the main events behind the local maxima of the U.S. SBI. A similar graphical analysis is performed in Appendix B for the other countries.[8]

Figure 3 shows that the main spikes in the pre-COVID period are related to three kinds of events: wars, natural disasters, and energy crises. For instance, the U.S. SBI captures the impact on

[8]For the rest of countries in the post-COVID period, we include in the charts some additional peaks that would be left out following the restrictive one-standard-deviation criterion.

supply chains of the Gulf and Iraq Wars, Hurricanes Katrina and Harvey, the Japan Earthquake of 2011, and the energy crisis in California. Instead, after 2019 (see Figure 4) spikes are related to the disruptions caused by the COVID-19 pandemic and the invasion of Ukraine, the global supply chain problems in health and energy products, semiconductors, and raw materials, as well as logjams in maritime transport.

The list in Appendix E reports a more detailed description of the events behind the SBI's spikes, for the United States and for all the other countries. The results of this audit exercise let us conclude that the SBI's spikes capture correctly both local and global events leading to supply bottlenecks.

#### *2.3.2 Supply Bottlenecks Narratives*

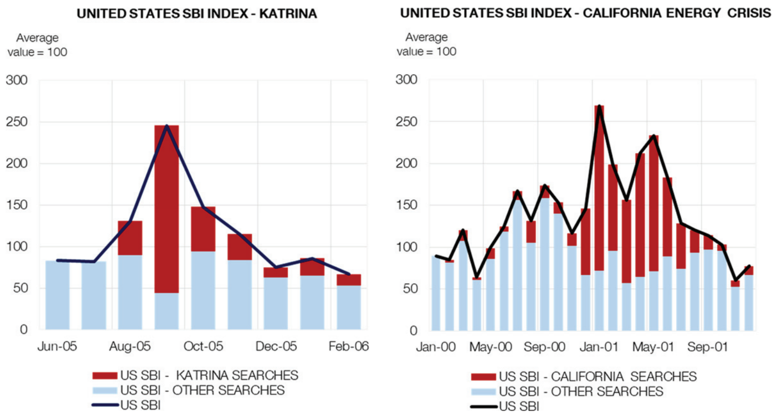
The text-based nature of our index also allows for a detailed narrative analysis of the contribution of specific events to aggregate bottlenecks. For example, Hurricane Katrina hit the United States in summer 2005, causing supply disruptions and fears of oil supply shortages due to damages at the Gulf Coast refineries. In Figure 5 (left-hand panel), we show that Hurricane Katrina contributed significantly to the increase in the U.S. SBI over August and September 2022. In particular, we count any article that includes our standard search plus the term "Katrina" in any place of the article. Similarly, in the right-hand panel of Figure 5, we show that the increase in the U.S. index observed at the beginning of 2001 was mainly due to the energy crisis in California. To wit, we relate to the energy crisis any article that includes our standard search plus a second search in any place of the article encompassing two additional groups of words, one related to the cities and the region of "California,"[9] and a second one related to "electricity" and "fuels,"[10] which have to appear within 10 words before or after each of the terms of the first group.

In a similar way, we can analyze the risk of supply disruptions due to the Brexit process by decomposing the SBI for the United

[9]Namely, "California," "San Jose," "San Francisco," "San Diego," "Los Angeles."

[10]"Electricity," "blackout," "blackouts," "power," "energy," and "fuel."

**Figure 5. Contributions of Specific News around the Date of Important Supply Chain Events**



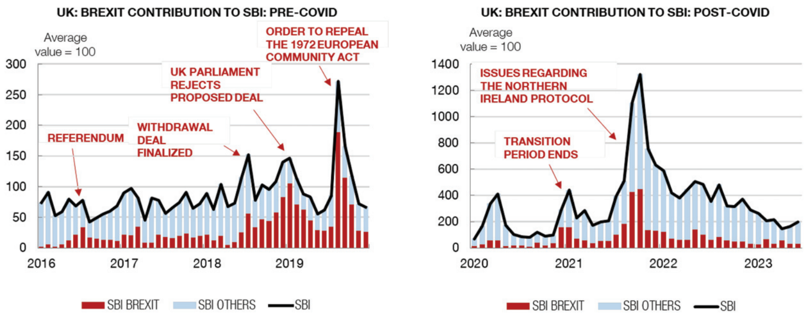

**Note:** U.S. SBI evolution around Hurricane Katrina (2005, left) and the California energy crisis (2000–01, right). The U.S. SBI is normalized to 100 throughout the 1990–2021 period. In blue, the contribution of the specific news about these topics to the index, calculated as described in Appendix A.

Kingdom into the contribution of Brexit-related news (identified by adding the word "Brexit" to our searches) and the contribution of all the other news (Figure 6). The Brexit-related risk of supply disruptions increased in correspondence to key policy events, such as the rejection by the U.K. parliament of the first proposed deal in January 2019; or the order, by the U.K. Brexit secretary, to repeal the 1972 European Community Act, in August of the same year; or the end of the transition period in January 2021. As shown in Appendix C, the Brexit component of our index is highly correlated with an alternative measure designed to reflect the same phenomenon, that is, the supply chain component of the Brexit Uncertainty Index of Chung, Dai, and Elliott (2022).

### *2.3.3 Using Machine Learning Techniques to Validate the Word Selection*

In order to further validate the news searches, we apply the word embedding technique that was first introduced by Mikolov et al.

**Figure 6. Risk of Supply Disruptions Due to Brexit**




**Note:** U.K. SBI evolution in the pre- (left) and post-COVID period (right). Red bars show the contribution of Brexit-related news to the index, calculated as described in Appendix A. We describe in red the main events behind the peaks of the Brexit-related component of the U.K. SBI. The U.K. SBI is normalized to 100 throughout the 1990–2021 period. Left panel: January 2016–December 2019. Right panel: January 2020–June 2023.

(2013). According to word embedding, the text of an article is a continuous vector representation of words in a suitable low-dimensional Euclidean space, and, therefore, syntactic and semantic similarities between words can be captured by associating words with a similar meaning with vectors that are closer to each other. The main idea is to obtain a substantial amount of the meaning of a word from its context words, that is, from the words surrounding it (Moreno Pérez and Minozzo 2022).

In particular, we use word embedding to validate the words that would be more useful to describe supply bottlenecks. In order to do this, we concentrate on the headlines, the snippets, and the first paragraph of the articles of the *New York Times* from January 1, 1990 until the end of June 2022.[11]

Figures 7–9 show word clouds with the 50 most similar words or combinations of words (tokens) to the vectors of words used to define the index: “supply,” “supplies,” “supply chain,” supply chains,”

[11] We compute the bigrams of the words with a frequency higher than 100 and the trigrams with a frequency higher than 150. We perform these computations using Word2Vec of the Gensim Python library. In particular, we consider the Skip-gram model with a hidden layer of H = 200 elements and a context window of size 10 on each side of the center word.

**Figure 7. Word Clouds of the 50 Most Similar Words to the Tokens "Supply" (left) and "Supplies" (right)**


**Note:** These word clouds show the 50 most similar tokens to the vectors of the tokens "supply" (left-hand side) and "supplies" (right-hand side) according to our results of word embedding. We excluded the words related to personal names, companies, countries, and regional names.

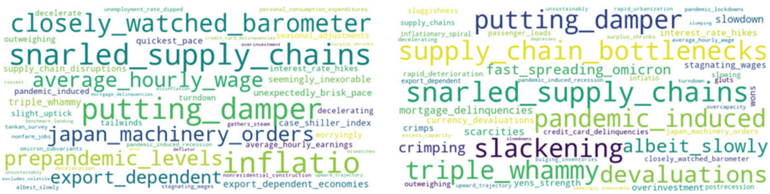
**Figure 8. Word Clouds of the 50 Most Similar Words to the Tokens "Supply Chain" (left) and "Supply Chains" (right)**


**Note:** These word clouds show the 50 most similar tokens to the vectors of the tokens "supply chain" (left-hand side) and "supply chain" (right-hand side) according to our results of word embedding. We excluded the words related to personal names, companies, countries, and regional names.

"supply chain bottlenecks," and "supply chain disruptions." The bigger the size of the words, the higher the similarity with the word of reference. For instance, Figure 6 shows that "supply" (left-hand side) and "supplies" (right-hand side) tend to appear more often close to words related to bottlenecks such as "shortages" or "scarcities" and to products that have suffered shortages since the COVID crisis and the Russian–Ukrainian war such as "antiviral_pills" or "nitrogen fertilizer."

According to Figure 7 the words "supply chain" (left) and "supply chains" (right) are related to sectors that have suffered supply

**Figure 9. Word Clouds of the 50 Most Similar Words to the Tokens "Supply Chain Bottlenecks" (left) and "Supply Chain Disruptions" (right)**




**Note:** These word clouds show the 50 most similar tokens to the vectors of the tokens "supply chain bottlenecks" (left-hand side) and "supply chain disruptions" (right-hand side) according to our results of word embedding. We excluded the words related to personal names, companies, countries, and regional names.

chain disruptions in the United States and Europe such as "semiconductor_manufacturing_equipment," "meat_processing_plants," or "chipmaking" and to trade policy terms such as "aluminium_tariffs" or "retaliatory_tariffs."

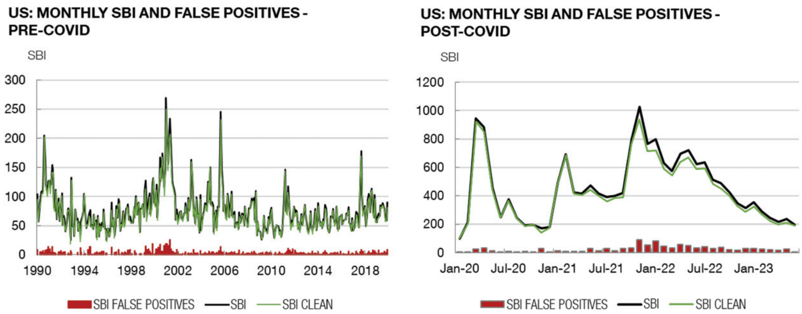
Figure 9 shows that the words "supply chain bottlenecks" and "supply chain disruptions" tend to appear close to several "words" with negative meanings such as "slowdown," "slackening," or "decelerating." Moreover, these words were often employed in the context of the pandemic, since they were often associated with COVID-related clauses, such as "fast_spreading_omicron" or "pandemic_induces," as well as to words related to the resulting economic crisis and higher prices, such as "inflationary_spiral."

### *2.3.4 The Index Is Robust to False Positives*

An important concern when using the frequency of newspaper news related to one topic to identify an economic phenomenon, is that of false positives—that is, the possibility that our search words capture news reflecting an easing, rather than a worsening, of supply chain problems. To control for this, we build a "false positives sub-index."

In particular, in the English-based indices we build the sub-index by adding to our searches the following words, to be

**Figure 10. U.S. SBI and False Positives**




**Note:** Comparison between the U.S. monthly SBI, the contribution of false positives to the U.S. SBI, and the U.S. SBI cleaned from false positives. The contribution of false positives is computed as explained in Section 2.3.4. The cleaned SBI is calculated as the difference between the overall SBI and the false positive component. Left panel: January 1990–December 2019. Right panel: January 2020–June 2023. U.S. SBI is normalized to 100 throughout the 1990–2021 period.

found in a range of five words with respect to the others[12]: "ease, easing, eased, overcome, overcoming, overcame, loose, loosening, loosed, improve, improving, improvement, improved, remove, removing, removed, fade, fading, faded, restore, restoring, restored, eliminate, eliminating, eliminated, ameliorate, ameliorating, amelioration, alleviate, alleviating, alleviated, mitigate, mitigating, mitigation, mitigated, lessen, lessening, lessened, reduce, reducing, reduced, reduction, diminish, diminishing, diminished."

As shown in Figure 10 for the United States, false positives are fairly unusual, representing, on average, 4.2 percent of the overall SBI in the full time sample (4.1 percent and 5.4 percent in the pre-COVID and in the post-COVID sub-samples, respectively). Moreover, these false positives have a negligible effect on the overall index, since the correlation coefficient between the overall SBI and the "clean" component of the index exceeds 0.9 both in the full sample and in the pre- and post-COVID sub-samples. Even in the

[12]We restrict the distance to avoid capturing as false positives other related developments described in the news. However, the method is robust to changes in the size of the range.

post-COVID decline phase of global bottlenecks (starting in January 2022), the contribution of false positives to the overall index remains below 11 percent in all months, with the only exception of November 2020, in which it reached 18 percent.

To confirm our findings, we perform an event study around a policy change directly related to an easing of bottlenecks, the removal of China's zero-COVID strategy in the final months of 2022, when this problem could potentially be more acute. In particular, we calculate the impact of this policy change on the sub-index of false positives within the Chinese monthly SBI. The restrictive zero-COVID measures were removed after massive protests took place in several Chinese cities between November 24 and 27, 2022. On December 7, the zero-COVID strategy was effectively ended as key measures were removed, although the official end was announced on January 8, 2023. In Figure 11 we show that false positives account for a limited percentage of the overall SBI (about 11 percent) between April 2022 and June 2023, leaving the overall trend of the index fairly unaffected. The correlation between the overall SBI and the SBI cleaned from the false positive component is 0.9 throughout the sample period.

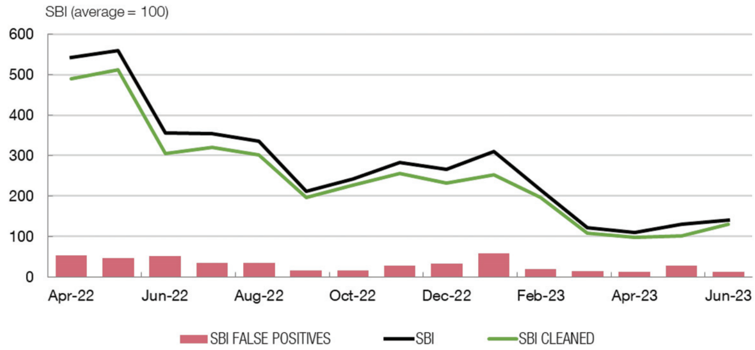
Overall, these exercises let us conclude that the presence of false positives is limited and does not affect significantly the evolution and the peaks of the SBI.

#### *2.3.5 Relation with Other Measures*

Our index seems to be a better measure of supply-side disruptions than the other measures available in at least three dimensions: it ensures the selection of only supply-side events, its high-frequency nature allows for a timelier analysis, and it covers the whole economy.

First, our text-based procedure guarantees the selection of only supply-side events. As shown in the previous section, the spikes of the index are related to supply-side bottlenecks. Before the COVID pandemic, we find several spikes that correspond closely to identified supply disruptions, such as strikes, Hurricane Katrina, or the Gulf War. After the COVID pandemic, although our index explodes, the spikes are related to the lack of global supplies such as semiconductors, raw materials, medical equipment, and COVID vaccines. This is confirmed first in the previous section by using a narrative approach

**Figure 11. Chinese SBI and False Positives around the Dates of the Zero-COVID Policy Removal**

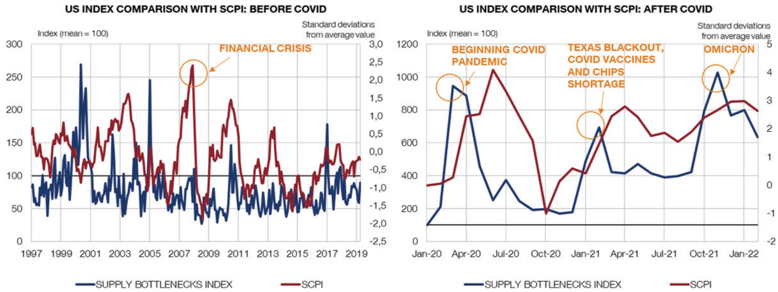



**Note:** Comparison between the Chinese monthly SBI, the contribution of false positives to the Chinese SBI, and the Chinese SBI cleaned from false positives around the dates of the zero-COVID policy removal. The contribution of false positives is computed as explained in Section 2.3.4. The cleaned SBI is calculated as the difference between the overall SBI and the false positive component. The zero-COVID policy was effectively removed on December 7, 2022; its official end was announced on January 8, 2023. China SBI is normalized to 100 throughout the 2010–21 period.

which confirms that most of the increase in the index around two specific events—the California energy crisis of 2001 and Hurricane Katrina in 2005—is in fact due to these events. In addition, using the word embedding technique (see previous section), we find that the words closer to our word criteria are related to supply chain pressures.

On the contrary, the widely used monthly PMI surveys on delivery times, backlogs, or purchased stocks seem to react to both demand and supply issues, as shown by Benigno et al. (2022). In turn, the measure proposed by these authors to try to correct these shortcomings of the monthly PMIs indicators of supply constraints by cleansing them of demand shocks, still falls short of our measure. In particular, when we compare our index for the United States to the Supply Chain Pressures Index (SCPI) proposed by Benigno et al. (2022), we find a moderate correlation between both indices for the pre-COVID period (see left-hand side of Figure 12). The highest spike in the SCPI index is related to the financial crisis—a period

**Figure 12. Comparison of U.S. SBI with Federal Reserve Bank of New York's U.S. SCPI: before COVID (left) and after COVID (right)**



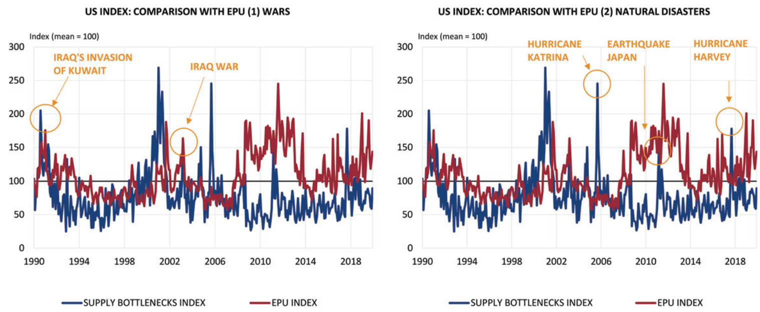

**Note:** U.S. SBI and Federal Reserve Bank of New York's U.S. SCPI (Benigno et al. 2022) from 1997 until March 2022. This index was discontinued in March 2022. Since that moment only a global index is available. The SBI is normalized to 100 throughout the 2001–21 period.

for which there is little evidence of supply bottlenecks—while the highest spike of our SBI is produced by the 2001 California blackout and energy crisis, followed by the impact of Hurricanes Rita and Katrina in 2005. Both indices capture the increase in supply disruptions after the Japan earthquake in 2011, but the SCPI shows little movement around Hurricane Katrina. During the pandemic period, on the contrary, the two indices are more correlated (see right-hand side of Figure 12).

Similar results are found when comparing the U.S. SBI with other more general measures of uncertainty, like the index of economic policy uncertainty (EPU) developed by Baker, Bloom, and Davis (2016). In Figure 13 we show that war events tend to increase both indices, while natural disasters only increase the SBI. Table C.1 in Appendix C reports the correlation of the monthly SBI and EPU with several economic variables in the pre-COVID period (results for the whole sample are similar, although in general the cross-correlation of economic variables increases). Interestingly, unlike the EPU, the SBI is not correlated with oil price or consumer sentiment developments.

Second, the high-frequency nature of the indicator, which can be retrieved daily, allows for real-time analysis of bottlenecks and

**Figure 13. Comparison of U.S. SBI with U.S. EPU: Wars (left-hand side) and Natural Disasters (right-hand side)**




**Note:** Comparison of U.S. SBI with U.S. EPU: wars (left-hand side) and natural disasters (right-hand side) from 1990 until 2019. The U.S. SBI is normalized to 100 throughout the 1990–2021 period.

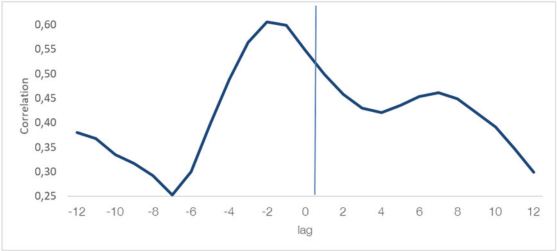
helps to better identify shocks to macro variables.[13] Our index displays a high correlation with some sub-components of the European Commission survey on production restrictions, as shown in Appendix C.[14] However, survey-based indicators, like this same survey, which is available at the quarterly frequency, or the monthly PMIs, tend to be more lagging than our measure of bottlenecks. In this sense, our index for the United States tends to lead the monthly one developed by Benigno et al. (2022). The dynamic maximum (monthly) correlation between the two indices (see Figure 14) is achieved with two lags of the news-based SBI. Furthermore, a Granger-causality test finds that the SBI causes (in the sense of Granger) the SCPI.[15] We observe this in two particular events such as in Hurricane Katrina and in the COVID crisis. For instance, as shown in Figure 15 (left panel), after Hurricane Katrina reached

[13] Other high-frequency indicators, such as the Baltic Dry Index or the Harpex Index for maritime transport, only cover specific sectors, being especially related to trade dynamics.

[14] The correlation is particularly high with the labor and machinery subcomponents, and especially in the full time sample, which includes the post-COVID period.

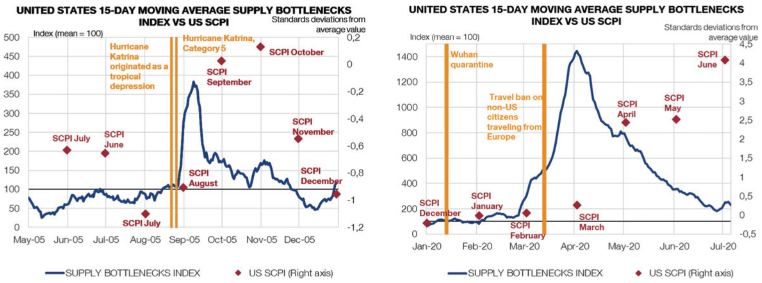
[15] A similar result was found when estimating the correlation between a similarly constructed SCPI and the SBI in the rest of the countries in our sample. Results are available upon request.

**Figure 14. Dynamic Correlations of U.S. SBI with U.S. Supply Chain Pressure Index (1997–2022)**




**Note:** Dynamic correlations from U.S. SBI with U.S. Supply Chain Pressure Index 1997 until March 2022. The U.S. SBI is normalized to 100 throughout the 1990–2021 period.

**Figure 15. U.S. 15-Day Moving-Average Supply Bottlenecks Index vs. U.S. Supply Chain Pressure Index**




**Note:** Evolution of the U.S. SBI (blue line, left axis) and U.S. Supply Chain Pressure Index from Benigno et al. (2022) (red dots, right axis), around Hurricane Katrina and the first wave of COVID-19. The U.S. SBI is normalized to 100 throughout the 1990–2021 period. The U.S. Supply Chain Pressure Index is measured in standard deviations from the average value.

Category 5 status at the end of August 2022, the U.S. SBI increased during the first half of September, a month before the U.S. SCPI data for September would have been available. This is even clearer during the COVID crisis (see right panel of Figure 13), when the SBI index started to increase in early February, reaching historical maxima during March, capturing the diverse problems in supply due to the COVID crisis, whereas the SCPI did not show any signs of bottlenecks until the beginning of May, when the data of April were available.

Third, our index spans a longer sample and covers the whole economy. In the U.S. case, the index is based on daily article searches from 11 nationwide newspapers since 1990, while the European indices start in the early or mid-2000s. Other supply bottlenecks indices commonly used only cover specific sectors, like the Harper and Baltic maritime trade indices (which are based on the prices of maritime trade across different locations), or lack a sufficiently big sample to provide inference, such as the Small Business Pulse Survey in the United States, or cover a more limited period, like the text-based index in Young et al. (2021), which uses quarterly S&P earnings calls as a source of information.

## 3. Macro Impact of Supply-Side Disruptions

To study the macro impact of the supply-side disruptions identified by the SBI, we follow Baker, Bloom, and Davis (2016) and construct a monthly VAR identified using a Cholesky decomposition in which we include the following seven variables, in the stated order: the bottlenecks index, the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index, plus a constant. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria.

The supply chain bottlenecks indices are clearly not purely exogenous variables (or shocks), since, for example, they are more binding when demand intensifies. To control with the VAR methodology for this potential feedback between activity and supply chain bottlenecks, we use the fact that bottlenecks are unlikely to react contemporaneously to activity. In fact, firms usually use inventories to accommodate demand shocks, and they increase their inventories when the supply chain risk is higher (Carreras Valle 2021). This means that the Cholesky identification proposed, placing the SBI first and the activity variables last, should be adequate. That is, we assume that shocks to the domestic variables may only be reflected with a lag in the bottlenecks index (as contemporaneous shocks will be absorbed by inventories), while supply chain disruptions may affect contemporaneously activity and prices.

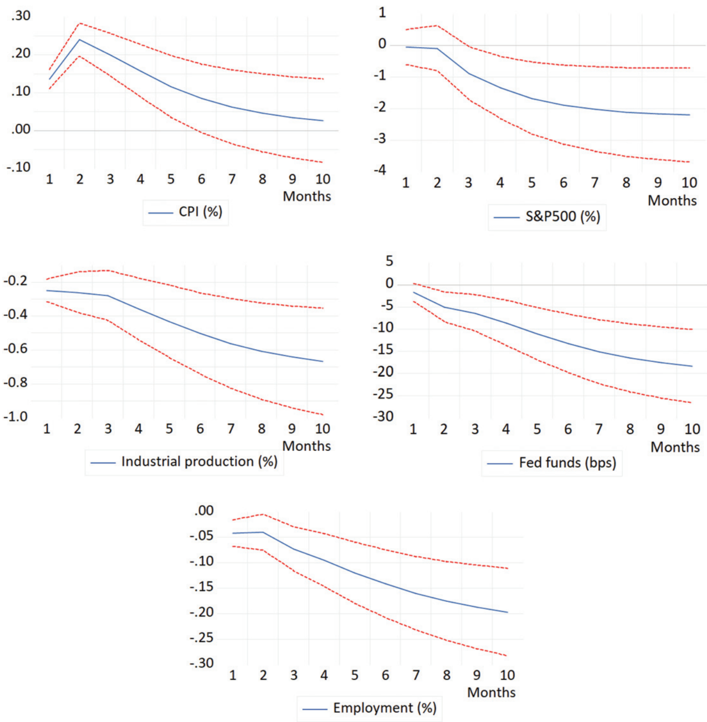
In this case, the recursive identification is compatible with the interpretation of the index as a proxy (or an instrument in the case of a regression framework, as explained in Plagborg-Møller and Wolf 2021) for supply problems. As supply problems are difficult to measure, researchers often rely on sign restrictions, which we deem unnecessary in our case, as the main spikes in the index refer to supply disruptions.

In our benchmark specification, we restrict the sample to the period from January 1999 to January 2020. We present impulse response functions (IRFs) to shocks in the VAR. As explained in Section 2.1, these shocks might have different sources. The impulse responses before the pandemic will show the average response of the economy to the structural shock, given the mix of shocks that form the SBI in that particular period.[16] As a result, out-of-sample inference of the impact of an SBI shock should take into account the source of the shock. For example, a supply chain malfunctioning might have a more delayed impact on the economy than a sudden disruption due to a natural disaster. On the other hand, the pandemic supply shock could have triggered aggregate demand effects (Guerrieri et al. 2022), which may not be a feature of more isolated supply shocks. Therefore, we avoid using the latest period, which is not comparable with the previous one as a result of the great negative effect of the COVID pandemic, and later we check that the results are comparable when extending the sample until 2022.

The results are presented in Figure 16. In particular, a shock of one standard deviation to the SBI (resulting in an increase of 60 points in the index over the whole sample) induces a significant decrease in employment of around 0.2 percentage point (pp) after 10 months, and a decrease in industrial production of 0.7 pp after 10 months. The effects on financial variables are more moderate, with a non-significant decrease in stock prices on impact and a decrease of around 2 percent after 10 months, together with a small (and non-significant during the first quarter) decrease in the federal funds rate. As for prices, the VAR evidence confirms the SBI shock is a pure

[16]This is also the case for different indices that try to capture the average response of the economy to a change in economic sentiment or in economic uncertainty, such as Baker, Bloom, and Davis (2016) or Caldara and Iacoviello (2022).

**Figure 16. Impulse Responses to an SBI Shock in the United States (1990–2020)**




**Note:** Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI, the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is an increase of 60 points in the SBI. The red lines denote one-standard-deviation confidence bands.

supply shock: prices rise significantly on impact, with CPI increasing by 0.25 pp in the first two months after the shock.

To illustrate the economic relevance of these results, it is worth calculating the impact of specific events as measured by the SBI. In particular, Hurricane Katrina in 2005 increased the U.S. SBI by around 150 basis points, which according to the VAR results would have implied an increase in the U.S. aggregate CPI by 0.75 pp after

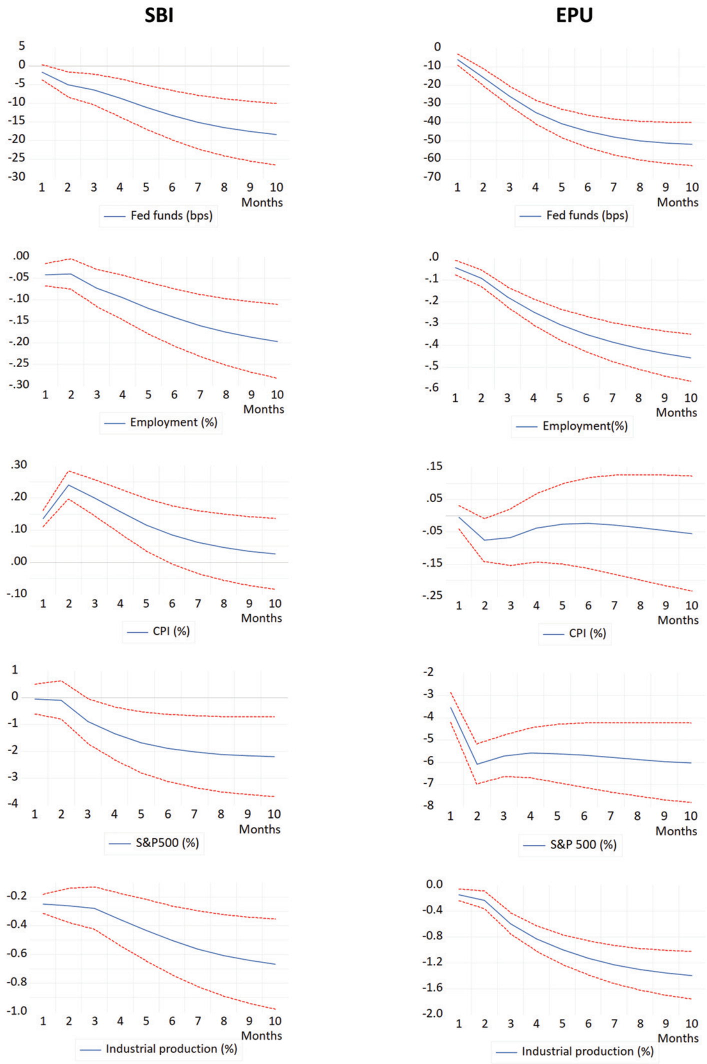
5 months and a contraction of U.S. aggregate industrial production by 1.5 pp after 10 months.

In Figure 17, we compare these results with those of a standard measure of economic policy uncertainty, the EPU by Baker, Bloom, and Davis (2016). The size of the shocks is the same as before (one standard deviation of the index, corresponding to an increase of 60 points in the index). The effects on industrial production and employment are also quite comparable. However, the EPU has a stronger impact on financial variables, which is consistent with the high relevance of uncertainty for stock prices. Interestingly, while the CPI is not affected by the EPU shock, it increases in the case of the SBI shock. As the SBI shock is a persistent supply shock, monetary policy faces a trade-off between prices and activity, which is reflected in the more cautious response of the federal funds rate in the case of the SBI shock (see, for example, Comin, Johnson, and Jones 2023 for a discussion on the role of monetary policy facing supply chain disruptions).

In Figure 18, we present several robustness exercises around our benchmark specification (blue line) for the response of the CPI index (left) and industrial production (right). First, we include the Michigan Index of Consumer Sentiment (orange line), ordered after the EPU index. It is well known that the response of economic variables to EPU is less strong when including forward-looking consumer variables. In the case of the SBI, the results remain unchanged. This is also evidence that past and future demand prospects are not affecting the index. Second, we change the ordering of variables, by putting the EPU first (green line). The significance of the results is not affected. Finally, we include the oil price as the first variable in the recursive VAR (red line). With this specification, we are not allowing for a contemporaneous effect of the bottlenecks index to the oil price, to avoid the possible concern that the SBI may be capturing mainly oil supply shocks. As can be seen, including oil prices slightly reduces the effect of the benchmark VAR, but it does not affect the significance of the results.

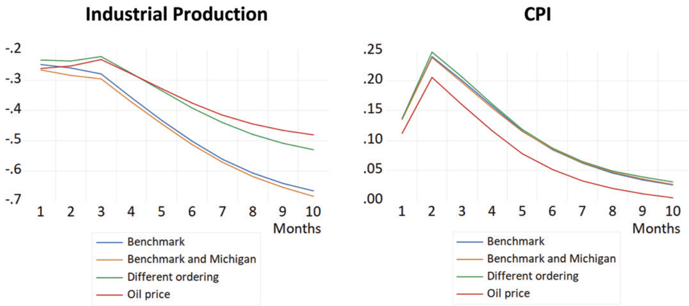
The next exercise is a comparison with a similar benchmark VAR computed using the SCPI as a bottlenecks indicator. As shown in Figure 19, the effects on the CPI are similar on impact (left-hand side), although more persistent in the case of the SCPI. However, the impact on industrial production (right-hand side) is

**Figure 17. Impulse Responses to an SBI Shock (left column) and the EPU Index (right column) in the United States (1990–2020)**




**Note:** Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI, the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is an increase of 60 points in the SBI (left) and 60 points in the EPU (right). The red lines denote one-standard-deviation confidence bands.

**Figure 18. Impulse Responses of Industrial Production (left) and CPI (right) to an SBI Shock (robustness)**



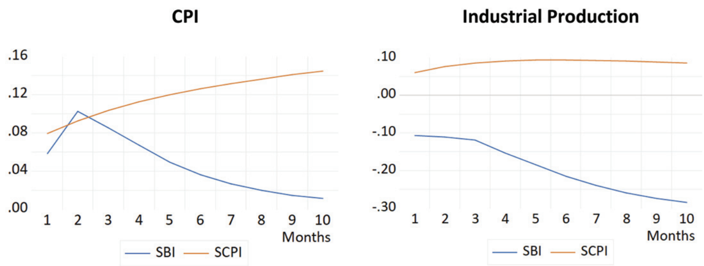

**Note:** Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition. The figure shows the response of industrial production to the SBI shock in the benchmark specification (see notes to Figure 13). The orange line includes eight variables in the stated order: SBI, the economic policy uncertainty index, the Michigan Index of Consumer Sentiment, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. The green line includes seven variables in this order: the economic policy uncertainty index, the SBI, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. Finally, the red line includes eight endogenous variables, adding the real oil price as the first variable in the recursive specification. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is normalized in all specifications to show an increase of 60 points in the SBI.

completely different. Counterfactually, the shock to SCPI increases (non-significantly) industrial production, while the SBI shock decreases it. We conclude that the SBI is more related to the supply side of bottlenecks.

For robustness, we also report in Figure 20 the impulse responses of a VAR estimated using data for the whole sample available, from January 1990 until May 2022.[17] Although qualitatively the results are not changed, some differences in the dynamics appear. First, the

[17]The large and persistent spike in the SBI after the pandemic can be thought of as a measure of the prominent importance of these shocks or as a structural change, and therefore it warrants some caution when interpreting the results using the whole sample.

**Figure 19. Impulse Responses of CPI (left) and Industrial Production (right) to a One-Standard-Deviation SBI or SCPI Shock in the United States (1990–2020)**

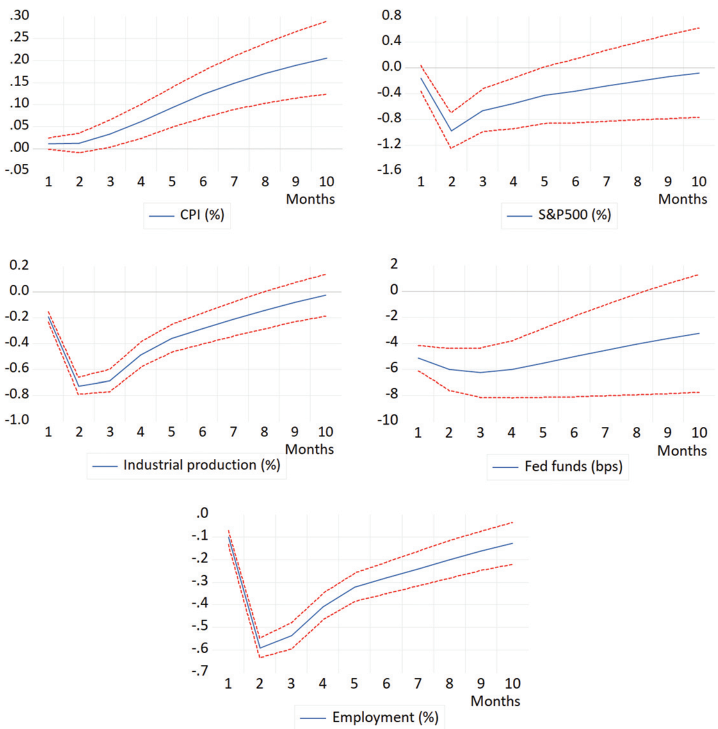



**Note:** Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI (blue) or the SCPI (orange), the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is a one-standard-deviation increase in the SBI (blue) or the SCPI (orange).

response of CPI is much more persistent than before. Second, the response of industrial production and employment is more immediate than in the previous exercises, with an immediate fall. This could be caused by the pandemic itself, as it created a very important and sudden bottlenecks shock, but also because of the different mix of shocks forming the SBI after this period and the response to them of supply chains during and after the pandemic (Bonadio et al. 2021).

Finally, we estimate a panel VAR for six countries (United States, United Kingdom, Spain, Italy, France, and Germany). The sample ranges from January 2007 to January 2020, given the restrictions on newspaper availability across countries. The shock is also one standard deviation, equal to a 60-point increase in the index. The panel VAR includes equivalent variables to the ones used before, but we use the unemployment rate, which is available at monthly frequency for all countries. In any case, as shown in Figure 21, the results for unemployment, industrial production, and the CPI are qualitatively similar to the ones presented before, although noisier, as is expected due to the shorter and more heterogeneous sample.

**Figure 20. Impulse Responses to a One-Standard-Deviation SBI Innovation in the United States (January 1990–May 2022)**

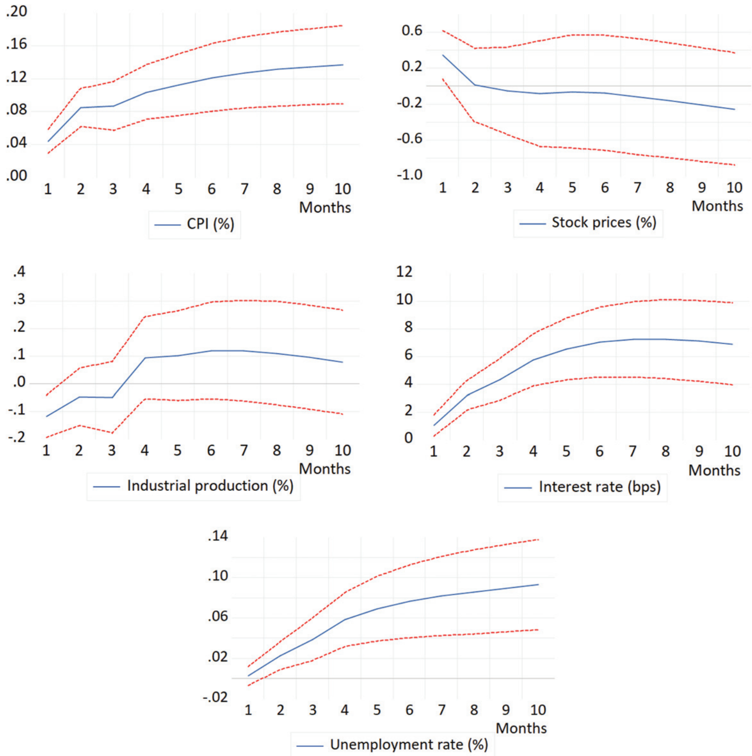



**Note:** Monthly VAR from January 1990 to May 2022 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI (blue) or the SCPI (orange), the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags following the Schwarz and Hannan-Quinn criteria. The red lines denote one standard deviation confidence bands. The shock is normalized in all specifications to show an increase of 60 points in the SBI.

## 4. Conclusions

We construct an index of supply bottlenecks using newspaper articles. An audit exercise based on a comparison with other possible sources of information, a human-based analysis of the main spikes,

**Figure 21. Impulse Responses to a One-Standard-Deviation SBI in the United States, United Kingdom, Germany, France, Italy, and Spain (pre-COVID sample)**




**Note:** Monthly panel VAR from January 2007 to January 2020 identified using a Cholesky decomposition. The countries included are the United States, the United Kingdom, Germany, France, Italy, and Spain. We include seven variables: the SBI, the EPU index of each country, a stock price index, the official interest rate, the unemployment rate, log industrial production, and log CPI. We include three lags following the Schwarz and Hannan-Quinn criteria. The red lines denote one-standard-deviation confidence bands. The shock is an increase of 60 points in the SBI.

and the use of machine learning techniques over a sample of articles let us conclude that the index captures the main events previously identified in the literature as leading to supply disruptions—including wars, natural disasters, strikes, and the notable supply chain bottlenecks during the COVID-19 pandemic. The index is calculated for the United States, the United Kingdom, the main economies in the euro area, and China.

The econometric analysis shows that supply bottlenecks have important effects on the economy, leading to a decrease in industrial production and employment and an increase in prices. As a consequence, the index is a good proxy for supply shocks (of different natures) affecting the economy. Overall, the evidence presented in this paper supports the view that supply bottlenecks should be carefully monitored and addressed by policymakers.

## Appendix A. Definition of the Index, Newspapers Used, and Data Sample

### *A.1 Definition of the SBI*

(i) Define $NR_t^i$ as the number of articles containing the words selected in each newspaper $i = 1, 2, \ldots p$ and time period $t$.

(ii) Let $X_t^i = \frac{NR_t^i}{N_t^i}$ be the relative frequency rescaled by the total number of articles in the same newspaper and period $t(N_t^i)$, to account for the fact that the overall volume of articles varies across newspapers and time, and let $T_1$ and $T_2$ denote the time intervals used in the standardization and normalization calculations.

(iii) Compute the variance and mean of variable $X_t^i$, in the interval $T_1$ for each newspaper $i$:

$$\sigma_{T_1}^{X^i} = \sqrt{\sum_{T_1} \left( \frac{NR_t^i}{N_t^i} - \mu_{T_1}^{X^i} \right)^2 / T_1}, \mu_{T_1}^{X^i} = \sum_{T_1} \frac{NR_t^i}{N_t^i} / T_1.$$

(iv) Standardize $X_t^i$ by dividing through by the standard deviation for all $t$. This operation yields, for each newspaper, a series $Y_t^i = \frac{X_t^i}{\sigma_{T_1}^{X^i}}$ with unit standard deviation in the interval $T_1$.

(v) Compute the mean over the $p$ newspapers of $Y_t^i$ in each period $t$ to obtain the series $Z_t = \sum_p Y_t^i/p$.

(vi) Compute $M = \sum_{T_2} Z_t/T_2$, the mean value of $Z_t$ in the interval $T_2$.

(vii) Multiply $Z_t$ by $(100/M)$ for all $t$ to obtain the normalized SBI time-series index $SBI_t = Z_t \frac{100}{M}$.

Therefore, putting all together, we have

$$SBI_t = \frac{\sum_p \frac{X_t^i}{\sigma_{T_1}^{X^i}}/p}{\sum_{T_2}\left(\sum_p \frac{X_t^i}{\sigma_{T_1}^{X^i}}/p\right)/T_2}100.$$

We can calculate the contributions of a subset of news on the index—for example, those related to a particular event like Hurricane Katrina—in the following manner. Count the number of news amongst those including the selected words which also contain a word describing that event ($NR_t^{S,i}$) and defined the rescaled frequency of this set of news as $X_t^{S,i} = \frac{NR_t^{S,i}}{N_t^i}$. In the current example we would add the word "Katrina." Then the contribution of this event to the SBI (${SBI^S}_t$) would be as follows:

$$SBI_t^S = \frac{\sum_p \left(\frac{X_t^{S,i}}{\sigma_{T_1}^{X^i}}\right)/p}{\sum_{T_2}\left(\sum_p \frac{X_t^i}{\sigma_{T_1}^{X^i}}/p\right)/T_2}100.$$

### *A.2 Newspapers and Sample*

The time period covered for the United States goes from January 1, 1990 until May 2022. The newspapers used are the following (in parentheses is the time they join the index if they did it later than January 1990 due to lack of data): the *Los Angeles Times*, the *San Francisco Chronicle*, the *Houston Chronicle*, the *New York Times*, the *Washington Post* (December 1997), the *Chicago Tribune* (January 2000), the *Wall Street Journal* (April 2001), the *Miami*

*Herald* (June 2001), the *Boston Globe* (September 2001), *USA Today* (February 2002), and the *Dallas Morning News* (May 2003).

The newspapers used for the United Kingdom are the following: the *Times*, the *Independent*, the *Guardian*, the *Telegraph*, the *Daily Mirror*, the *Daily Express*, the *Daily Mail*, the *Evening Standard*, the *Sun*, and the *Sunday Times*. The time sample starts January 1, 2001.

In the case of France, we adapt the words into the French language. In particular, we use the following words for each group:

1. chaine d'approvisionnement, chaines d'approvisionnement, chaine logistique, chaines logistiques, approvisionnement, approvisionnements;

2. goulot d'étranglement, goulots d'étranglement, pénurie, pénuries, perturbation, perturbations, problème, problèmes, rareté, raretés, absence de, absences de, manque de, retard, retards, délai, délais.

The sample starts on January 1, 2006. The newspapers used are the following (in parentheses is the time they join the index if they did it later than January 2006 due to lack of data): *Le Figaro, Le Monde, Les Echos, Le Progrès, Agence France Presse, Sud Ouest, Ouest France*, and *Midi Libre* (September 2006).

For Italy, we adapted the search words into Italian:

1. catena di approvvigionamento, catene di approvvigionamento, supply chain, supply chains, catena di fornitura, catena di forniture, fornitura, forniture, catena logistica, catene logistiche;

2. collo di bottiglia, rallentamento, rallentamenti, congestione, scarsità, carenza, carenze, assenza, assenze, interruzione, perturbazione, interruzioni, perturbazioni, problema, problemi, difficoltá, penuria, mancanza, mancanze, ritardo, ritardi, arretrato, arretrati, inevaso, inevasi.

The sample starts on January 1, 2007. The Italian newspapers used are the following: *ANSA, Agenzia Giornalistica Italia, Corriere* *della Sera, La Stampa, Il Sole 24 ore, La Repubblica, Il Giornale, La Nazione, Il Resto del Carlino, Il Giorno.*

For Spain, we adapted the search words into Spanish:

1. cadena de suministro, cadena de suministros, cadenas de suministro, cadenas de suministros, suministro, suministros;

2. cuello de botella, cuellos de botella, escasez, escaseces, interrupción, perturbación, paralización, interrupciones, perturbaciones, paralizaciones, problema, dificultad, problemas, dificultades, carencia, carencias, falta de, atraso, retraso, atrasos, retrasos.

The sample starts on January 1, 2007. The Spanish newspapers used are the following (in parentheses is the time they join the index if they did it later than January 2007 due to lack of data): *ABC*, *El Mundo, El País, El Economista* (May 2008), *Expansión*, and *Cinco Días.*

For Germany, we adapted the search words into German. However, we created a new group of words due to the characteristics of the German language that have words that by itself mean "supply bottleneck," such as "Versorgungsengpass." Thus, in the German search, we count the article as 1 if we find the same search as for the other languages (group 1 and 2 simultaneously) or any word belonging to group 3.

1. Lieferkette, Lieferketten, Lieferung, Beschaffung, Lieferungen, Beschaffungen.

2. Engpass, Kapazitätsengpass, Mangel, Knappheit, Mängel, Knappheiten, Störung, Betriebsstörung, Störungen, Betriebsstörungen, Problem, Probleme, Verknappung, Verknappungen, Fehlen von, Verzug, Verzögerung, Verspätung, Verzögerungen, Verspätungen, Rückstand, Nachholbedarf, Rückstau, Arbeitsrückstand, Rückstände, Arbeitsrückstände, Schwierigkeit, Schwierigkeiten.

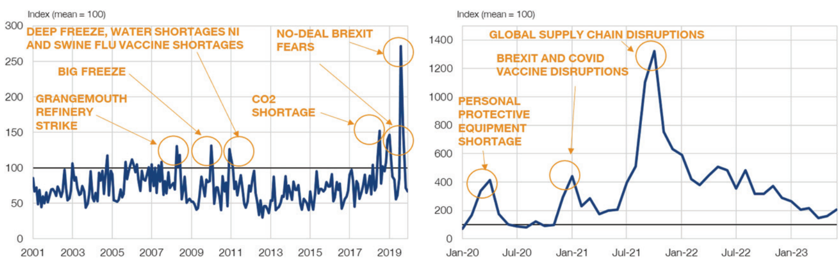
3. Lieferengpass, Lieferengpässe, Versorgungsengpass, Versorgungsengpässe, Beschaffungsprobleme, Lieferrückstand.

The sample starts on January 1, 2007. The German newspapers used are the following (in parentheses is the time they join the index if they did it later than January 2007 due to lack of data): *Die Welt, Frankfurter Allgemeine Zeitung* (March 2013), *Handelsblatt* (March 2013), *Die Welt, Der Tagesspiegel, Die Tageszeitung, Bild* (April 2013), *Rheinische Post, Frankfurter Rundschau, Stuttgarter Zeitung*, and *Berliner Morgenpost.*

For China, the sample starts on January 1, 2010. The newspapers used are the following: the *Wall Street Journal, China Daily*, the *South China Morning Post, Reuters News*, and *Dow Jones Institutional News.* We restrict our search to include only news related to China.

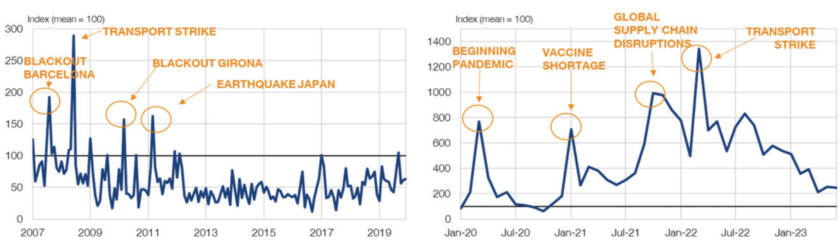
## Appendix B. Explanations of Spikes in the SBI (Rest of Countries)

### Figure B.1. United Kingdom Supply Bottlenecks Index



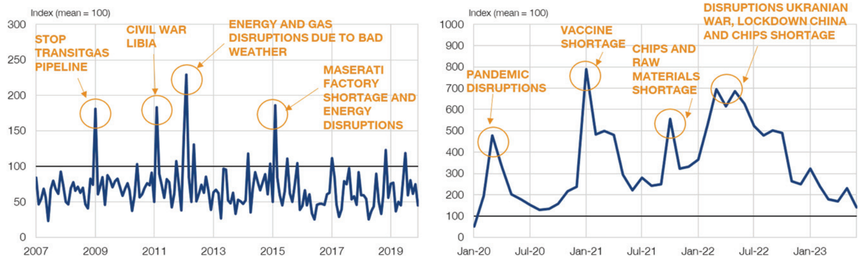

**Note:** U.K. SBI from 2001 until June 2023. U.K. SBI is normalized to 100 throughout the 2001–21 period. We describe in yellow the main events behind the spikes of the U.K. SBI.

### Figure B.2. Spain Supply Bottlenecks Index



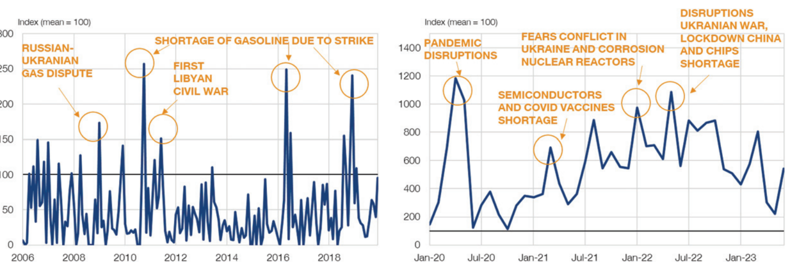

**Note:** Spain SBI from 2007 until June 2023. The Spain SBI is normalized to 100 throughout the 2007–21 period. We describe in yellow the main events behind the spikes of the Spain SBI.

### Figure B.3. Italy Supply Bottlenecks Index



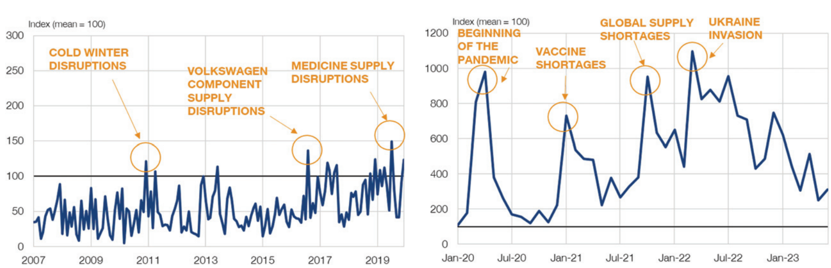

**Note:** Italy SBI from 2007 until June 2023. Italy SBI is normalized to 100 throughout the 2007–21 period. We describe in yellow the main events behind the spikes of the Italy SBI.

### Figure B.4. France Supply Bottlenecks Index



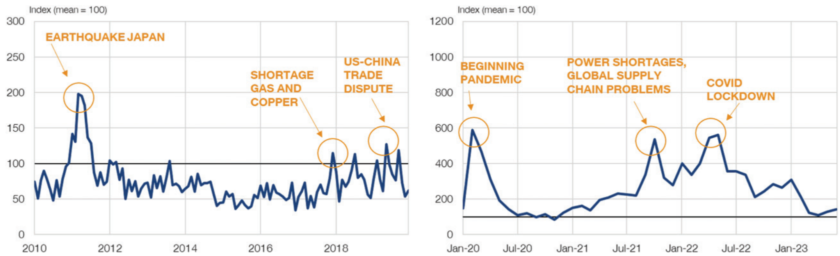

**Note:** France SBI from 2006 until June 2023. France SBI is normalized to 100 throughout the 2006–21 period. We describe in yellow the main behind the spikes of the France SBI.

### Figure B.5. Germany Supply Bottlenecks Index




**Note:** Germany SBI from 2007 until June 2023. Germany SBI is normalized to 100 throughout the 2007–21 period. We describe in yellow the main events behind the spikes of the Germany SBI.

**Figure B.6. China Supply Bottlenecks Index**




**Note:** China SBI from January 2010 until June 2023. China SBI is normalized to 100 throughout the 2010–21 period. We describe in yellow the main behind the spikes of the China SBI.

## Appendix C. Comparison with Other Measures

**Table C.1. Correlations of SBI with EPU and Michigan Index of Consumer Sentiment Measures (1990–2019)**

| Variable | SBI | EPU | Consumer Sentiment |
|---|---|---|---|
| SBI | 1.000 | –0.039 | 0.116 |
| EPU | –0.039 | 1.000 | –0.589 |
| FI | –0.010 | 0.096 | 0.230 |
| IPI | –0.027 | 0.099 | 0.091 |
| IR | 0.308 | –0.482 | 0.376 |
| OIL | –0.098 | 0.402 | –0.454 |
| CPI | –0.163 | 0.330 | –0.123 |
| Sentiment | 0.116 | –0.589 | 1.000 |
| PPI | –0.180 | 0.392 | –0.210 |
| Employment | –0.060 | 0.176 | 0.064 |
| VIX | 0.035 | 0.374 | –0.339 |

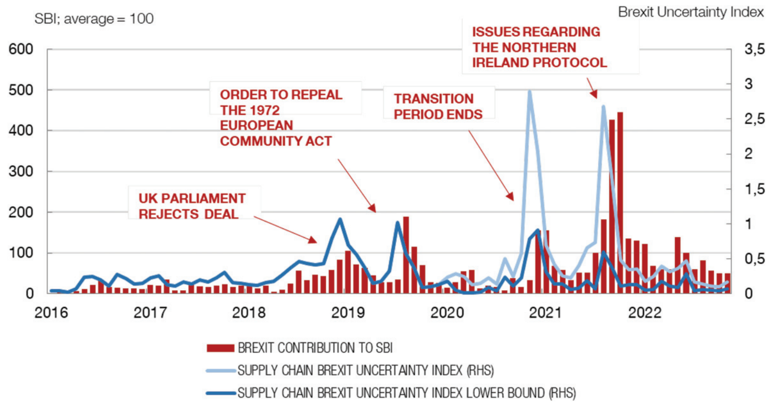
**Note:** Correlation of U.S. SBI with the EPU, the Michigan Index of Consumer Sentiment, the S&P 500 (FI), industrial production index (IPI), the federal funds rate (IR), the Brent oil price, the CPI, producer price index, employment, and the VIX. With the exception of the EPU and the SBI, the rest of the variables are retrieved from the Federal Reserve Economic Data (FRED) statistical database of the Federal Reserve Bank of St. Louis.

**Table C.2. Correlations of SBI with the Machinery and Labor Sub-components of the European Commission Survey on Production Restrictions**

| | DEU | FRA | ITA | ESP | EMU |
|---|---|---|---|---|---|
| *SBI—Labor* | | | | | |
| 2007:Q1–2019:Q4 | 0.51 | 0.21 | –0.22 | 0.16 | 0.26 |
| 2007:Q1–2023:Q2 | 0.68 | 0.50 | 0.52 | 0.71 | 0.70 |
| *SBI—Machinery* | | | | | |
| 2007:Q1–2019:Q4 | 0.31 | 0.25 | –0.11 | 0.19 | 0.38 |
| 2007:Q1–2023:Q2 | 0.44 | 0.22 | 0.37 | 0.48 | 0.67 |
| *SBI—Labor and Machinery* | | | | | |
| 2007:Q1–2019:Q4 | 0.55 | 0.23 | –0.21 | –0.07 | 0.31 |
| 2007:Q1–2023:Q2 | 0.80 | 0.56 | 0.52 | 0.70 | 0.78 |

**Note:** Correlation of Germany, France, Italy, Spain, and EMU SBI with the respective machinery and labor sub-components of the European Commission survey on production restrictions. EMU SBI is computed as the average of the SBI of the four main EU economies. European Commission indices are normalized.

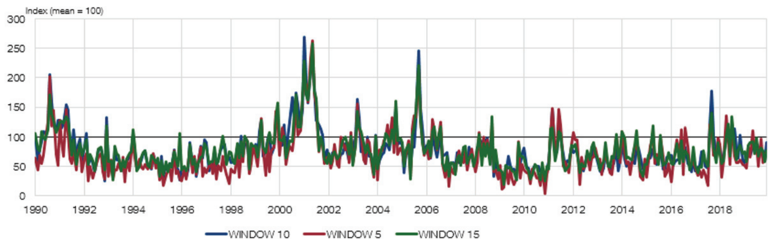
**Figure C.1. Comparison of UK Brexit-Related SBI with the Supply Chain Brexit Uncertainty Index (2016–22)**




**Note:** Comparison between the Brexit-related component of the U.K. monthly SBI and the supply chain component of the Brexit Uncertainty Index (Chung, Dai, and Elliott 2022). The Brexit contribution to the U.K. SBI is calculated as explained in Appendix A.

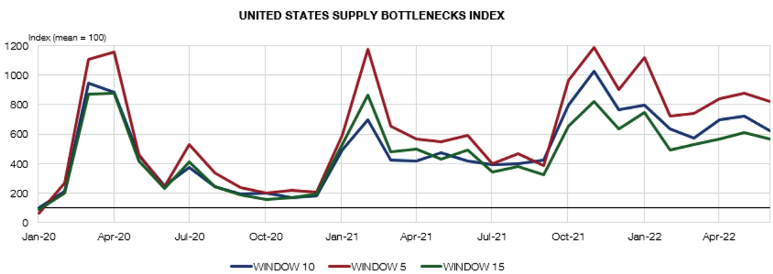
## Appendix D. Different Windows for News Search

**Figure D.1. U.S. Monthly SBI with Different Search Windows before COVID-19**




**Note:** U.S. SBI from 1990 until the end of 2019. The SBI is normalized to 100 throughout the 1990–2021 period. We create two groups of words, one with the terms “supply” and “supply chain” that aim to capture the nature of the article, and another related to negative sentiment, such as “bottleneck” and “shortage.” Then we search, within a predefined window, for a coincidence of one word of the first group with another of the second group. Windows 5, 10, and 15 indicate for each U.S. SBI the maximum number of words between the two groups of words in our search.

**Figure D.2. U.S. Monthly SBI with Different Search Windows after COVID-19**




**Note:** U.S. SBI from 2020 until the end of June 2022. The SBI is normalized to 100 throughout the 1990–2021 period. We create two groups of words, one with the terms “supply” and “supply chain” that aim to capture the nature of the article, and another related to negative sentiment, such as ”bottleneck” and ”shortage.” Then we search, within a predefined window, for a coincidence of one word of the first group with another of the second group. Windows 5, 10, and 15 indicate for each U.S. SBI the maximum number of words between the two groups of words in our search.

## Appendix E. Audit of the Main Events

This appendix lists the events behind the spikes of each national SBI to ensure that they capture correctly supply disruptions. For each country, we classify as spikes all the observations that are one standard deviation above the mean, using sample-specific mean and standard deviation for the pre-COVID and the post-COVID sample. To deduce the main events behind the spikes of each national SBI, we read all the articles that comply with our SBI searches.

### United States

**Pre-COVID**:
Jul. 1990 (SBI=116): rhodium shortage, risk of water shortages in California
Aug. 1990 (SBI=205): risk of oil supply shortages due to Gulf War
Sept. 1990 (SBI=161): risk of oil supply shortages due to Gulf War
Oct. 1990 (SBI=120): risk of oil and propane supply shortages due to Gulf War
Dec. 1990 (SBI=127): risk of oil supply shortages due to Gulf War
Jan. 1991 (SBI=128): risk of oil supply shortages due to Gulf War
Feb. 1991 (SBI=115): risk of water shortages in California, shortages in military supplies, vulnerability to oil supply shortages
Mar. 1991 (SBI=122): risk of water shortages in California, vulnerability to oil supply shortages
Apr. 1991 (SBI=154): risk of water shortages in California
May 1991 (SBI=145): risk of water shortages in California
Aug. 1991 (SBI=111): risk of oil supply shortages from Soviet Union, copper supply shortages, risk of water shortages in California
Dec. 1992 (SBI=132): risk of shortages in steel and lumber production, risk of supply shortages of palladium from Russia and South Africa
Apr. 1999 (SBI=127): gasoline supply shortages, risk of supply shortages of palladium from Russia
Nov. 1999 (SBI=123): risk of Y2K-related disruptions, supply disruptions for electronics makers due to Taiwan earthquake
Dec. 1999 (SBI=131): risk of Y2K-related disruptions
Mar. 2000 (SBI=120): risk of oil, gas, and gasoline supply shortages, risk of water shortages in California

Jun. 2000 (SBI=124): debate on oil and gasoline supply shortages (related to gasoline price spikes)
Jul. 2000 (SBI=167): debate on oil and gasoline supply shortages, risk of electricity shortages in California
Aug. 2000 (SBI=131): risk of heating oil shortage for the coming winter, risk of electricity shortages in California, tire shortages due to Bridgestone/Firestone Inc. tire recall, blood shortage
Sept. 2000 (SBI=174): risk of energy crisis (oil and electricity), flu vaccine shortage
Oct. 2000 (SBI=153): risk of energy crisis (oil and electricity), flu vaccine shortage, supply shortages to electronics firms
Nov. 2000 (SBI=116): risk of energy crisis (oil and electricity), flu vaccine shortage
Dec. 2000 (SBI=146): risk of energy crisis (electricity), supply shortages to electronics firms
Jan. 2001 (SBI=269): blackouts and energy crisis in California
Feb. 2001 (SBI=198): California energy crisis, tetanus vaccine shortage
Mar. 2001 (SBI=156): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California
Apr. 2001 (SBI=212): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California
May 2001 (SBI=233): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California
Jun. 2001 (SBI=183): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California, blood shortages related to mad cow disease
Jul. 2001 (SBI=128): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California, blood shortages
Aug. 2001 (SBI=120): risk of energy crisis in several states and at the national level (mostly gasoline and electricity), blood shortages
Sept. 2001 (SBI=114): risk of energy crisis in several states and at the national level (mostly gas and gasoline)

Mar. 2003 (SBI=163): disruptions in oil supply due to Iraq War and to political unrest in Nigeria and Venezuela, supply shortages to U.S. troops in Iraq
Apr. 2003 (SBI=131): risk of oil shortages due to Iraq War, supply shortages to U.S. troops in Iraq
Aug. 2004 (SBI=126): risk of oil shortages due to disruptions from Russia's top oil producer (Yukos), Iraq War, and election in Venezuela, flu vaccine shortage
Oct. 2004 (SBI=150): risk of oil shortages due to disruptions from Russia's top oil producer (Yukos), Iraq War, and election in Venezuela, flu vaccine shortage, delays in Los Angeles and Long Beach ports
Aug. 2005 (SBI=130): Hurricane Katrina supply disruptions (fears of oil supply disruptions due to damage at Gulf Coast refineries)
Sept. 2005 (SBI=245): Hurricane Rita and Hurricane Katrina supply disruptions (fears of oil supply disruptions due to damage at Gulf Coast refineries)
Oct. 2005 (SBI=147): Hurricane Wilma supply disruptions, discussion of supply disruptions of Hurricane Rita and Hurricane Katrina, flu vaccine shortage
Nov. 2005 (SBI=115): past hurricanes disruptions (especially construction materials), flu vaccine shortage
Mar. 2011 (SBI=146): Tôhoku earthquake and tsunami supply chain disruptions (auto makers, batteries, etc.), fears of oil disruptions due to military intervention and conflict in Libya
Jun. 2011 (SBI=118): disruptions of oil in Libya, supply disruptions related to Tôhoku earthquake
Aug. 2017 (SBI=118): fears of oil disruptions and supply disruption caused by Hurricane Harvey
Sept. 2017 (SBI=178): supply disruption in Puerto Rico after Hurricane Maria and supply disruptions caused by Hurricanes Irma and Harvey
Aug. 2018 (SBI=114): fears of supply disruptions due to trade-war tensions with China

**Post-COVID**:
Mar. 2020 (SBI=946): pandemic disruptions
Apr. 2020 (SBI=885): pandemic disruptions

Oct. 2021 (SBI=794): pandemic-related disruptions and congestion in Long Beach and Los Angeles ports
Nov. 2021 (SBI=1028): pandemic-related disruptions and congestion in Long Beach and Los Angeles ports
Dec. 2021 (SBI=767): pandemic-related disruptions (omicron)
Jan. 2022 (SBI=798): pandemic-related disruptions (omicron), chip shortages, risk of oil and gas disruptions related to RUS–UKR war

**United Kingdom**

**Pre-COVID**:
Jan. 2003 (SBI=106): school staff supply shortages
Oct. 2004 (SBI=117): risk of oil supply shortages, flu vaccine shortages
Sep. 2005 (SBI=108): gasoline and organic milk supply shortages
Dec. 2005 (SBI=105): petrol supply shortages due to a fire in the oil terminal Hemel Hempstead
Jan. 2006 (SBI=112): risk of gas shortages
Feb. 2006 (SBI=103): oxygen supply shortages
Apr. 2006 (SBI=105): energy supply shortages
Nov. 2006 (SBI=101): winter flu vaccine shortages
Jan. 2007 (SBI=105): disruption to power supplies due to storms in London and the southeast
May. 2007 (SBI=103): housing-sector supply shortages
Jul. 2007 (SBI=108): food supply shortages due to floods from heavy rains
Apr. 2008 (SBI=130): Grangemouth refinery strike
May. 2008 (SBI=101): beef supply shortages, oil supply disruptions
Jun. 2008 (SBI=118): scarce oil supply, fuel supply problems
Jan. 2010 (SBI=131): disruptions related to Big Freeze
Dec. 2010 (SBI=126): disruptions related to Big Freeze, swine flu vaccine shortages
Jan. 2011 (SBI=114): water supply disruptions, swine flu vaccine shortages
Jun. 2018 (SBI=115): CO2 shortages, risk of supply disruptions associated with possible no-deal Brexit
Jul. 2018 (SBI=152): risk of supply disruptions associated with possible no-deal Brexit

Sep. 2018 (SBI=102): risk of supply disruptions associated with possible no-deal Brexit
Nov. 2018 (SBI=108): winter flu vaccine shortages, risk of supply disruptions associated with possible no-deal Brexit
Dec. 2018 (SBI=140): risk of supply disruptions associated with possible no-deal Brexit
Jan 2019 (SBI=146): risk of supply disruptions associated with possible no-deal Brexit
Feb. 2019 (SBI=114): risk of supply disruptions associated with possible no-deal Brexit
Aug. 2019 (SBI=272): drugs supply shortages, risk of supply disruptions associated with possible no-deal Brexit
Sept. 2019 (SBI=166): drugs supply shortages, risk of supply disruptions associated with possible no-deal Brexit
Oct. 2019 (SBI=117): drugs supply shortages, risk of supply disruptions associated with possible no-deal Brexit

**Post-COVID:**
Sept. 2021 (SBI=1104): delays and supply shortages related to COVID and Brexit
Oct. 2021 (SBI=1323): delays and supply shortages related to COVID and Brexit
Nov. 2021 (SBI=755): delays and supply shortages related to COVID and Brexit

**Spain**

**Pre-COVID**:
Jan. 2007 (SBI=126): interruptions in electricity supply due to adverse weather conditions
Jul. 2007 (SBI=125): interruptions in electricity supply in Barcelona
Aug. 2007 (SBI=192): interruptions in electricity supply in Barcelona and Valencia
Sep. 2007 (SBI=103): storm-related disruptions in southern regions, risk of oil supply disruptions associated with price spikes
Oct. 2007 (SBI=114): disruptions in electricity supply (particularly power outages in Barcelona, Leon, and Sevilla)
Apr. 2008 (SBI=109): risk of water shortages due to extreme heat
May. 2008 (SBI=111): risk of water shortages due to extreme heat, risk of oil supply disruptions associated with price spikes

Jun. 2008 (SBI=289): transport strike
Jan. 2009 (SBI=127): storm-related disruptions in northern regions
Aug. 2009 (SBI=101): water and electricity shortages in southern regions (particularly in Sevilla and Cadiz)
Mar. 2010 (SBI=157): interruptions in electricity supply in Girona due to adverse weather conditions
Aug. 2010 (SBI=101): interruptions in electricity supply in coastal areas
Mar. 2011 (SBI=163): supply interruptions related to the Fukushima earthquake
Dec. 2011 (SBI=107): gas supply disruptions from the Algeria-Spain pipeline
Feb. 2012 (SBI=104): shortage of selected medicaments
Jan. 2017 (SBI=101): bacterial meningitis vaccine shortages, cold weather supply disruptions
Sep. 2019 (SBI=105): power outage in Canary Islands, risk of supply disruptions associated with possible no-deal Brexit

**Post-COVID:**
Oct. 2021 (SBI=993): chip shortages, risks to gas supply from Algeria
Nov. 2021 (SBI=978): pandemic-related disruptions
Mar. 2022 (SBI=1344): transport strike

**Italy**

**Pre-COVID**:
Jan. 2009 (SBI=180): interruption of gas supply from Russia
Jun. 2010 (SBI=103): gas supply disruptions due to disagreement between Belarus and Russia
Feb. 2011 (SBI=183): risk of gas interruption from Libya, due to civil war
Oct. 2011 (SBI=107): hospitals supply shortages, supply disruptions due to earthquake in Liguria
Jan. 2012 (SBI=142): electricity and gas disruptions due to bad weather
Feb. 2012 (SBI=229): electricity and gas disruptions due to bad weather
May 2012 (SBI=130): refunds for bad weather in January

Mar. 2014 (SBI=118): risk of gas supply disruptions due to the Ukrainian crisis
Dec. 2014 (SBI=104): cold weather disruptions in gas supply
Feb. 2015 (SBI=186): Maserati factory supply shortages, electricity supply disruptions
Jul. 2015 (SB1=111): water supply disruptions
Nov. 2015 (SBI=105): water supply shortages, Alfa Romeo factory supply disruptions
Jan. 2017 (SBI=112): cold weather supply disruptions
Nov. 2018 (SBI=123): energy and water supply disruptions due to bad weather
Jul. 2018 (SBI=118): shortage of selected medicaments

**Post-COVID:**
Jan. 2021 (SBI=789): vaccine shortages
Oct. 2021 (SBI=555): chips and raw material shortage
Mar. 2022 (SBI=696): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
Apr. 2022 (SBI=614): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
May 2022 (SBI=686): risk of oil and gas stop from Russia
Jun. 2022 (SBI=628): risk of oil and gas stop from Russia

**France**

**Pre-COVID:**
Apr. 2006 (SBI=101): water supply shortages due to low levels of underground water reserves
Jun. 2006 (SBI=111): steel supply shortages
Aug. 2006 (SBI=149): water supply shortages
Nov. 2006 (SBI=119): diverse supply shortages (electricity, electronic components, textile manufacturers' input materials)
Jan. 2007 (SBI=146): roads blocked by snowed caused supply disruptions in the factories of Peugeot-Citroën, gas disruptions due to 2007 Russia–Belarus energy dispute
Jun. 2007 (SBI=116): fish market supply disruptions
Dec. 2007 (SBI=102): transport strike, water supply issues, problems in input supplies to auto industry
Apr. 2008 (SBI=127): organic food supply shortages, strike in Coca-Cola factory

Jan. 2009 (SBI=173): interruption of gas supply from Russia
Dec. 2009 (SBI=141): oil supply disruptions due to a pipeline rupture, energy supply disruptions due to multiple worker strikes
Oct. 2010 (SBI=257): oil shortages due to pension reform strike
Mar. 2011 (SBI=121): supply problems related to the Fukushima earthquake
Jun. 2011 (SBI=151): oil supply disruptions from Libya, due to civil war
Jun. 2013 (SBI=110): crops supply shortages due to hailstorms and heavy rains
May. 2016 (SBI=249): oil shortages due to new labor law strike
Jul. 2016 (SBI=159): fuel shortages due to strikes, bad weather supply disruptions
Aug. 2018 (SBI=155): different supply problems
Sep. 2018 (SBI=110): bitumen supply shortages
Nov. 2018 (SBI=145): oil shortages due to Gilets Jaunes strike
Dec. 2018 (SBI=240): oil shortages due to Gilets Jaunes strike
Feb. 2019 (SBI=109): supply shortage of medicines

**Post-COVID:**
Apr. 2020 (SBI=1182): pandemic disruptions
May. 2020 (SBI=1026): pandemic disruptions
Aug. 2021 (SBI=885): pandemic-related disruptions (semiconductors and raw materials)
Jan. 2022 (SBI=973): chip shortages, risk of oil and gas disruptions related to RUS–UKR war, problems with nuclear power stations over corrosion
May. 2022 (SBI=1086): supply shortages, risk of oil and gas disruptions related to RUS–UKR war, problems with nuclear power stations over corrosion
Jul. 2022 (SBI=884): supply shortages, risk of oil and gas disruptions related to RUS–UKR war

**Germany**

**Pre-COVID**:
Dec. 2007 (SBI=89): Mercedes Benz and Sharp TV key components supply disruptions
Dec. 2010 (SBI=121): cold weather supply disruptions

Apr. 2011 (SBI=107): electricity companies supply disruptions due to shutdowns in gas and coal power plants
Nov. 2012 (SBI=87): delay in delivery of new regional transportation trains intended for winter
Dec. 2012 (SBI=100): supply shortages of medicines, domestic train manufacturers supply disruptions
Jun. 2013 (SBI=113): long-distance trains supply shortages
Nov. 2013 (SBI=84): medicines supply disruptions
Aug. 2016 (SBI=136): Volkswagen key component supply disruptions
Dec. 2016 (SBI=99): medicines supply disruptions
Apr. 2017 (SBI=119): medicines supply disruptions (particularly anesthetic deliveries)
May. 2017 (SBI=109): BMW components supply disruptions
Jul. 2017 (SBI=105): Bayern painkillers supply shortages
Aug. 2017 (SBI=116): disruptions in egg supply, closure of Rhine Valley railway route
Jul. 2018 (SBI=88): risk of water shortages due to extreme heat
Aug. 2018 (SBI=95): risks for German car manufacturers due to U.S. and Mexico free-trade agreement, shortage of truck drivers
Oct. 2018 (SBI=104): fuel delivery shortages by maritime routes due to low water levels, Frankfurt Airbus plant production disruptions
Dec. 2018 (SBI=124): flu vaccines supply disruptions
Feb. 2019 (SBI=109): construction materials supply disruptions (particularly sand)
Mar. 2019 (SBI=86): medicines supply disruptions (particularly oxytocin)
Apr. 2019 (SBI=113): power generation supply disruptions due to energy transition, risk of supply disruptions associated with possible no-deal Brexit
May. 2019 (SBI=87): Loewe supply disruptions; closure of Russian oil pipeline
Jul. 2019 (SBI=149): medicines supply disruptions
Nov. 2019 (SBI=91): multi-day strike in Amazon, Leipzig, medicines supply disruptions (particularly antidepressants and epilepsy related)
Dec. 2019 (SBI=123): medicines supply disruptions

**Post-COVID:**
Mar. 2020 (SBI=809): pandemic disruptions
Apr. 2020 (SBI=980): pandemic disruptions
Oct. 2021 (SBI=952): pandemic-related disruptions (particularly chip shortages)
Mar. 2022 (SBI=1096): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
Apr. 2022 (SBI=824): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
May. 2022 (SBI=878): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
Jun. 2022 (SBI=812): chip shortages, risk of oil and gas disruptions related to RUS–UKR war

**China**

**Pre-COVID:**
Jan. 2011 (SBI=142): cold weather disruptions in transportation and energy supply, steelmakers supply shortages due to floodwaters disrupting vital coal supplies from Australia
Feb. 2011 (SBI=130): farm products supply shortages (particularly vegetables and grain), refined oil products supply shortages
Mar. 2011 (SBI=198): supply interruptions related to the Fukushima earthquake
Apr. 2011 (SBI=195): supply interruptions related to the Fukushima earthquake (particularly car makers), power outages supply disruptions in aluminum and lead-acid battery industries
May. 2011 (SBI=182): power generation supply disruptions due to a shift in investment to new energies, supply disruptions related to a drought along the Yangtze River
Jun. 2011 (SBI=137): energy supply shortages
Jul. 2011 (SBI=128): energy and copper supply shortages
Jan. 2012 (SBI=104): fuel supply shortages
Dec. 2017 (SBI=115): gas supply shortages
Jul. 2018 (SBI=113): tariff war with the United States resulting in supply shortages of soybeans, sport-utility vehicles, and chemicals
Feb. 2019 (SBI=104): risk of supply disruptions associated with a possible no-tariff relief with the United States, iron ore supply shortages

May. 2019 (SBI=127): copper supply shortages, housing supply shortages in Hong Kong
Sep. 2019 (SBI=119): nickel ore supply disruptions, pork supply shortage caused by African swine fever

**Post-COVID:**
Feb. 2020 (SBI=590): pandemic disruptions
Mar. 2020 (SBI=469): pandemic disruptions
Oct. 2021 (SBI=536): energy supply disruptions related to shortage of coal supply, labor force shortages related to pandemic restrictions
Apr. 2022 (SBI=545): manufacturers supply shortages related to pandemic disruptions
May. 2022 (SBI=560): labor force shortages related to pandemic restrictions

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# The Economic Effects of Global Inflation Uncertainty*

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This paper investigates the impacts of inflation uncertainty on inflation and economic activities. We take three steps. We first put together various measures of inflation uncertainty—including survey based and model based—and extract a common measure for the group of seven advanced economies and seven large emerging market economies. Using the novel cross-country data, we estimate a panel structural VAR model to analyze how inflation uncertainty affects macroeconomic and financial variables. Finally, we explore the transmission channels of the uncertainty shock through the lens of the dynamic stochastic general equilibrium (DSGE) model. We find that inflation uncertainty has sharply risen globally since the COVID-19 pandemic, reaching historically high levels comparable to those of the 1970s and 1980s. The empirical results suggest that higher inflation uncertainty has been unambiguously followed by large economic growth declines, particularly in investment. Meanwhile, the relationship between inflation uncertainty and inflation has been heterogeneous across countries and time varying. The simulation results from our DSGE model suggest that different types of propagation channels, through demand and supply, of inflation uncertainty shocks could lead to negative business cycle co-movement and heterogeneous consequences on inflation.

JEL Codes: E31, E32, F42.

*The findings, interpretations, and conclusions expressed in this article are entirely those of the authors and do not necessarily represent the views of the World Bank and the Bank of Korea. The comments and suggestions by the co-editor Òscar Jordà improved the paper significantly. We thank M. Ayhan Kose, Franziska Ohnsorge, Valerie Anne Mercer Blackman, Franz Ulrich Ruch, Daehee Jeong, Sora Chon, and all participants at the 2023 IJCB conference, the KRAIC-BOK-PNU conference, and the internal seminars at the World Bank, the Bank of Korea, and the Korean Development Institute. An earlier version of this paper has been circulated under the title "Global Inflation Uncertainty: Measures and Applications." Author e-mails: jongrimha@worldbank.org and ihsoh@bok.or.kr.

## 1. Introduction

This paper examines the impacts of inflation uncertainty—defined as a common component from various types of inflation uncertainty measures—on economic activities (output, consumption, investment, and industrial production) and inflation. While global inflation and short-term inflation expectations have risen sharply since the COVID-19 pandemic, the uncertainty about future inflation developments has also heightened sharply, reflecting a variety of underlying factors that have altered the perceptions on future inflation after the pandemic's commodity market disruptions, lockdowns, and pent-up demand, supply bottlenecks, and fluctuations in currency values. Inflation uncertainty, which often refers to unpredictable inflation volatility, is an essential concept in economic theory, as it affects consumers' savings and investors' and policymakers' decisions (Rossi, Sekhposyan, and Soupre 2016).

The literature often documents the evidence that higher inflation uncertainty is typically associated with economic slowdowns. However, the causal relationship between inflation uncertainty and inflation is ambiguous and time varying (Bachmann, Berg, and Sims 2015 and Binder 2017 among many others).[1] If inflation uncertainty is expected to rise further in the near future, it will make the prediction of inflation more difficult and strain the recovery of the global economy, which will inevitably complicate the design of macroeconomic policies.

This paper seeks to answer the following questions:

- How has global inflation uncertainty evolved, particularly since the COVID-19 pandemic?
- What is the relationship between inflation uncertainty, inflation, and economic growth?
- What are the economic channels behind the propagation of inflation uncertainty shocks?

We take three steps to answer these questions. First, we uniquely compile a variety of measures for inflation uncertainty: so-called survey-, model-, forecast-, and news-based measures of inflation

[1]A detailed review of the related literature is presented in Appendix A.

uncertainty, as well as common components across the measures. We then adopt a structural vector-autoregressive (SVAR) specification to assess the effects of inflation uncertainty on inflation and real economic activities. More specifically, using monthly (from 2004 to 2019) and quarterly data (1970–2019), we estimate a panel SVAR model that consists of inflation uncertainty, inflation, output, consumption and investments (or industrial production for goods and non-durable goods in the case of monthly frequency), interest rates, and exchange rates in seven of the largest advanced economies (G7) and seven of the largest emerging market economies (EM7).[2]

Finally, to understand further the transmission channels of inflation uncertainty shocks into macroeconomic conditions, we construct a dynamic stochastic general equilibrium (DSGE) model that explicitly incorporates the inflation uncertainty into the New Keynesian framework. In this model, inflation uncertainty is assumed to affect nominal bond yields and a firm's costs in changing nominal prices, altering consumption, investments, and labor demand and supply. Hence, the model allows us to examine the transmission of inflation uncertainty shocks into the economy on both demand and supply side.

The main findings of this paper are summarized as follows. First, inflation uncertainty rose sharply with the onset of the COVID-19 pandemic, consistent across countries and based on different types of inflation uncertainty measures. The post-pandemic level of uncertainty, based on the cross-country averages, was beyond the level of the late 2000s and almost comparable to the level in the 1970s and 1980s when the global economy was hit by oil crises and soaring inflation, followed by global recessions as a result of tightening monetary policies to rein in inflation.

Second, over the recent five decades, heightened inflation uncertainty has been unambiguously followed by large declines in output, in particular in investment and consumption of durable goods, which is entirely consistent with the predictions by Bachmann, Berg, and Sims (2015) and Binder (2017). However, the relationship between inflation uncertainty and inflation has changed over time. In G7

[2] G7 includes the United States, Canada, France, Germany, Italy, Japan, and the United Kingdom, while EM7 encompasses Brazil, China, Mexico, India, Indonesia, Russia, and Turkey.

economies, for instance, inflation persistently rose following heightened uncertainty in the 1970s and 1980s, whereas it declined in the 2000s and 2010s. The changing reactions of inflation over time may reflect the evolving nature of underlying shocks (and their transmission channels) behind the inflation uncertainty around the episodes of the global events—e.g., large adverse supply shocks in the 1970s and 1980s or negative demand shocks around the global financial crisis in the late 2000s.

Third, our empirical results suggest heterogeneous consequences of inflation uncertainty across G7 and EM7. The negative impacts of inflation uncertainty on economic activities were more sizable and statistically significant for G7 countries; a one-standard-deviation increase in inflation uncertainty was associated with a decline in industrial production by up to 10 percent within two years after the shock. Meanwhile, the impacts were relatively short-lived and less sizable (up to 6 percent decline) in EM7 countries. The impacts of inflation uncertainty on inflation were again heterogeneous across the country groups. Among G7 economies, inflation (along with outputs) significantly declined following a positive inflation uncertainty, suggesting that inflation uncertainty might have played a main role as a negative demand shock. On the contrary, among EM7, inflation uncertainty was followed by a substantial increase in inflation (and a reduction in economic activities), possibly reflecting some supply-side forces that led to the opposite directional movements of inflation and outputs in the economies.[3]

Finally, our New Keynesian DSGE model sheds some more light on the propagation mechanism of inflation uncertainty shocks into the economy. On the one hand, the model generates negative comovement among output, investment, and consumption from a rise in inflation uncertainty, leading to adverse fluctuations in the aggregate demand. The dampened consumption demand triggered by heightened inflation uncertainty causes a decline in output according to the national account identity and in investment due to a decreased marginal revenue product of capital. The reduced demand in turn leads to declines in inflation. On the other hand, a heightened inflation uncertainty raises markups of the firms and inflation together

[3]This observation is consistent with the synchronized episodes of high inflation and inflation uncertainty in those countries in the 2000s and 2010s.

and thereafter lowers the firm's demand for labor inputs. This can reduce the final production (supply) to the extent that it offsets the effects of the increased precautionary labor supply by households. Reflecting these different channels, our simulation results suggest that inflation can either rise or decline in response to the heightened inflation uncertainty depending upon the main underlying channels behind the shock, which are determined by the structure of the model economy (as reflected in the model parameters)—including the degree of risk aversion of economic agents.

The paper is expected to contribute to the literature in three ways. First, to our investigation, this paper is one of the first to put together various types of cross-country inflation measures in a wide range of countries and to examine the global (common) effects of inflation uncertainty. Second, this paper contributes to the literature on inflation uncertainty and economic growth. Our finding is largely in line with the classical theory proposed by Friedman (1977) that inflation brings about high uncertainty about the future, thereby leading to high unemployment and low output, and with the main empirical evidence in a large body of studies including Davis and Kanago (1998), Grier and Perry (2000), Elder (2004), and Binder (2017).[4] Our results are, however, in contrast to those studies that find positive or negligible relation (Clark 1997; Barro 1998; Fountas 2010; Baharumshah, Slesman, and Wohar 2016).[5]

This study is also expected to shed more light on the debates on the relation between inflation uncertainty and inflation by exploring the data in a broad panel of countries over the long term. Our empirical results based on the data over the period of the 1970s–1990s are in line with the theories such as by Cukierman and Meltzer (1986) as well as the empirical findings in Leduc, Sill, and Stark

[4]These studies use different estimation methods. For example, Grier and Perry (2000) apply a generalized autoregressive conditional heteroskedasticity (GARCH) model to test the adverse impact of uncertainty on output, and Binder (2017) uses round number responses from surveys to show that higher uncertainty explains low consumption on durable goods, cars, and homes.

[5]Armantier et al. (2015) and Baharumshah, Slesman, and Wohar (2016) explain that the positive relation between inflation uncertainty and output growth can partly reflect the precautionary consumption and consumer behaviors. Main mechanisms of the relationship could be understood in a New Keynesian framework as briefly discussed in Section 5.

(2007) that argue the positive relation between inflation uncertainty and inflation. Fountas (2010) also documents the inflationary effect of inflation uncertainty, along with some country-specific evidence in Berument, Yalcin, and Yildirim (2012) for the United States, Ozdemir (2010) for the United Kingdom, Berument, Yalcin, and Yildirim (2011) for Turkey, and Jiang (2016) for China. Our result based on more recent (post-2000) data, to the contrary, supports the Holland hypothesis (Holland 1995), which explains the negative relationship from the viewpoint of social cost, supported by the empirical findings of Balcilar and Ozdemir (2013) based on the estimation of a Markov-switching VAR model.

The paper is organized as follows. Section 2 introduces the measures of inflation uncertainty and its evolution. Section 3 explains an empirical model and data and Section 4 discusses the main empirical results. In Section 5, the key empirical features of macroeconomic response to inflation uncertainty are explored in a New Keynesian framework. Section 6 concludes. Related literature, the details of empirical and theoretical models, and robustness checks are discussed in the appendices.[6]

## 2. Inflation Uncertainty Measures

Inflation uncertainty is an unobserved variable, and many different measures have been proposed in the literature. Some studies adopt a survey-based approach, while others depend on the volatility derived from time-series models. Another strand of literature uses the realized forecast errors of inflation. Each measure is derived from different assumptions that are likely to suffer from idiosyncratic measurement errors. Empirical results on the impact of inflation uncertainty substantially differ depending on the choice of the uncertainty measure.

Against this background, we employ four different types of inflation uncertainty: namely, survey-, model-, forecast-, and news-based

[6] In Appendix A, an extensive body of related literature is reviewed. Appendix B presents the results based on the alternative measures of inflation uncertainty. Appendix C reports additional figures. Appendix D provides the details of the DSGE model.

measures. The common measure of inflation uncertainty is extracted from them using the principal component analysis and is employed as the benchmark indicator of inflation uncertainty. Each specific measure is used for empirical analyses for robustness checks. Table 1 summarizes each measure, and Appendix A provides more technical details.

### *2.1 Measures of Inflation Uncertainty*

**Survey-Based Measure.** We first use individual surveys for headline consumer price index (CPI) inflation from professional forecasters conducted by Consensus Economics. It reports average annual growth rates of expected inflation for the current and the next year on a monthly basis. The survey has an advantage in collecting responses from knowledgeable, professional forecasters who are well-informed about the economy's current condition.[7] Dovern and Weisser (2011) find that individual forecasts of U.S. inflation are largely unbiased. Following Bomberger and Frazer (1981) and Giordani and Söderlind (2003), we use cross-sectional dispersion of short-term (one-year-ahead) forecasts. We interchangeably use two types of dispersion index: standard deviation and the difference between high and low forecasts within the month.

**Model-Based Measure.** Next, we estimate the stochastic volatility of inflation as a proxy for inflation uncertainty using a GARCH (1,1) model and an unobserved component stochastic volatility in the mean (UCSVM) model.

Many different types of ARCH models have been used extensively to model inflation uncertainty. A GARCH model with time-varying parameters accommodates events such as alterations in monetary regimes or variations in steady-state inflation. This has the advantage of being flexible to allow for a non-stationary inflation rate. The model is given by a conditional mean (signal) equation (1), a state equation (2), and an evolution of conditional error variance (3).

[7]Additionally, the survey includes individual data and identifies the forecasters by name rather than just assigning them a number. This creates a strong motivation for forecasters to make accurate predictions to protect their reputation.

**Table 1. Measures of Inflation Uncertainty**

| Measures of Inflation Uncertainty | | Details | References |
|---|---|---|---|
| A. Model Based | SVM | Decompose inflation into random drift and variance terms | Chan (2017) |
| | | Stochastic variance terms follow AR process | Stock and Watson (2016) |
| | GARCH (1,1) | Estimate condition variance of residuals in inflation | |
| | | Mean equation is assumed to follow AR process | Batchelor and Dua (1996) |
| B. Forecast Based | VAR | Standard deviation of forecast error of inflation using VAR model of inflation, output, oil prices, exchange, and interest rates | Giordani and Söderlind (2003)<br>Peng and Yang (2008) |
| C. Survey Based | Consensus Forecast | Mean-squared error of consensus forecasts | Cukierman and Wachtel (1982)<br>Batchelor and Dua (1996) |
| | | Cross-sectional disagreement | Giordani and Söderlind (2003) |
| | | (standard deviation) of surveys | Bomberger (1996) |
| | | Dispersion index (high–low) or interquartile range | Mankiw, Reis, and Wolfers (2003) |
| D. News Based | Google Trends | Total search of keywords “Inflation” in the news articles | Bloom (2014)<br>Castelnuovo and Tran (2017) |
| E. Global Measure | | First principal component of the various uncertainty measures | Grimme, Henzel, and Wieland (2014) |

$$\pi_t = a_{0,t} + a_{1,t}\pi_{t-1} + a_{2,t}\pi_{t-2} + e_t^{\pi}, \quad e_t^{\pi} \sim \mathcal{N}(0, h_t) \tag{1}$$

$$A_t = A_{t-1} + e_t^{A}, \quad e_t^{A} \sim \mathcal{N}(0, Q), \quad \text{where} \quad A_t = [a_{0,t}, a_{1,t}, a_{2,t}]' \tag{2}$$

$$h_t = d + \phi(e_{t-1}^{\pi})^2 + \gamma h_{t-1}, \tag{3}$$

where $A_t$ is a vector of time-varying coefficients. We assume inflation $\pi_t$ follows an AR(2) process. The coefficient vector follows a random walk. $h_t$ describes conditional error variance from a GARCH(1,1) process. $Q$ is a homoskedastic covariance matrix of shocks $e_t^A$. The variance combines model uncertainty emerging from time variation of the coefficients and uncertainty emerging from the shock process $e_t^A$ (Evans 1991).

Along with the GARCH model, the UCSVM model is used (Kim, Shephard, and Chib 1998; Stock and Watson 2007; Chan 2017). Following Chan (2017), we consider a time-varying parameter model with stochastic volatility where the stochastic volatility also enters the conditional mean equation. Unlike GARCH models, where error variance is fully described by its own past, the variance of first-moment shocks is assumed to be driven by an exogenous stochastic process. The state-space representation is given by Equations (4), (5), and (6):

$$\pi_t = \tau_t + \alpha_t \exp(\theta_t) + \epsilon_t^{\pi}, \quad \epsilon_t^{\pi} \sim \mathcal{N}(0, \exp(\theta_t)) \tag{4}$$

$$\gamma_t = \gamma_{t-1} + \epsilon_t^{\gamma}, \quad \epsilon_t^{\gamma} \sim \mathcal{N}(0, \Omega), \quad \text{where} \quad \gamma_t = [\tau_t, \alpha_t]' \tag{5}$$

$$\theta_t = \mu + \phi(\theta_{t-1} - \mu) + \beta_t \tau_{t-1} + \epsilon_t^{\theta}, \quad \epsilon_t^{\theta} \sim \mathcal{N}(0, \sigma^2), \tag{6}$$

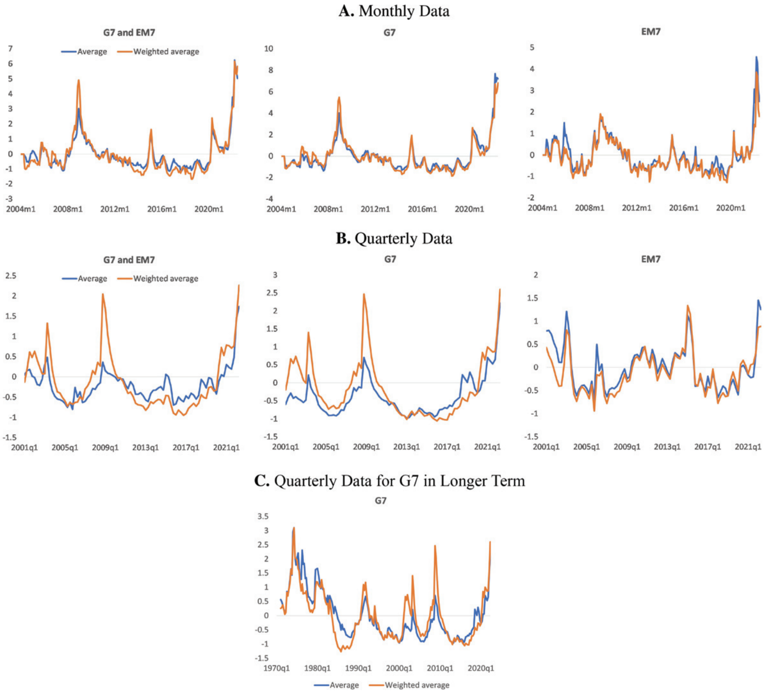
where $\epsilon_t^{\pi}$ is a short-term shock in the measurement equation (4) with variance $\exp(\theta_t)$. The disturbances $\epsilon_t^{\pi}$ and $\epsilon_t^{\theta}$ are mutually and serially uncorrelated. The log-volatility $\theta_t$ follows a stationary AR(1) process with $\mid \phi \mid < 1$, and it is initialized with $\theta_1 \sim \mathcal{N}(\mu, \sigma^2/(1-\phi^2))$. Moreover, the trend component $\tau_t$ follows a random walk driven by a (level) shock. $\Omega$ is a covariance matrix of the innovation vector $\epsilon_t^{\gamma}$. The model is estimated with the Gibbs sampler.

**Forecast-Based Measures.** As a complement to the survey- and model-based measures, a forecast-based approach is suggested, which relies on inflation-forecasting models. For instance, in Giordani and Söderlind (2003), a single VAR model was recursively estimated, and the standard deviation of the forecast error for inflation was calculated for each period. Chua, Kim, and Suardi (2011) implemented this idea by generating error bands using the recursive bootstrapped VAR models introduced by Peng and Yang (2008). We similarly employ a measure of uncertainty derived from VAR residuals, which are assumed to be homoskedastic. More specifically, we estimate monthly and quarterly VAR models that consist of inflation, outputs, consumption, investment, interest rates, and exchange rates (again, for monthly models, consumption and investment are replaced by industrial productions for durable and non-durable goods, respectively).

**News-Based Measure.** More recently, a growing number of studies have proposed an alternative measure of so-called news-based uncertainty that employs the density of certain keywords in news articles (Bloom 2014, among many others). Following Castelnuovo and Tran (2017), we construct Google Trends based inflation uncertainty indices for the countries of interest. Google Trends inflation uncertainty indices are based on the assumption that economic agents, represented by Internet users, search for online information when they feel uncertain. This assumption implies that the search frequency of terms associated with future uncertain events increases when the level of uncertainty is high. The index is based on keywords of "*inflation*" or "*price*."

**Common Measure of Inflation Uncertainty.** As previously discussed, individual measures may be contaminated by idiosyncratic measurement errors. In addition, each measure may deliver economic implications in different aspects, reflecting its underlying drivers (Kozeniauskas, Orlik, and Veldkamp 2018; Cascaldi-Garcia et al. 2023). This calls into question whether an individual measure delivers a reliable signal. A simple average over individual measures could be a viable measure that delivers a robust indicator of inflation uncertainty. However, it does not entirely account for the variability in the data. In general, individual measures have a greater tendency to diverge during periods of turbulence. Furthermore, when macroeconomic variables become more volatile, a researcher may encounter survey participants who adhere to the consensus rather than expressing their own views. Therefore, to capture each measure's variations,

**Figure 1. Inflation Uncertainty**




**Note:** These figures show inflation uncertainty measures based on monthly (A) and quarterly (B) data. Panel (C) uses longer-term data for G7 countries starting from 1970. The uncertainty is based on the first principal components of the survey-, model-, forecast-, and news-based measures of inflation uncertainty. Please see Section 3 for more details.

we employ the first principal component to capture common information in different uncertainty measures. The first principal component loads broadly equally on each measure and helps alleviate the measurement error problem.

### *2.2 Evolution of Inflation Uncertainty*

Over the recent two decades, the global inflation uncertainty, proxied by the average across G7 and EM7, has fluctuated around global economic events, as shown in the first chart of panel A in Figure 1. It has been relatively stable (below the long-term average) during the period leading up to the global financial crisis. The uncertainty rose sharply from late 2007 until it started to decline in early 2009 when global inflation fluctuated significantly amid a widespread collapse in global commodity prices, followed by the global financial crisis in late 2008. In 2014–15, the inflation uncertainty rose due mainly to the significant oil price plunges, although the degree of the uncertainty rise was around one-half of that around the global financial crisis.

Since the onset of the COVID-19 pandemic, inflation uncertainty has risen sharply. It jumped in March and April 2020 when the global economy was hit hard by sizable adverse health and economic shocks due to the pandemic. The inflation uncertainty then declined to around the long-term average before it rose again in the third quarter of 2021. As of June 2022, the inflation uncertainty is four to seven standard deviations higher from the long-term average, depending on the country groups and the aggregation method, which is higher than the peak in the late 2000s.

We also report the evolution of inflation uncertainty across different groups of countries, G7 and EM7. The results are broadly consistent across the country groups, as shown in the two right charts in panel A of Figure 1. The inflation uncertainty rose sharply around the global financial crisis in 2008–09, and oil price plunged in the mid-2010s in both country groups. However, the inflation uncertainty for EM7 countries was more volatile in the early 2000s and the late 2010s when some EM7 countries experienced domestic financial and economic crises.

The evolution of inflation uncertainty is consistent with quarterly, model-based measures, as shown in panel B of Figure 1. When using long-term quarterly data that span to the 1970s, where we use GDP-weighted or simple average of G7 inflation uncertainty, the results suggest that the inflation uncertainty spiked in the mid-1970s and the early 1980s when the global economy suffered the first and second oil crises and the subsequent global recessions in 1975 and 1982 (panel C of Figure 1).

Country-specific results are presented in Figure C.1 of Appendix C. Inflation uncertainty measures in G7 economies were more broad based than those in EM7 economies. Among G7 economies, Germany and Italy exhibit higher volatility of inflation uncertainty than other G7 economies. In most G7 countries except the United

States and Japan, the uncertainty level as of June 2022 has already exceeded that of the global financial crisis.

Meanwhile, the inflation uncertainty has been more heterogeneous across EM7 economies. Brazil, Mexico, and Indonesia experienced a surge in inflation uncertainty from the early to mid-2000s. Brazil experienced considerable inflation uncertainty between late 2002 and early 2003 when economic confidence plunged, caused by a reversal in capital flows and unstable domestic political conditions.[8] In Mexico, the rise of uncertainty in 2008–09 was driven by the global financial crisis and its reliance on the United States as an export market. In Indonesia, the inflation uncertainty rose sharply in 2005 due to soaring energy prices (International Monetary Fund 2008).

In India, Russia, and Turkey, inflation uncertainty rose sharply in the mid-to-late 2010s. While India's inflation uncertainty rose sharply around the global financial crisis, the uncertainty spiked again in late 2013, when higher domestic inflation was followed by increasing food prices and domestic structural problems.[9] In Russia, food supply shocks and currency depreciation seem to have caused a surge in inflation uncertainty.[10] Meanwhile, in Turkey, a substantial currency devaluation in 2018 and concerns about the central bank's independence and diplomatic issues with the United States led to a surge in inflation and inflation uncertainty.

Furthermore, the inflation uncertainty exhibits analogous movements across different measures. As shown in Figure C.1 of Appendix C, the survey-based inflation measure generally followed the common factor for inflation uncertainty. Based on model- and forecast-based measures, the uncertainty reached a somewhat greater level in the 1970s and 1980s than after the 2000s. That said, in the United

[8]Markets feared that shifts in political power from elections would lead to different attitudes toward capital accounts and monetary policy (Bevilaqua and Loyo 2005).

[9]Rising food prices were driven by rising farm wages, increasing global food prices, and loose fiscal and monetary policies as well as market support prices for farmers, which continued to grow even without natural disasters, thus causing market distortions (Gulati and Saini 2013).

[10]The government imposed bans on food imports from the United States, the European Union, and other countries in response to sanctions over Russia's actions in Ukraine. Sharp ruble depreciation, which started in the second half of 2014, also increased the cost of imports.

States, the uncertainty was most significant in the late 2000s, and the level in 2022 was also comparable to that in the 1970s and 1980s. Meanwhile, based on the news-based measure available only after 2004, the level was the highest in 2022.

### *2.3 Inflation Uncertainty and Other Variables*

Our inflation uncertainty measures are constructed based on various approaches, and they can be mirroring other structural shocks, in particular those associated with inflation. Also, the measure may contain common information with different types of uncertainty. To check these issues, we carry out a battery of univariate regressions that test the exogeneity of the inflation uncertainty measure, following the preceding studies (Kozeniauskas, Orlik, and Veldkamp 2018; Berger, Dew-Becker, and Giglio 2020):

$$z_t = \alpha + \beta_i m_{i,t} + \theta_{i,t}, \tag{7}$$

where $z_t$ denotes our measure of inflation uncertainty and $m_i$ corresponds to the different macro variable or uncertainty measure $i$. We test the null hypothesis of $\beta_i = 0$ to determine whether the inflation uncertainty measure correlates with $m_i$.

Regarding $m_i$, we mainly consider two groups of variables. First, different measures of uncertainty are compared with the inflation uncertainty. In doing so, we examine whether our measure of inflation uncertainty delivers distinct information from other types of uncertainty in the literature or reflects similar information to them. In this vein, we employ VIX (Bloom 2009), economic policy uncertainty (Baker, Bloom, and Davis 2016), geopolitical risk (Caldara and Iacoviello 2022), financial and macroeconomic uncertainty (Jurado, Ludvigson, and Ng 2015), monetary policy uncertainty (Husted, Rogers, and Sun 2020; Arce-Alfaro and Blagov 2023), trade policy uncertainty (Caldara et al. 2020), and world uncertainty (Ahir, Bloom, and Furceri 2022) for $m_i$.[11]

Second, various macroeconomic and financial shocks related to inflation and economic activity are considered based on the previous

[11] For a recent extensive survey of uncertainty measures, see Cascaldi-Garcia et al. (2023).

studies. This is expected to help understand the underlying nature of inflation uncertainty and its interlinkage with business and financial cycles (Gilchrist and Zakrajšek 2012; Baker, Bloom, and Davis 2016). In addition, various policy shocks, such as monetary policy (Gürkaynak, Sack, and Swanson 2005) and fiscal policy (Romer and Romer 2010) shocks are also tested. Correlated with news shocks, uncertainty shocks may act as potential drivers of business cycles (Beaudry and Portier 2014; Berger, Dew-Becker, and Giglio 2020). Hence, news shocks (Barsky and Sims 2011) and productivity shocks (Levchenko and Pandalai-Nayar 2020) are also used as a regressor. Considering the relationship among uncertainty, commodity market, and economic activity, oil prices and production are employed (Kilian 2008; Ha, Kose, and Ohnsorge 2019). Finally, given a close relation between inflation uncertainty and expectation, we also compare its movements with inflation expectations (Drakos, Konstantinou, and Thoma 2020).

The estimation results for global inflation uncertainty are summarized in Table 2. In most cases, our estimation does not reject the null hypothesis of $\beta_i = 0$ at the 1 percent significance level, suggesting that our measure of inflation uncertainty is not significantly correlated with different types of uncertainty and other structural shocks. For the robustness of results, we also implement similar tests on the inflation uncertainty measures for the sub-groups of G7 and EM7, each reported in Table C.1 of Appendix C, respectively. By and large, the results are consistent with the case of global inflation uncertainty. These indicate that global inflation uncertainty delivers distinct information from other uncertainties and does not only mirror other structural shocks in the economy.[12]

That said, there are a few exceptional cases where our measure of inflation uncertainty exhibits a correlation with structural shocks at the 5 or 10 percent significance level. Notably, such cases include financial shocks in common, and policy shocks in particular in EM7. These significant correlations may indicate that inflation uncertainty

[12]This point is also confirmed by our robustness checks using VIX and EPU in the panel SVAR framework, as documented in Appendix B. In addition, although not reported, we conduct residual tests by comparing the residuals of endogenous variables in the VAR with inflation uncertainty. All the correlation coefficients are shown to be insignificant.

**Table 2. Regression Results of Global Inflation Uncertainty on Other Uncertainties and Structural Shocks[1]**

| Structural Shocks | | Country | Related Studies | $\beta$ | SE | $P$-value | Obs. | Sample |
|---|---|---|---|---|---|---|---|---|
| Uncertainty | VIX | US | Bloom (2009) | 0.00 | 0.01 | 0.73 | 185 | 2004:M8–2019:M12 |
| | Macro Uncertainty ($h = 3$)[2] | US | Jurado, Ludvigson, and Ng (2015) | –0.06 | 0.22 | 0.78 | 185 | 2004:M8–2019:M12 |
| | Financial Uncertainty ($h = 3$)[2] | US | Jurado, Ludvigson, and Ng (2015) | –0.06 | 0.19 | 0.74 | 185 | 2004:M8–2019:M12 |
| | Geopolitical Risk | Global | Caldara and Iacoviello (2022) | –0.03 | 0.03 | 0.36 | 185 | 2004:M8–2019:M12 |
| | Monetary Policy Uncertainty | US | Husted, Rogers, and Sun (2020) | –0.03 | 0.03 | 0.25 | 185 | 2004:M8–2019:M12 |
| | Trade Policy Uncertainty | Global | Caldara et al. (2020) | –0.04 | 0.04 | 0.23 | 185 | 2004:M8–2019:M12 |
| | Economic Policy Uncertainty | Global | Baker, Bloom, and Davis (2016) | –0.03 | 0.03 | 0.34 | 185 | 2004:M8–2019:M12 |
| | World Uncertainty (All) | Global | Ahir, Bloom, and Furceri (2022) | –0.02 | 0.01 | 0.20 | 80 | 2000:Q1–2019:Q4 |
| Monetary Policy[3] | MP1 | US | Gertler and Karadi (2015), Gürkaynak, Sack, and Swanson (2005) | –1.33 | 1.22 | 0.28 | 179 | 2004:M8–2019:M6 |
| | MP2 | | | –2.53 | 2.11 | 0.23 | 179 | 2004:M8–2019:M6 |
| | FF1 | | | –5.75 | 5.18 | 0.27 | 179 | 2004:M8–2019:M6 |
| | FF2 | | | –1.98 | 2.20 | 0.37 | 179 | 2004:M8–2019:M6 |
| Fiscal Policy[4] | Government Spending (1) | US | Romer and Romer (2010) | 0.00 | 0.00 | 0.37 | 32 | 2000:Q1–2007:Q4 |
| | Government Spending (2) | | | 0.00 | 0.00 | 0.31 | 32 | 2000:Q1–2007:Q4 |
| Financial[5] | GZ Spread (1) | US | Gilchrist and Zakrajšek (2012) | 0.18 | 0.08 | 0.03 | 74 | 2004:M8–2010:M9 |
| | GZ Spread (2) | | | 0.18 | 0.11 | 0.09 | 74 | 2004:M8–2010:M9 |

(*continued*)

## Table 2. (Continued)

| Structural Shocks | | Country | Related Studies | $\beta$ | SE | $P$-value | Obs. | Sample |
|---|---|---|---|---|---|---|---|---|
| Inflation | Breakeven Inflation (10-year) | US | Drakos, Konstantinou, and Thoma (2020), Kose et al. (2019) | –0.07 | 0.05 | 0.15 | 185 | 2004:M8–2019:M12 |
| | Inflation Expectation (Consensus Forecast, US) | | | –0.05 | 0.07 | 0.49 | 185 | 2004:M8–2019:M12 |
| Oil Price | Oil Production | Global | Kilian (2008) | 0.00 | 0.00 | 0.97 | 41 | 2004:M8–2007:M12 |
| | Oil Price | Global | Ha, Kose, and Ohnsorge (2019) | 0.00 | 0.00 | 0.69 | 41 | 2004:M8–2007:M12 |
| News Shock | VAR(3) Residual | US | Barsky and Sims (2011) | –0.10 | 0.14 | 0.47 | 51 | 2000:Q1–2012:Q3 |
| | VAR(4) Residual | US | Beaudry and Portier (2014) | –0.05 | 0.07 | 0.51 | 51 | 2000:Q1–2012:Q3 |
| Productivity[6] | VAR(6) Residual | US | Levchenko and Pandalai-Nayar (2020) | –0.07 | 0.16 | 0.66 | 72 | 2000:Q1–2017:Q4 |

**Note:** 1. This table reports the estimates ($\beta_i$) of regression (7). Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors are reported.
2. MP1, MP2, FF1, and FF2 indicate the monetary policy shocks identified using intraday movements of federal funds futures rates as suggested by Gertler and Karadi (2015).
3. Three-month-ahead measures of macro and financial uncertainty are taken from Jurado, Ludvigson, and Ng (2015).
4. Exogenous tax changes (1) and those based on the present value (2) are taken from Romer and Romer (2010).
5. Predicted GZ spreads (1) and those controlled for the term structure and interest effects (2) are taken from Gilchrist and Zakrajšek (2012).
6. Following Levchenko and Pandalai-Nayar (2020), residuals of labor productivity are regarded as a proxy for productivity, estimated in the six-variable VAR: labor productivity, real GDP, private consumption, investment, employment, and consumer price.

often coincided with global financial distress in the late 2000s, which led to subsequent global slowdowns, and policy spillovers from a center country. However, the explanatory power, as measured by $\bar{R}^2$ in the regression, was generally less than 5 percent.[13]

In a similar vein, Figure C.6 provides a summary of correlation coefficients between inflation uncertainty and other shocks in a box chart format. Each box and whisker is characterized by 14 (G7 and EM7) correlations between inflation uncertainty in an individual country and the aforementioned shocks or uncertainties. The results largely align with our findings, demonstrating no significant correlations between inflation uncertainty and other structural shocks except in a few cases, such as monetary policy shocks (FF1), financial shocks (GZ spreads), and financial uncertainty.

## 3. Empirical Framework

Following the previous literature that examines the effects of uncertainty on economic activities, we estimate a panel SVAR model that includes seven endogenous variables—inflation uncertainty, consumer price inflation, GDP, consumption, investment, interest rates, and exchange rates. For the monthly data set, GDP, consumption, and investment are replaced by industrial production and the production of durable and non-durable consumption goods.

### *3.1 Methodology*

In its structural form, the panel SVAR model is represented by

$$B_{i,0}Z_{i,t} = A_i + \sum_{j=1}^{L} B_{i,j}Z_{i,t-j} + \epsilon_{i,t}, \tag{8}$$

where $Z_{i,t}$ consists of seven endogenous variables for each country $i$. The vector $\epsilon_{i,t}$ consists of a shock to the inflation uncertainty ("*inflation uncertainty shock*") and other types of structural

[13]Except in the case of GZ credit spreads that do not control for term structure and interest rate effects, $\bar{R}^2$ of the correlation regression reaches around 28 percent. This high explanatory power of GZ credit spreads might be, at least partly, due to the short sample period (2004:M8–2010:M9), which includes the global financial crisis.

macroeconomic and financial shocks corresponding to the other variables. The model enables us to assess the impacts of inflation uncertainty shocks on output, inflation, and financial variables.

The baseline strategy for the identification of global inflation uncertainty shocks is to employ recursive restrictions by using Cholesky decomposition of variance-covariance as in Baker, Bloom, and Davis (2016), Leduc and Liu (2016, 2020), and Levchenko and Pandalai-Nayar (2020). The inflation uncertainty indicator is ordered first, assuming that a structural shock in inflation uncertainty does affect other variables within a period while other structural shocks do not influence the inflation uncertainty indicators. This short-run identification assumption considers that the surveys on inflation are executed during the current period ($t$)—usually around the middle of the month—while the macroeconomic and inflation variables are observed at the time ($t + 1$).

That said, the direction of causation between inflation uncertainty and inflation and economic activity remains debatable. In this regard, to check the sensitivity of the baseline results, we additionally consider two alternative identification schemes: (i) Cholesky restriction that orders the uncertainty last, or (ii) generalized impulse response functions that are not conditional on the variable ordering.

Bayesian method is used in estimating the SVAR model. The procedure draws 1,000 iterations with 500 burn-ins. In reporting the impulse response functions, we present the median of the 500 draws and 16–84 percentile confidence intervals for each forecasting horizon. In the Bayesian estimation, the independent normal-Wishart priors are used.

### *3.2 Data*

Following Barsky and Sims (2012), Leduc and Liu (2020), and Levchenko and Pandalai-Nayar (2020), we include various macro and financial indicators in the VAR system. Monthly data are employed as a baseline for 2004–19.[14] For the estimation of the panel SVAR model, G7 and EM7 data are pooled together or by country groups.

[14] In the literature on the impact of uncertainty, many existing studies used quarterly data, partly due to the unavailability of monthly GDP data. By employing monthly data, it is expected that the identification of the impacts of inflation uncertainty is more accurately obtained.

First, levels of inflation uncertainty indicators are employed. As explained in the previous section, each measure of inflation uncertainty is subject to measurement errors, and we use here the common inflation uncertainty, estimated by using the first principal component of different inflation uncertainty measures. Month-on-month growth rates of industrial output (total, consumption goods on durable and non-durable goods) are employed as proxies for business cycle fluctuations. Inflation rates are based on month-over-month inflation rates of the consumer price index. Interest rates are based on three-month Treasury-bill (TB) yields or policy rates depending on the data availability. For exchange rates, nominal effective exchange rates (NEERs) are used.

To supplement the monthly results, examine the impact of inflation uncertainty on private consumption and investment, and date back to a more extended period up to the 1970s; the panel SVAR model is also estimated using quarterly data. In this case, GDP, private consumption, and investments are used along with inflation, interest rates, and exchange rates as endogenous variables.

## 4. Empirical Results

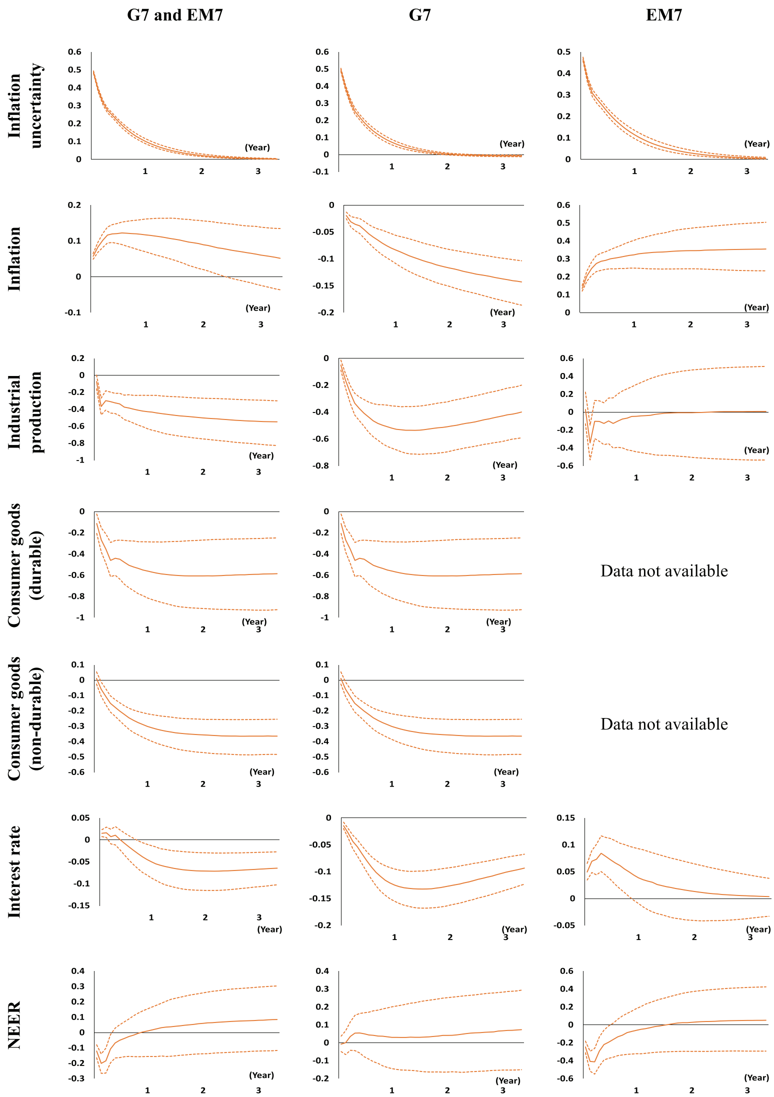
### *4.1 Impact of Inflation Uncertainty on Economic Growth*

Figure 2 presents the dynamic responses of the macroeconomic and financial variables in G7 and EM7 to a positive inflation uncertainty shock, based on monthly (panel A) and quarterly (panel B) data sets. We first explore the results based on monthly data and then check the quarterly results. The sample periods are 2004–19 for both exercises.

**Output.** Inflation uncertainty exhibits countercyclical properties (as shown in the first column of the figure for the combined results for G7 and EM7). Following a one-standard-deviation increase in the uncertainty, monthly industrial production declines by up to 0.6 percentage point (about 7 percentage points annually), whereas the production for durable goods (0.6 percentage point) declines more dramatically than non-durable goods (0.3 percentage point). The negative responses of outputs following the inflation uncertainty shock are in line with, inter alia, the *wait-and-see* effect that economic agents would optimally pause their investments in

## Figure 2. Impulse Responses of Variables to Inflation Uncertainty

**A.** Monthly Data

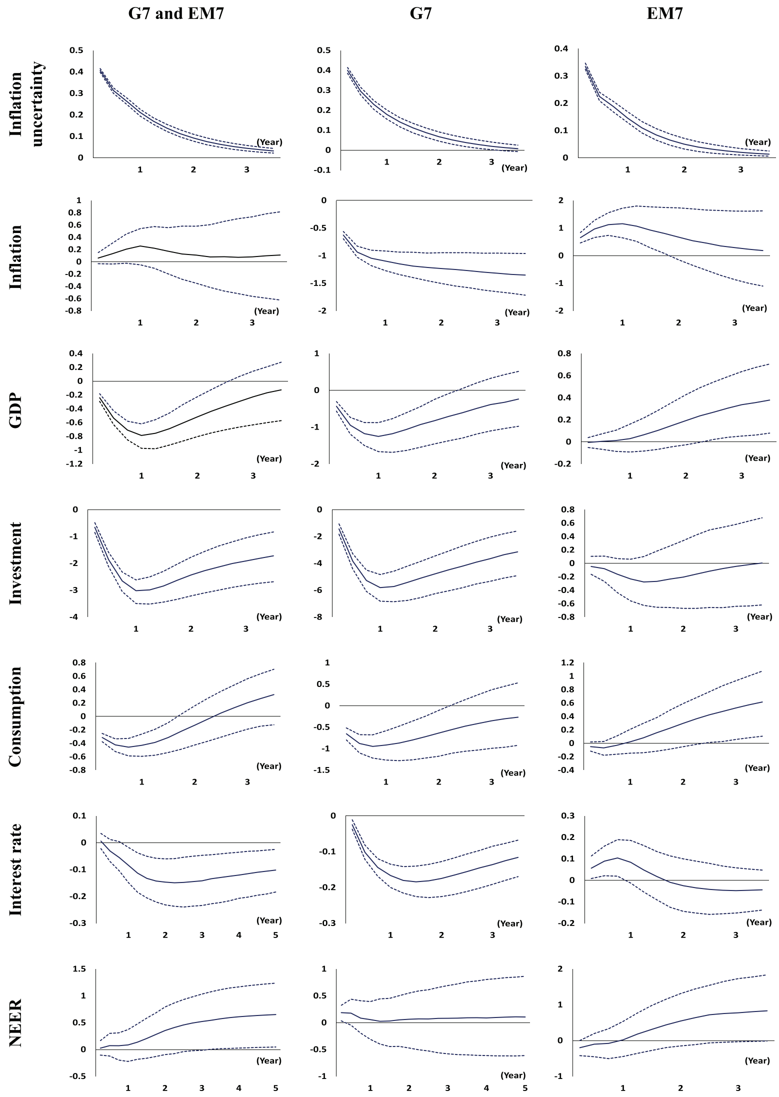



**Note:** The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16 and 84 percentiles of the empirical distribution based on Bayesian estimation.

(*continued*)

# Figure 2. (Continued)

**B.** Quarterly Data




**Note:** The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16 and 84 percentiles of the empirical distribution based on Bayesian estimation.

productive activities and purchases in durable goods and wait until the uncertainty mainly disappears. This is consistent with the finding of Binder (2017) that more uncertain consumers are more reluctant to spend on durable goods, cars, and homes. Our results also align with Grier and Perry (2000), or more recently with Caglayan, Kocaaslan, and Mouratidis (2016), who use time-series models to show the contractionary effects of inflation uncertainty.

**Inflation.** The dynamic responses of CPI inflation following the inflation uncertainty shock are moderately positive (up to 0.1 percentage point) over the forecasting horizon.[15] This relationship is consistent with what Cukierman and Meltzer (1986) argued. Combined with the dynamic responses of output variables, these results suggest that the main drivers of inflation uncertainty may have been supply-side shocks, including oil price shocks or domestic crises and the subsequent currency depreciation, at least based on the combined data of G7 and EM7.[16]

**Financial Variables.** Interest rates (three-month TB yields) fall persistently by up to 0.1 percentage point following an increase in inflation uncertainty. The negative effects may reflect the responses to accommodative policy, which aims to attenuate domestic economic slowdowns. NEERs do not point to any significant reactions, at least based on an aggregate (panel) result.

**Results Using Quarterly Data.** As shown in panel B of Figure 2, the results are consistent when employing quarterly data over the same sample period. Following a heightened inflation uncertainty, domestic output unambiguously declines while inflation responds positively (although statistically insignificant). That said, there are some nuanced differences in the reactions of output variables: the responses of outputs and consumption return to normal levels around three years after the shock. Meanwhile, the impacts are most sizable and persistent on investment, consistent with the results from monthly frequency data, which report more pronounced impacts on durable than non-durable goods. Based on quarterly data, the effects

[15] As will be discussed in the next sub-section, the moderate response of inflation is partly attributable to the heterogeneous responses of the variable across different country groups.

[16] Underlying channels of demand- or supply-driven uncertainty shocks will be discussed further in Section 5.

on interest rates are negative (accommodative), and those on NEER are not statistically significant.

### *4.2 Group-Specific Evidence*

We now present the empirical results across two different groups of countries: G7 (in the second column of Figure 2) and EM7 (in the third column). The results are both similar and different across the two country groups based on the variables.

**Output.** The dynamic responses of output (monthly industrial production) are overall (qualitatively) consistent but quantitatively different across G7 and EM7. More specifically, the negative impacts of inflation uncertainty on economic activities are much more sizable for G7 economies such that industrial production declines by 0.5 percentage point (6 percentage points annually), and the impacts are maximized around two years after the shock. Meanwhile, the negative impacts on industrial production are up to around 0.3 percentage point in EM7 (3–4 percentage points annually). The more sizable and significant effects on outputs in G7 may reflect more synchronized movements of outputs among G7 than among EM7.[17] In the case of G7, where the data for durable and non-durable goods consumption are available for all countries, the impacts of inflation uncertainty are again more sizable for the consumption of durable goods than non-durable goods.

**Inflation.** The impacts on inflation were dynamically opposite across the country groups.[18] Among G7, inflation significantly and consistently declines following a positive inflation uncertainty shock, suggesting that inflation may have been driven mainly by negative demand shocks (Leduc and Liu 2016; Basu and Bundick 2017). On the contrary, inflation uncertainty is followed by a rapid, albeit short-lived, increase in inflation in EM7, which observation

[17]Although not shown in the paper, we also estimated the models based on country-specific data (rather than panel data). The results are quite homogeneous among G7 economies, while they were more heterogeneous regarding the magnitude, persistence, and statistical significance of the impulse response functions.

[18]Indeed, inflation uncertainty rose sharply around the global financial crisis in 2008–09 in all G7 countries.

is consistent with the positive correlation between inflation uncertainty and inflation around the episodes of sharp rising food and energy prices in those countries, as explained in Section 2.[19] This positive relationship is also documented in Fountas (2010), Berument, Yalcin, and Yildirim (2011), and Jiang (2016), supporting the Cukierman–Meltzer (1986) hypothesis.[20]

**Financial Variables.** The responses of interest rates are again in the opposite direction across G7 and EM7 economies. Interest rates decline in G7 following a heightened inflation uncertainty while they rise in EM7. The effects on NEER are insignificant in G7, while the heightened inflation uncertainty leads to currency depreciation in EM7 countries, which could have been another important source of inflationary effects of the inflation uncertainty.

**Results Using Quarterly Data.** Again, the heterogeneous results across G7 and EM7 are confirmed with the estimation using quarterly data (as shown in panel B of Figure 2). These include more sizable and persistent effects of inflation uncertainty on investments than consumption in both G7 and EM7 and heterogeneous impact on inflation and interest rates across the two country groups.

**Policy Implication.** Inflation uncertainty shocks have different impacts across the country groups. Unlike their consistent contractionary impacts in G7 and EM7, albeit stronger in G7, the uncertainty shocks lower inflation in G7 but raise it in EM7. This implies that the shocks resemble demand-side shocks in G7 and supply-side shocks in EM7. Remarkably, short-term interest rates decline in G7 upon the shocks, while the rates rise in EM7. As elaborated upon above, these heterogeneous responses to the inflation uncertainty shocks may reflect the different underlying drivers of inflation uncertainty or the different states of the economy in each group.

From the perspectives of policy reaction to inflation, the dynamic responses of short-term interest rates are consistent with the effects of inflation uncertainty on inflation—i.e., policy accommodation

[19] An increase in inflation could also reflect the pricing behavior of firms, which will be elaborated upon in Section 5. Firms prefer to adjust their current prices to insure themselves from the risks of being stuck with low prices in the future. In economies with a historical prevalence of high inflation, this pricing behavior and the associated supply-side channel are likely to be more pronounced.

[20] See also Mumtaz and Theodoridis (2015) and Katayama and Kim (2018) for the related theoretical mechanisms.

against deflationary pressure in G7 and policy tightening in reaction to inflationary pressure in EM7. The adoption of inflation targeting has facilitated the policy action being more aggressive in this process (McGettigan et al. 2013; Thornton and Vasilakis 2017).

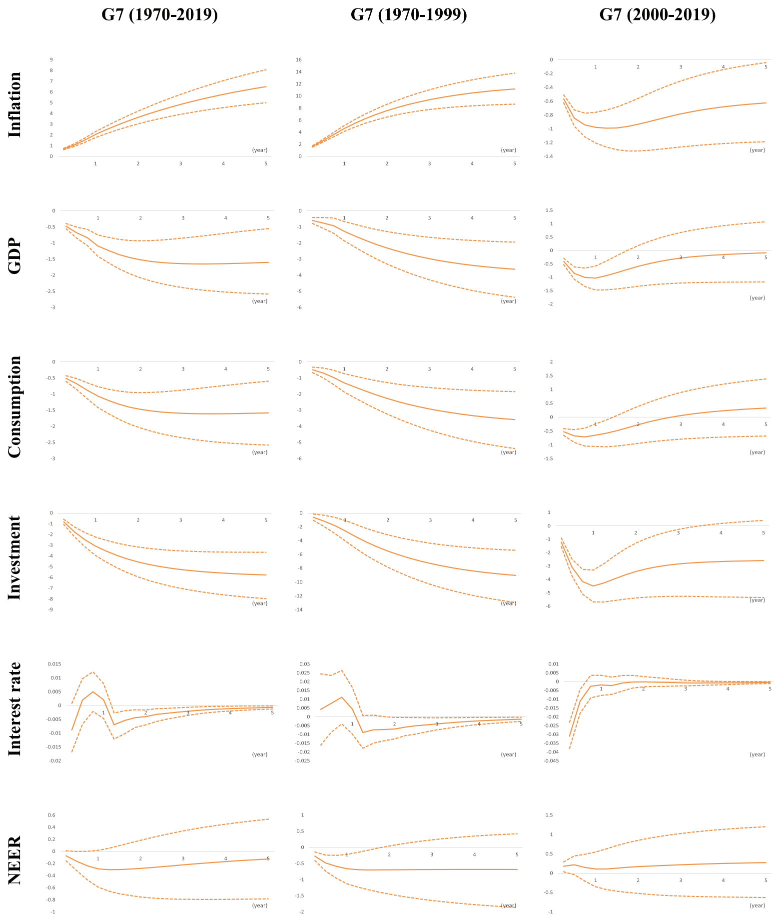
The policy reaction, in conjunction with the responses of output and exchange rates, can also provide alternative implications from a different angle. A large literature on the cyclical properties of policy documents that monetary policy in practice is countercyclical (or acyclical) in advanced economies, but it is procyclical in emerging market economies (*when it rains, it pours* phenomenon; Kaminsky, Reinhart, and Végh 2005). Given the correlation between short-term rates and the business cycle, this implies that in bad (good) times, the interest rate is reduced (raised) in advanced economies while it is raised (reduced) in emerging economies, a pattern also observed in our results. Particularly, monetary policy procyclicality in emerging economies may be at least partially because central banks seek to defend their currency against depreciation in times of negative shocks (*fear of floating;* Calvo and Reinhart 2002). Put differently, the capacity of central banks to implement countercyclical policy is often constrained by the potential devaluation of their exchange rates due to capital outflows (Cordella and Gupta 2015; Ocampo and Ojeda-Joya 2022).[21]

### *4.3 Time-Specific Evidence*

In G7 economies, quarterly data are available for a longer-term period, dating back to the 1970s. Using the quarterly data, we now investigate whether the impacts of inflation uncertainty have changed over time. To this end, the sample periods are divided into two sub-groups: 1970–99 and 2000–19. The latter sub-sample overlaps with our baseline sample period (2004–19). During the first period, the global economy experienced a series of global recessions in 1975, 1982, and 1991, mainly associated with the historical oil crises. The second sample period coincides with the Great Moderation, although global inflation registered significant volatility around

[21]Végh et al. (2017) and Ocampo and Ojeda-Joya (2022) argue that the monetary policy dilemma, which involves making decisions between economic growth and stable inflation in response to negative supply shocks, is more pronounced in emerging markets because of procyclical capital flows.

**Figure 3. Impulse Response to Inflation Uncertainty: 1970:Q1–2019:Q4**




**Note:** The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16 and 84 percentiles of the empirical distribution based on Bayesian estimation.

the global financial crisis in 2008–09 and the period of large oil price plunges in the mid-2010s.

As depicted in Figure 3, the impacts of inflation uncertainty have changed over time. The effects on GDP growth were contractionary over both periods. However, the consequences were much more sizable and significant during the first period (up to –4 percentage points following a one-standard-deviation inflation uncertainty shock) than the second period (1 percentage point).

Inflation significantly rose following a heightened inflation uncertainty in the pre-2000 sample period, while it declined in the post-2000 period. Again, the results suggest potential differences in the underlying shocks that have driven inflation uncertainty. Increases in inflation uncertainty may reflect the large adverse supply shocks—including the oil crises in the 1970s and 1980s and the early 1990s, as argued by Leduc, Sill, and Stark (2007) based on U.S. data. Meanwhile, the heightened inflation uncertainty after the global financial crisis in 2008–09, as well as the euro-area debt crises and oil price plunges in the mid-2010s, may point to the effects of large negative demand or positive supply shocks. The halved magnitude of the impacts on inflation during the second sample period may also reflect the better-anchored inflation expectations—with the help of the improved monetary policy frameworks including inflation targeting—that are expected to make the effects of demand- and supply-side economic shocks less persistent.[22] Consistent with the dynamic responses of output and inflation, interest rates clearly and significantly declined in the second period. In contrast, the reactions of interest rates are moderately positive, although not statistically significant, during the first period.

## 5. Theoretical Channels of the Inflation Uncertainty

Our empirical results clearly show that adverse shocks in inflation uncertainty were significantly associated with declines in output, consumption, and investment in both G7 and EM7 countries. However, an anomaly in the response of inflation to the shocks is also observed across the two country groups and over the sample periods. This may reflect the different nature of underlying shocks behind

[22]In fact, the studies provide the abundant evidence that, counteracting more aggressively against inflationary pressure, monetary policy is implemented now with more agility than in the past (Lubik and Schorfheide 2004; Cogley and Sargent 2005).

the inflation uncertainty and their propagation into the economy.[23] In this section, we provide a further explanation for the transmission channels of inflation uncertainty in a DSGE model as described below.

### *5.1 Main Features of the Model*

Our model is primarily an extension of Basu and Bundick (2017), which incorporates the role of uncertainty in the model economy. This choice offers several advantages.

First, the framework enables us to reproduce the negative comovement of macro variables easily—including output—caused by inflation uncertainty shocks, which was observed in our empirical exercises. In fact, Basu and Bundick (2017)'s original model adopts the preference uncertainty in a New Keynesian framework, successfully generating the stylized facts of business cycle co-movements among output, consumption, investment, and employment following uncertainty shocks. However, less attention has been paid to the response of inflation in their model, which can be heterogeneous, as shown in Section 4. Together with the impacts of the shocks on the macroeconomy, we will explore the response of inflation.

Another appealing feature of the model is that it considers demand- and supply-side drivers of inflation uncertainty. Specifically, in the model, a heightened inflation uncertainty leads not only to a decline in consumption (or an increase in precautionary saving) but also to an increase in labor supply. Depressed consumption, in turn, reduces aggregate demand, thereby dampening labor demand. Hence, inflation uncertainty in nature may simultaneously bring about varying effects on the labor market. Under the assumption of sticky prices and countercyclical markups, a decrease in labor demand may surpass the effects of an increase in labor supply, and as a result, employment (hours worked) would decline. Furthermore, inflation uncertainty has additional impacts, which raise inflation

[23] As argued in the previous sections, following a rise in inflation uncertainty, for instance, inflation can decline if the inflation uncertainty is mainly driven by adverse demand shocks—i.e., deflationary pressures. Meanwhile, inflation would rise when inflationary adverse supply shocks are more critical in driving inflation uncertainty.

and price markups by affecting firms' pricing decisions. Considering the effects of inflation uncertainty on demand and supply, we can explore the different views on the relationship of inflation uncertainty with economic growth and inflation. (For detailed discussions on the different views in the literature, see Appendix A.)

Given the similarities between our model and Basu and Bundick (2017), this section focuses solely on the critical features of the model, particularly the relationship between inflation uncertainty and macro variables. (A more detailed description of the model is presented in Appendix D.) Specifically, our model deviates from Basu and Bundick (2017) by considering the inflation uncertainty process, which affects both demand- and supply-side channels. In our setup, we consider the inflation uncertainty, which evolves with a stochastic process, parameterized as

$$\Gamma_t = (1 - \rho_\Gamma)\,\Gamma + \rho_\Gamma \Gamma_{t-1} + \sigma^\Gamma_{t-1}\varepsilon^\Gamma_t \tag{9}$$

$$\sigma^\Gamma_t = (1 - \rho_{\sigma^\Gamma})\,\sigma^\Gamma + \rho_{\sigma^\Gamma}\sigma^\Gamma{}_{t-1} + \sigma^{\sigma^\Gamma}\varepsilon^{\sigma^\Gamma}_t, \tag{10}$$

where $\varepsilon^\Gamma_t$ and $\varepsilon^{\sigma^\Gamma}_t$ denote first- and second-moment shocks which capture innovations to the stochastic process for the level and the volatility of inflation uncertainty, respectively. The two stochastic shocks are orthogonal and follow the standard normal distribution. The second-moment shocks are referred to as the inflation uncertainty shock.

We assume that this process affects the model economy in two ways. First, it works as an ingredient that determines nominal bond yields. Specifically, motivated by the recent macro-finance literature (e.g., Haubrich, Pennacchi, and Ritchken 2012; Hördahl and Tristani 2012; Bianchi, Kung, and Tirskikh 2018), we adopt the relationship that a nominal bond rate $R_t$ can be decomposed into inflation risk-free rate $R^*_t$ and premium compensated for variations of inflation risk $\Theta_{t+1}$. In real terms, $\Theta_{t+1}$ represents a wedge between inflation risk-free real rates and ex ante real rates. In addition, $\Theta_{t+1}$ is assumed to be a linear function of an evolution of the stochastic process of $\Gamma_t (= E_t[\Gamma_{t+1}/\Gamma_t])$.[24]

[24]Our focus is not on embedding the term structures, which typically relies on flexible features of the pricing kernel, but on investigating directly the impacts of

$$R_t = R_t^* \Theta_{t+1} \tag{11}$$

Second, inflation uncertainty can affect a firm's price setting. To the extent that higher inflation uncertainty leads to a more flexible price change, we assume that a quadratic cost of adjusting nominal price $P_t(i)$ that each monopolistic firm $i$ faces is subject to the inverse of $\Gamma_t$, as given by

$$\frac{\phi_p}{2\Gamma_t}\left[\frac{P_t(i)}{\Pi P_{t-1}(i)} - 1\right]^2 Y_t, \tag{12}$$

where $\phi_p$ denotes the degree of nominal price rigidity and $Y_t$ denotes the final good. Similar to Bundick and Smith (2021), this setup can be interpreted that inflation uncertainty affects price adjustment cost via the long-term inflation level ($\Pi$).[25]

These properties together allow us to rethink the main equations in the model—nominal Euler equation and the Rotemberg-type New Keynesian Phillips curve (NKPC henceforth)—deviated from those of the standard model. First, the Euler equation for a zero net supply of nominal bonds can be reformulated in terms of inflation risk-hedged yield and inflation risk premium, which is a function of $\Gamma_t$ as in (13):

$$1 = R_t E_t\left[\frac{M_{t+1}}{\Pi_{t+1}}\right] = R_t^* E_t\left[\frac{M_{t+1}}{\Pi_{t+1}}\Theta_{t+1}\right], \tag{13}$$

---

inflation uncertainty on the nominal bond yields. In addition, $\Theta_{t+1}$ differs to some extent from the conventional *inflation risk premium.* As elaborated in Bianchi, Kung, and Tirskikh (2018), inflation risk premium can be typically expressed in terms of the second-moment relations between inflation and stochastic discount factor in the Euler equation. Hence, $\Theta_{t+1}$ can be viewed as the uncertainty-related process which induces the shocks into such second-moment relations.

[25] Another interpretation for this feature is that the uncertainty around inflation directly affects price misalignment from the desired level, and thus raises the probability of price adjustment (Grier and Perry 1996; Luo and Villar 2021). For example, Drenik and Perez (2020) conjecture that the aggregate price level is subject to the state of the economy (named as the common knowledge component) and the standard deviation of the noise of the aggregate price signal, which is time dependent. In addition, Jin and Wu (2021) show that high uncertainty attenuates cost stickiness by deteriorating firms' expectations of future demand and adjustment costs.

where $M_{t+1}$ and $\Pi_{t+1}$ are a stochastic discount factor (SDF) and an inflation rate between $t$ and $t+1$, respectively.[26,27]

In addition, with a cost of changing prices given as (12), solving the maximization problem of a firm's cash flows yields the Phillips curve as

$$\begin{aligned}\phi_P\left(\frac{\Pi_t}{\Pi\Gamma_t}-1\right)\left(\frac{\Pi_t}{\Pi\Gamma_t}\right) &= 1-\theta_\mu+\frac{\theta_\mu}{\mu_t}\\ &+\phi_P E_t\left[M_{t+1}\frac{Y_{t+1}}{Y_t}\left(\frac{\Pi_{t+1}}{\Pi\Gamma_{t+1}}-1\right)\left(\frac{\Pi_{t+1}}{\Pi\Gamma_{t+1}}\right)\right], \qquad (14)\end{aligned}$$

where $\mu_t$ is the markup of price over marginal cost, and $\theta_\mu$ is the elasticity of substitution for intermediate goods. Because all firms face the same maximization problem, the same price and the same quantity are chosen, i.e., $P_t(i)=P_t$ and $Y_t(i)=Y_t$, and the NKPC can be expressed in a symmetric equilibrium.

## *5.2 Transmission Channels of Inflation Uncertainty*

Guided by the two modified equations, we now investigate the main mechanisms of interaction between inflation uncertainty and macro variables.

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[26]Since we consider the representative household's utility maximization problem under Epstein-Zin preferences identical to Basu and Bundick (2017), $M_{t+1}$ is derived as

$$M_{t+1}=\beta\frac{a_{t+1}}{a_t}\left(\frac{u(C_{t+1},\ N_{t+1})}{u(C_t,\ N_t)}\right)^{\frac{1-\sigma}{\theta_V}}\left(\frac{C_t}{C_{t+1}}\right)\left(\frac{V_{t+1}^{1-\sigma}}{E_t\left[V_{t+1}^{1-\sigma}\right]}\right)^{1-\frac{1}{\theta_V}},$$

where $u(C_t,\ N_t)=C_t^\eta(1-N_t)^{1-\eta}$ and $\sigma$, $\psi$ are risk aversion and intertemporal elasticity of substitution, respectively, ($\theta_V=(1-\sigma)\left(1-\frac{1}{\psi}\right)^{-1}$).

[27]It is noteworthy that this allows us to reinterpret the monetary policy rule such that the central bank in the model adjusts $R_t^*$, additionally taking the evolution of inflation risk into consideration.

$$\begin{aligned}log\left(R_t^*\right) &= \left(1-\rho_{R^*}\right)\left[log\left(R^*\right)+\rho_\Pi log\left(\frac{\Pi_t}{\Pi}\right)+\rho_Y log\left(\frac{Y_t}{Y_{t-1}}\right)\right]\\ &+\rho_{R^*}log\left(R_{t-1}^*\right)-log\left(\Theta_{t+1}\right)\end{aligned}$$

In Equation (13), higher inflation uncertainty brings about a precautionary saving effect by dampening the demand for consumption goods. The fall in consumption leads to a decline in aggregate demand, thereby reducing output through the national income account identity ($Y_t = C_t + I_t$). A decrease in output ($Y_t$) also deteriorates the marginal revenue product of capital and labor, thus lowering the demand for capital stock ($K_t$) and labor ($N_t$) as well as firms' marginal costs. The reduced investment puts more downward pressure on output. Notably, this demand-side channel would be prone to the degree of risk aversion: the more risk-averse households are, the less they consume.

On the other hand, increased inflation uncertainty induces two different effects on firms' pricing decisions. To examine the firms' decision for pricing, (14) is rewritten in infinite sum form as

$$\left\{ E_t \sum_{j=0}^{\infty} M_{t,t+j} \left(1 - \theta_\mu + \frac{\theta_\mu}{\mu_{t+j}}\right) Y_{t+j} \right\} - \phi_P \left(\frac{\Pi_t}{\Pi\Gamma_t} - 1\right) \frac{\Pi_t}{\Pi\Gamma_t} Y_t = 0. \quad (15)$$

According to Equation (15), firms first lower their prices to boost the demand for output, implying a decline in inflation, when they face a fall in marginal costs caused by inflation uncertainty. Due to the existence of price adjustment costs, a decrease in the prices is smaller than that of the marginal costs, thereby inducing a rise in markups. Furthermore, Equation (15) also indicates that inflation uncertainty shocks raise inflation and markups by shifting up the New Keynesian Phillips curve. In the labor market, these effects lower labor demand in sequence, and thus, despite an increase in precautionary labor supply, hours worked ($N_t$) would finally decline in response to a heightened inflation uncertainty.[28]

[28]As illustrated in Basu and Bundick (2017), an increase in uncertainty also reduces labor demand as markups rise under the assumption of price stickiness. Intuitively, this is because labor is the only input that can change, consistent with a reduction of output. Subsequently, for a firm's labor

In short, swings in inflation uncertainty would negatively influence both aggregate demand and supply, leading to a contraction in output and its components including consumption and investment.[29] Unlike the reactions of other macro variables, however, inflation can either increase (similar to Cukierman and Meltzer 1986) or decrease (Holland 1995) in response to inflation uncertainty shocks. This is because the inflation response would be finally determined by the relative significance of the aforementioned demand- and supply-side channels. Among the determinants which produce such a difference between aggregate demand and supply, we focus on the risk appetite of economic agents because it substantially affects the size of the household's precautionary savings and firms' markups.[30]

### *5.3 Quantitative Results*

We now quantitatively examine the impacts of inflation uncertainty shocks on macro variables. The model is calibrated and solved, primarily taking the parameter values from Basu and Bundick (2017). Notably, for our baseline simulation, we also set the risk-aversion parameter $\sigma$ as 80. In addition, those for the stochastic process of the first- and the second-moment inflation uncertainty are chosen such that $\rho_\Gamma$ and $\rho_{\sigma^\Gamma}$ are set to 0.85, and $\sigma^{\sigma^\Gamma}$ is set to 0.001.

---

demand to decrease, markup should rise, as given by the labor demand equation:

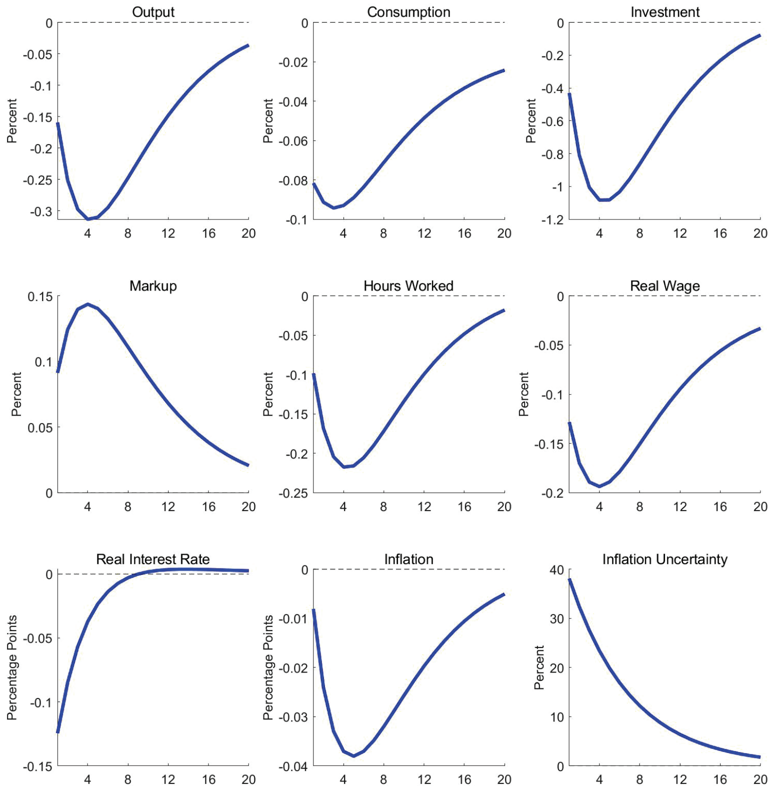
$$\frac{W_t}{P_t} N_t(i) = \frac{1-\alpha}{\mu_t} \left[K_t(i) U_t(i)\right]^{\alpha} \left[Z_t N_t(i)\right]^{1-\alpha}.$$

[29] Under the assumption of price flexibility, however, hours worked increase due to precautionary labor supply while labor demand stays unchanged. Hence, depending on the price stickiness and the relative significance of impacts on aggregate demand and supply, inflation uncertainty can have either positive or negative impacts on economic growth, as summarized in Appendix A.2.

In addition, under the Calvo pricing setup, the uncertainty shocks can generate additional effects on firms' pricing decisions. Different from the Rotemberg model, the Calvo model assumes relative price dispersion so that it allows firms to determine their prices in a risk-averse manner. Hence, on an uncertainty shock, firms set their prices higher than those under certainty to maximize their profits and to insure against future potential losses from low prices. As a consequence, inflation increases as markups rise by more (*precautionary pricing effect;* Oh 2020).

[30] See Fernández-Villaverde and Guerrón-Quintana (2020) for the detailed explanation on the determinants.

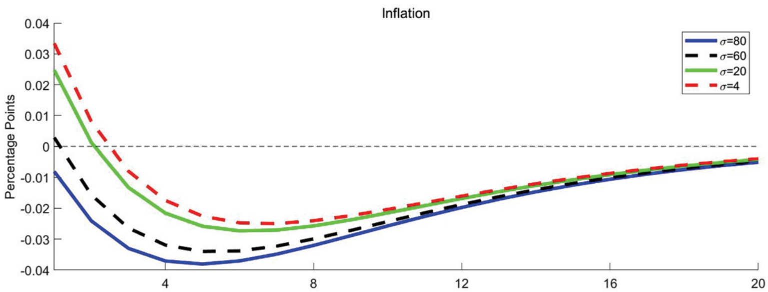
**Figure 4. Model-Implied Responses to the Inflation Uncertainty Shock**




**Note:** The x-axis represents the quarters after inflation uncertainty shocks, and the y-axis is the deviation from the steady state in percent (percentage points).

Figure 4 summarizes the impulse responses for the second-moment shock (i.e., inflation uncertainty) with the baseline parameter values. The impulse responses of the model are in line with our prediction and our empirical findings: output, consumption, investment, and hours worked all decrease while markup rises in a countercyclical manner. More specifically, on an inflation uncertainty shock, households consume less due to the demand channel postulated mainly in (13), and it reduces output. Consequently, this leads to a fall in marginal revenue of capital, and thus investment declines. Also, hours worked in equilibrium decrease since an

**Figure 5. Responses to the Inflation Uncertainty Shock under Different Risk Aversion**




**Note:** The x-axis represents the quarters after inflation uncertainty shocks, and the y-axis is the deviation from the steady state in percentage points.

increase in markups triggered by inflation uncertainty shocks reduces labor demand. In sum, both demand- and supply-side channels of inflation uncertainty have negative impacts on economic activities, as observed in our empirical analysis in Section 4 and the recent literature including Binder (2017).

The responses of inflation, however, turn out to be heterogeneous depending upon the degree of risk aversion. Figure 5 compares the impulse responses of inflation with four values of the risk-aversion parameter ($\sigma = 80$ for the baseline and $\sigma \in \{4, 20, 60\}$ for comparison). The response of inflation remains negative throughout the simulation periods with the baseline risk-aversion value ($\sigma = 80$, blue line). However, with smaller risk aversion, inflation exhibits even a positive response to the impacts and then it reverses to negative no later than one year after the shock. This heterogeneous response of inflation implies that the demand-side channel of inflation uncertainty dominates in a risk-averse state of the economy while the supply-side channel acts more strongly in a risk-tolerant state, at least in the short run.

## 6. Conclusion

This paper adopts four different measures for inflation uncertainty (survey, model, forecast, and news based) and identifies key trends of the uncertainty over the past two decades. The fluctuations of uncertainty broadly coincide with major global crises as well as country-specific events. The current level of inflation uncertainty, mainly due to the COVID-19 pandemic, is as high as in the previous global crises of the late-2000s and 1970s/1980s.

Using a Bayesian panel SVAR, we empirically test the impacts of inflation uncertainty across country groups and periods. Our results suggest that heightened inflation uncertainty generally leads to weakening economic activities, including output, investment, and consumption, with G7 countries experiencing more output losses due to inflation uncertainty than EM7 countries. Meanwhile, the impact of the uncertainty on inflation appears mixed across the country groups. Our results also show that in G7 countries, the impact of uncertainty on inflation has varied over time. Unlike G7 countries, where the inflation rate drops in response to higher uncertainty, EM7 countries usually experience higher inflation. The inflation uncertainty had negative (dis-inflationary) impacts on the inflation rate in the 2000s/2010s, potentially due to adverse demand shocks. In comparison, it had positive (inflationary) effects in the 1970s through 1990s, when adverse supply shocks frequently occurred.

With the help of a simple DSGE model incorporating inflation uncertainty, we also investigate the transmission channels of inflation uncertainty to macroeconomic variables. Consistent with our empirical findings, this exercise suggests that inflation uncertainty shocks have adverse impacts on outputs, consumption, and investments but have heterogeneous effects on the inflation rates depending upon the primary underlying sources of inflation uncertainty. More specifically, the inflation uncertainty shocks transmitted mainly through the economy's demand channels tend to lead to lowered inflation rates. In contrast, those through supply-side channels result in higher inflation rates. Moreover, the degree of risk aversion plays a vital role in determining the dominant channels in the economy.

Policymakers should adjust the assessments of economic and inflation conditions and outlook, including the expected effects of their monetary policies on future economic conditions, flexibly and preemptively. On the one hand, our results suggest that the heightened uncertainty for future inflation will strain long-term economic growth, mainly through weakening investments. This implies that the policymakers should react aggressively, even to small deviations from an inflation target, to avoid the adverse effects of inflation deviations from a target. Having said that, on the other hand, our results also imply that for policymakers to reduce policy errors due to misunderstanding about future economic conditions and finally have an appropriate policy stance, they must clearly understand the underlying sources of the uncertainty for future inflation.[31] In doing so, central banks should take more caution when delivering forward guidance to reduce adverse impacts of inflation uncertainty on the economy.

In this paper, we focused on the causal effects of inflation uncertainty on economic growth and inflation and did not explore the opposite directional relationship—such as the impacts of inflation shocks or real business cycle shocks on inflation uncertainty. We will leave these for future research.

## Appendix A. Literature Review

### *A.1 Inflation Uncertainty Measures*

Given that inflation uncertainty is an unobserved variable, many different types of uncertainty measures have been proposed in the literature. Some studies rely on survey measures, while others depend on inflation volatility derived from time-series models. Another strand of literature employs realized forecast errors. Since each measure is based on distinct assumptions unlikely to be fulfilled, they are prone to idiosyncratic measurement errors. Hence, the empirical results on the impact of inflation uncertainty depend crucially on the choice of the uncertainty measure.

Several studies have compared various types of inflation uncertainty measures. For instance, Batchelor and Dua (1993, 1996) compared inflation uncertainty derived from subjective probability distributions obtained from the U.S. Survey of Professional Forecasters with model-based measures. They find little significant correlation

[31]For instance, by using a medium-scale DSGE model, Madeira, Madeira, and Monteiro (2023) investigate how dissent in the Federal Open Market Committee is affected by structural macroeconomic shocks. They find that dissent is less (more) frequent when demand (supply) shocks are the predominant source of inflation fluctuations and that supply shocks are found to raise private-sector forecasting uncertainty about the path of interest rates.

between both categories. Using uncertainty measures obtained from professional forecasts as a reference point, Giordani and Söderlind (2003) conclude that model-based estimates generally struggle to detect regime changes promptly. However, they point out that the standard deviation of a VAR-estimated uncertainty on a rolling window successfully tracks the time profile of SPF uncertainty. Meanwhile, Giordani and Söderlind (2003) also compare different inflation uncertainty measures: standard deviation of point forecast, survey based, and time-series model based. They show that cross-sectional dispersion and standard deviations from the VAR model perform well. Chua, Kim, and Suardi (2011) employ a particular GARCH model that closely matches the professional forecast measure. In what follows, we provide more details of the related studies, particularly survey-based and model-based measures.

### *A.1.1 Survey-Based Measures*

Some studies use surveys of professional forecasts for CPI inflation conducted by Consensus Economics. Besides the advantages listed in Section 2, using Consensus Economics data is beneficial because it is provided on a monthly frequency. Since uncertainty can experience sudden shifts, it becomes more challenging to discern many of the effects we wish to measure when using low-frequency data.

For the measurement of uncertainty, Bomberger and Frazer (1981), Bomberger (1996, 1999), and Giordani and Söderlind (2003) propose the cross-sectional dispersion (disagreement) of point forecasts. Since the forecast horizon varies for each month, the cross-sectional dispersion of forecasts is likely to be strongly seasonal and to converge towards zero at the end of each year (Lahiri and Sheng 2010). To obtain 12-month-ahead inflation forecasts, Dovern and Weisser (2011) calculate a weighted moving average of the annual forecasts. In addition, as the dispersion index does not consider the form of the distribution, Rich and Tracy (2010) suggest using a histogram-based entropy, which indicates the relative frequency of individual forecasts.

The literature has used density forecasts to study whether disagreement is a valuable proxy for average uncertainty but found conflicting evidence (Zarnowitz and Lambros 1987; Boero, Smith, and Wallis 2008; Lahiri and Sheng 2010; Rich and Tracy 2010).

Boero, Smith, and Wallis (2015) find that when the economy is turbulent, disagreement among professional forecasters can be a good indicator for average uncertainty; however, high-frequency movements in disagreement and uncertainty are not strongly correlated. While Bomberger and Frazer (1981), Bomberger (1996, 1999), and Giordani and Söderlind (2003) find supportive results for the usefulness of disagreement as a proxy for uncertainty, other studies report only a weak relationship or even reject the relationship (Zarnowitz and Lambros 1987; Lahiri, Tiegland, and Zaporowski 1988; Rich and Butler 1998; Döpke and Fritsche 2006; Rich and Tracy 2010). Lahiri and Sheng (2010) argue that disagreement is a reliable proxy for overall uncertainty, provided the forecast environment is stable.

Relatedly, micro-level inflation uncertainty measure has also been actively considered for a closer examination of the link between uncertainty and reported outcomes. Bachmann, Berg, and Sims (2015), for instance, discovered that survey participants who hold higher inflation expectations tend to report less favorable attitudes toward spending on durable goods such as cars and homes. When including the uncertainty measure based on rounding in comparable regression analyses, it becomes evident that more uncertain consumers also exhibit less favorable attitudes toward spending. Moreover, the coefficient on expected inflation remains small and negative. Binder (2017) uses round responses in pre-existing survey data and finds that inflation uncertainty is countercyclical and correlated with inflation disagreement, volatility, and the Economic Policy Uncertainty index. In addition, high-income consumers, college graduates, males, and stock market investors have the lowest level of uncertainty. Higher uncertainty leads to less favorable spending toward durables, cars, and homes.

#### *A.1.2 Model-Based Measures*

**Conditional Forecast Error Variance.** Autoregressive conditional heteroskedasticity (ARCH) models of many different types have been extensively used to model inflation uncertainty. Many studies have pointed out the existence of structural breaks in the inflation process. To accommodate events such as changes in monetary regime or variations in the level of steady-state inflation, the use of a generalized ARCH (GARCH) model with time-varying parameters is common practice. The flexibility of the GARCH model provides an advantage in that it accommodates non-stationarity in the inflation rate. By employing time-varying coefficients, Evans (1991) distinguishes between two types of inflation uncertainty: uncertainty regarding the short-term outlook for inflation, which is measured using the conditional variance of the residuals from the inflation equation, and uncertainty regarding the long-term outlook for inflation, which is measured using the varying coefficients of the inflation equation. Using time-varying coefficients, Berument, Kilinc, and Ozlale (2005) similarly distinguish among impulse uncertainty, structural uncertainty, and steady-state uncertainty. Caporale, Onorante, and Paesani (2012) estimate inflation uncertainty using AR-GARCH models and examine the linkage with inflation in a multivariate VAR framework.

**Stochastic Volatility in Mean.** Along with the GARCH model, an unobserved component stochastic volatility in mean (UCSVM) model is used (Kim, Shephard, and Chib 1998; Stock and Watson 2007, 2016; Chan 2017). Kim, Shephard, and Chib (1998) uses Markov chain Monte Carlo sampling methods to estimate stochastic volatility models and shows that SVM fits better than the GARCH model. Berument, Yalcin, and Yildirim (2009) employ SVM to construct monthly inflation uncertainty, and based on this, Chan (2017) develops SVM with time-varying coefficients in the conditional mean. Stock and Watson (2007, 2016) employ univariate and multivariate models that allow for common persistent and transitory factors, time-varying factor loadings, and stochastic volatility in the common and sectoral components.

## *A.2 Inflation Uncertainty, Inflation, and Economic Growth*

### *A.2.1 Inflation Uncertainty and Economic Growth*

Both the theoretical and empirical studies have documented mixed results on the relationship between inflation uncertainty and real economic activity.

**Theories.** There is still no consensus in the theoretical literature regarding the impact of inflation uncertainty on economic growth (Friedman 1977; Cecchetti 1993; Tommasi 1994; Dotsey and Sarte 2000; Berument, Kilinc, and Ozlale 2005). Tobin (1965), one of the pioneering studies in this area, argues that inflation uncertainty incentivizes households to hold a greater amount of real capital assets, which, in turn, promotes capital productivity and economic growth.[32] Dotsey and Sarte (2000) also suggest a positive correlation between economic growth and inflation uncertainty. When the volatility of money growth (inflation) increases, the expected return on money balances becomes uncertain. This leads to a decrease in the demand for real money balances and consumption. This increases precautionary savings, which in turn stimulates economic growth through a larger pool of investment resources, as higher anticipated inflation encourages investment.[33] Another explanation provided by Aghion and Saint-Paul (1998) and Blackburn (1999) relies on the models where technological change is the outcome of deliberate (internal) learning or research and development (R&D) activity. Increased uncertainty is then likely to enhance the long-run growth prospects through economic actions that substitute production activities.

The stagflation of the 1970s, however, stemming mainly from increases in oil prices, debunked the ideas and cast doubts on the existence of a positive relationship between inflation and economic growth (Friedman 1977; Ball 1992). Some studies suggest that inflation uncertainty reduces investment by hindering long-term contracts or by increasing the option value of delaying an irreversible investment (Kantor 1983; Kimball 1990; Lusardi 1998). Therefore, inflation uncertainty, as either the cause or the effect of inflation, negatively affects economic variables including consumption, investment, and growth. Inflation uncertainty implies uncertainty about real income, which would increase precautionary saving, and about the real return on saving, which would make saving less attractive for risk-averse consumers. Similarly, some argue that inflation uncertainty deteriorates the allocative efficiency of the price system if it is associated with increased variation in relative prices. Inflation can

[32]Tobin (1965) suggests that higher anticipated inflation can lead to an increase in capital per head, as households adjust their asset portfolios by moving away from non-interest-bearing money (real money balances) and toward real capital assets (more productive forms).

[33]See also Loayza, Schmidt-Hebbel, and Servén (2000) for the precautionary motive of savings.

raise the cost of capital by dampening capital accumulation and by lowering its productivity (De Gregorio 1993) and thereupon inhibiting long-run growth.[34] Jordà and Salyer (2003) show that monetary uncertainty tends to lower nominal interest rates.

Cecchetti (1993) suggests that general equilibrium, representative-agent models do not convincingly produce an unambiguous result about the impact of uncertainty on real economic activity. He concludes that the aggregate impact of inflation uncertainty is therefore fundamentally an empirical issue. The empirical literature on inflation uncertainty, however, has also reported conflicting results.

**Empirical Results.** While empirical studies using uncertainty proxies typically find a negative connection between inflation uncertainty and real activity (Evans and Wachtel 1993; Davis and Kanago 1996; Judson and Orphanides 1999; Grier and Perry 2000; Elder 2004), some find a positive or negligible relationship (Coulson and Robins 1985; Clark 1997; Barro 1998).

*Negative Relation.* Durable consumption, which is costly to reverse and highly volatile, is particularly sensitive to uncertainty (Bertola, Guiso, and Pistaferri 2005). Judson and Orphanides (1999) and Barro (2013) examine the joint effect of inflation and inflation uncertainty on economic growth. Based on panel data analysis, Judson and Orphanides (1999) find that both inflation and its uncertainty are negatively correlated with economic growth of high-inflation countries. More precisely, the magnitude of the negative impacts of the uncertainty is smaller in non-OECD countries with higher inflation. The authors conclude that a sound policy should aim to both reduce and stabilize the level of inflation. They further argue that inflation stability is more important than the level of inflation itself in promoting high economic growth. This means that neglecting the effect of inflation uncertainty in the growth model could lead to underestimating the negative impact of high inflation levels on economic growth. That said, more recent studies show negative effects (Apergis 2004). Grier and Grier (2006) find that

[34]Friedman (1977) conjectures that the more volatile inflation is as a consequence of the increase in its average, the less effective the price mechanism to coordinate economic activities is. Ball (1992) formalizes Friedman's proposition in the context of a repeated game between the monetary authority and the public. A high inflation rate produces greater uncertainty about the direction of future government policy, and thus about the future inflation rates.

economic growth and inflation uncertainty in Mexico are negatively correlated.

Most recent literature studies the impact of inflation expectation on consumer behaviors (e.g., Armantier et al. 2015; Coibion et al. 2019; Candia, Coibion, and Gorodnichenko 2020; Crump et al. 2020; D'Acunto, Hoang, and Weber 2022). However, there exist a few papers focusing on inflation uncertainty. For instance, Binder (2017) finds that higher inflation uncertainty reduces consumers' incentive to purchase durable goods, which is consistent with a precautionary saving channel. Consistent with expected utility theory, Armantier et al. (2015) report experimental evidence showing that inflation expectations and uncertainty determine people's investment decisions. Ben-David et al. (2019) complement the literature by showing that higher inflation uncertainty is associated with more caution in households' consumption, investment, and borrowing behaviors.

*Positive Relation.* Meanwhile, earlier studies, using mainly U.S. data, find positive growth effects of inflation uncertainty (e.g., Coulson and Robins 1985). Employing much longer historical time-series data, Fountas (2010) argues that uncertainty about inflation leads to higher growth due to precautionary motives, supporting Dotsey and Sarte (2000)'s theoretical argument. Similar results are reported for the case of G7 countries (Bredin and Fountas 2005; Fountas and Karanasos 2007) and Asian countries (Bredin, Elder, and Fountas 2009; Baharumshah, Hamzah, and Sabri 2011; Mohd, Baharumshah, and Fountas 2013). They typically rely on GARCH-type models, which require high-frequency time-series data.

*Mixed Results.* Holland (1993a) summarizes 4 studies that find a positive or insignificant relationship between inflation uncertainty and real economic activity, together with 14 that report a negative relationship. While there is a robust negative relationship between inflation and economic growth in the literature, the relationship between inflation uncertainty and growth is more tenuous. In other words, it is challenging to find consistent results across different samples and specifications. Barro (2013) also examines the simultaneous interactions of inflation and inflation uncertainty based on a wide range of countries, and provides contradicting results. The author's findings suggest that inflation level, even at low rates, has a significant negative impact on growth, while inflation uncertainty is not significantly related to growth when controlling for other important factors that drive growth, such as institutions. Barro (2013) tests non-linear relationships between inflation and economic growth, but does not find enough empirical evidence to support such a pattern. In addition, the estimated effects of inflation uncertainty vary substantially in terms of magnitude and timing.

*A.2.2 Inflation Uncertainty and Inflation*

Another large body of the literature contributes to the ongoing debate about the link between inflation and inflation uncertainty.

**Theories.** At least four types of hypotheses are proposed to explain the relation. The Friedman-Ball hypothesis posits that high inflation rates may lead to increased inflation uncertainty which brings about economic cost (Bernanke and Mishkin 1997). Based on theoretical perspectives, Friedman (1977) argues that higher inflation rates are less predictable than lower rates.[35] Ball (1992) develops (Friedman-Ball hypothesis) into a formal model that incorporates a repeated game between the monetary authority and the public.[36] In contrast, Cukierman and Meltzer (1986) argue that the causality is from inflation uncertainty to inflation. They claim that, in an economy populated with agents who are highly uncertain, the central bank has an incentive to create surprise inflation to lower unemployment (Cukierman-Meltzer hypothesis).

Another important view is provided by Pourgerami and Maskus (1987). They suggest a negative relation between inflation and inflation uncertainty, rejecting the hypothesis of a harmful effect of high inflation on price predictability (Pourgerami-Maskus hypothesis). Contrary to the Friedman-Ball hypothesis, they argue that higher

[35] Using cross-sectional data for 17 OECD countries for the period 1951–68, Okun (1971) argues that inflation is positively associated with its volatility (standard deviation). According to Okun (1971) there is a positive correlation between inflation and inflation variability since monetary policy becomes more unpredictable during the period of high inflation.

[36] With regard to the effect of inflation on inflation uncertainty, Friedman (1977) and Ball (1992) argue for a positive effect. For example, Ball (1992) develops a repeated game model that incorporates conservative and liberal policymakers and a public in the economic system. The cost of inflation is considered moderate for the liberal policymaker, while it is considered very high for the conservative policymaker. The public does not have information about whether the policymaker will implement a contractionary monetary policy to curb inflation when it is high. Therefore, inflation will co-vary positively with inflation uncertainty.

**Table A.1. Theories between Inflation and Inflation Uncertainty**

| Causality | Sign (+) | Sign (−) |
|---|---|---|
| Inflation Causes Uncertainty | Friedman (1977), Ball (1992) | Pourgerami and Maskus (1987) Ungar and Zilberfarb (1993) |
| Uncertainty Causes Inflation | Cukierman and Meltzer (1986) | Holland (1995) |

inflation causes economic agents to invest more in generating accurate predictions, subsequently reducing their prediction error (Ungar and Zilberfarb 1993). Therefore, with inflation on the rise, agents may forecast inflation more accurately because they invest more resources in prediction.

Finally, Holland (1993b) suggests that higher inflation uncertainty lowers inflation due to policymakers' motives for stabilizing the economy. Thus, there exists a negative relationship between inflation uncertainty and inflation (Holland hypothesis). Holland (1995) provides an explanation for this negative relationship, stating that it stems from the social costs associated with inflation uncertainty. Inflation uncertainty will raise social costs but also reduce social welfare. To alleviate such adverse effects, policymakers implement stabilization policies, thereby reducing inflation. (See Table A.1.)

**Empirical Evidence.** Empirical studies also provide conflicting findings for the relationship between inflation and inflation uncertainty. While some studies show a positive relationship between them, others indicate a negative relationship. Furthermore, Grier and Perry (1998, 2000), Grier et al. (2004), and Berument, Kilinc, and Ozlale (2005) document mixed results regarding the direction of the causality.

Such inconsistency in the empirical results can be attributed to the differences in the sample countries, sample periods, or measures of inflation uncertainty. Barnett, Jawadi, and Ftiti (2020) find a significant relationship between inflation and inflation uncertainty that varies depending on the periods and data frequency. The relationship seems to be positive in the short to medium term during the stable periods, confirming the Friedman-Ball theory. However, it turns to be negative during crisis periods.

Using survey-based measure of inflationary shocks, Leduc, Sill, and Stark (2007) suggest that, prior to 1979, the Federal Reserve accommodated temporary shocks to expected inflation, which then resulted in persistent increases in actual inflation. Ungar and Zilberfarb (1993) show that the impact of inflation on inflation uncertainty varies with different levels of inflation, finding a positive effect when inflation is high, while this effect weakens as inflation decreases to lower levels. Focusing on the effect of inflation uncertainty on inflation, the literature also reports mixed results. Many empirical studies support a positive association between inflation uncertainty and inflation, while other studies find no significant or even negative relationship. Recent studies find that the effect highly depends on the business cycles (Holland 1995; Bredin and Fountas 2010).

**Country-Specific Evidence.** In the framework of the aforementioned different hypotheses, empirical studies generally focused on the advanced economies. Among them, GARCH-type methods have been popularly employed in empirical investigations on the inflation uncertainty since the estimated conditional volatility can perform better as a proxy for the uncertainty than other measures. According to a comprehensive survey by Davis and Kanago (2000), the studies focusing on the advanced countries mostly supported the Friedman-Ball hypothesis rather than the Cukierman-Meltzer hypothesis. In addition, there was also very little evidence to advocate the Pourgerami-Maskus hypothesis and the Holland hypothesis.

Fountas (2010) used a GARCH-in-Mean (GARCH-M) model augmented with lagged inflation in the conditional variance equation for long-term inflation data spanning over one century for 22 advanced economies. He found evidence for the positive effect of inflation uncertainty on inflation supporting the Cukierman-Meltzer hypothesis. Using EGARCH for five European countries, Fountas, Ioannidis, and Karanasos (2004) documented that inflation causes inflation uncertainty in France and Italy, but not in Germany. They also found that uncertainty causes declines in inflation in France and Germany. By using the ARFIMA-FIGARCH approach for the monthly data in the United States, the United Kingdom, and Japan from 1962 to 2001, Conrad and Karanasos (2005) examined the nexus between inflation and its uncertainty. They showed that inflation significantly raises inflation uncertainty in the United States and the United Kingdom as predicted by the Friedman-Ball hypothesis while the results from Japan support the Cukierman-Meltzer hypothesis.

Grier and Perry (1998) explored the relation between inflation and uncertainty for the case of G7 economies from 1948 to 1993 based on a two-step procedure. They first estimated a GARCH model to generate a measure of inflation uncertainty and then tested the Granger causality to examine the relationship between inflation and inflation uncertainty. They provided evidence that inflation significantly raises inflation uncertainty in all G7 countries as predicted by the Friedman-Ball hypothesis. Similarly, Fountas and Karanasos (2007) applied univariate GARCH models for inflation by using monthly data over the periods of 1957–2000 for the G7 countries. Their approach estimated the conditional variance of unanticipated shocks to inflation as proxies for the uncertainty and then implemented the causality test. The result strongly supported the Friedman-Ball hypothesis.

Among the studies focusing on the individual country cases, Bhar and Mallik (2010) reported that inflation uncertainty significantly increased inflation in the United States from 1957 to 2007 by using an EGARCH-M model and bivariate Granger-causality test. Hwang (2001) explored the link of inflation with uncertainty in the United States with long monthly data series from 1926 to 1992 employing various ARFIMA-GARCH-type models. He found that inflation has weakly negative impacts on its uncertainty whereas uncertainty affects inflation insignificantly. Thus, unlike the Friedman-Ball hypothesis, he argued that a high inflation rate does not necessarily result in a high variance of inflation. Wilson (2006) constructed a bivariate EGARCH-M model with inflation data in Japan spanning from 1957 to 2002 to examine the links among inflation, inflation uncertainty, and growth. The author found that in Japan, higher uncertainty is linked to both higher average inflation and lower average growth. Fountas (2001) estimated GARCH-type models using a long data series of the United Kingdom for the decade-long period of 1885–1998. The result supports the Friedman-Ball hypothesis and also provides an important implication that higher inflation uncertainty leads to lower output growth. Kontonikas (2004) examined the relationship between inflation and its uncertainty by estimating the impacts of inflation-targeting policy for the U.K. data over the period of 1972–2002. In the study, the estimated conditional volatility is computed from symmetric and asymmetric component GARCH-M models of inflation, and is used as a proxy for inflation uncertainty. Empirical results indicate a positive association between inflation and uncertainty.

**Differences across Countries.** Many existing studies suggest that higher inflation rates raise inflation uncertainty in all economies, strongly supporting the Friedman-Ball hypothesis. By contrast, the results on the effect of inflation uncertainty on monthly average inflation are more mixed. Higher inflation uncertainty leads to lower average inflation in Colombia, Israel, Mexico, and Turkey, consistent with the Holland hypothesis; however, it results in higher average inflation in Hungary, Indonesia, and Korea, in line with the hypothesis of Cukierman-Meltzer.

**Time-Varying Relation.** Assuming the non-normal density and independent regime shifts in inflation developments, Chang (2012) finds that the relationship between inflation uncertainty and inflation has changed over time. The results show that inflation uncertainty has no impacts on inflation, regardless of inflation pressure. That said, inflation has negative impacts on inflation uncertainty during the periods of high inflation volatility, while it has insignificant impacts during the periods of low inflation volatility.

### *A.2.3 Sources of Inflation Uncertainty*

Among the concerns of monetary policymakers, uncertainty about future inflation has been considered as the most important inflation cost. According to Cukierman and Meltzer (1986) and Evans and Wachtel (1993), inflation uncertainty can occur through at least two main sources. First, significant differences among international monetary policy regimes could lead to uncertainty, as through conventional versus unconventional monetary policies. Second, the uncertainty could also be induced by policy regime uncertainty. Furthermore, as economic agents often use new information to update their perceptions regarding the actions of central banks, it is expected that the uncertainty would be time varying and potentially complex to measure.

Inflation uncertainty may reflect the influence of unexpected movements in commodity prices and foreign exchange rates, as well as that of idiosyncratic developments unrelated to broader economic conditions. These factors could easily push overall inflation above or below the target rates for a time. Such disturbances, however, are not a great concern from a policy perspective as long as their effects shortly fade away and inflation expectations remain anchored.

Another source of uncertainty is inflation expectations. In standard economic models, inflation expectation is an important determinant of actual inflation. For instance, inflation expectations affect the economy when companies consider the future overall inflation rate in determining wages and prices for their products and services at a given time. The central bank's monetary policy is believed to be crucial in shaping these expectations by affecting the average inflation rate experienced over extended periods of time and providing direction for the inflation targets that the central bank aims to achieve in the future. Even so, economists have only a limited understanding of how and why inflation expectations change over time. They do not directly observe the inflation expectations relevant to wage and price setting. Instead, they can only imperfectly infer how the inflation expectations might have changed based on the survey responses and other data.

In addition, our framework for understanding inflation dynamics could be misspecified in some aspects because the econometric models overlook some factors that will restrain inflation in the coming years despite solid labor market conditions.

**Crisis.** Only a handful of papers have studied how households update their inflation expectations in times of crisis. In particular, Galati, Poelhekke, and Zhou (2011) document that inflation expectations increased during the 2007–09 Great Recession, while Gerlach, Hoerdahl, and Moessner (2011) and Trehan and Zorrilla (2012) find that this effect vanished quickly once the recession subsided. Using the data from the Survey of Consumer Expectations (SCE), from the Federal Reserve Bank of New York, Ben-David et al. (2019) show that consumers with higher forecast uncertainty (about inflation, national home price changes, and wage growth) tend to have more cautious consumption, investment, and borrowing behaviors.

**COVID-19.** Due to the unique features of the pandemic, at the early stage of the COVID-19 crisis, it was difficult to predict whether it would have inflationary or deflationary effects (Binder 2020; Cochrane 2020). On the one hand, weak consumer demand (e.g., for travel, entertainment, or leisure and hospitality) and a prolonged economic slowdown might put downward pressure on inflation. On the other hand, some expected that supply chain disruptions, the rising levels of government debt, and the unprecedented expansion of the Federal Reserve's balance sheet would raise the pressure on future inflation. Furthermore, it has been suggested that households tend to associate deteriorating economic outcomes with higher future inflation (Kamdar 2019; Candia, Coibion, and Gorodnichenko 2020). These opposing forces may have an impact not only on aggregate inflation expectations but also on the level of inflation disagreement among individuals, as well as the degree of uncertainty one may perceive about the future path of inflation.

Binder (2020) documents that greater concerns about COVID-19 were initially associated with higher inflation expectations. Dietrich et al. (2022) report the results of daily surveys that they conducted in the second half of March 2020. They find that short-term inflation expectations actually declined slightly in their surveys, although the median respondent answered that the pandemic should have an inflationary effect. Similarly, Coibion, Gorodnichenko, and Weber (2020) compare two surveys conducted in January and April 2020 and find a decrease in one-year-ahead inflation expectations and an increase in short-term inflation uncertainty. Also, Candia, Coibion, and Gorodnichenko (2020) report that households' inflation expectations subsequently increased in July 2020. The authors argue that this result is consistent with consumers' tendency to associate a worsening economy with higher future inflation.

Another group of studies focuses on the inflation expectations of U.S. firms during COVID-19 and reports conflicting results. Candia, Coibion, and Gorodnichenko (2020) suggest that, similar to households, firms view the pandemic as an inflationary supply shock. In contrast, Meyer, Prescott, and Sheng (2022) report that, similar to market participants and professional forecasters, firms lowered their one-year-ahead inflation expectations in response to COVID-19, as they regard the pandemic as a demand shock. Furthermore, Meyer, Prescott, and Sheng (2022) find that, as of June 2020, firms' longer-run inflation expectations have changed little throughout the pandemic and remained reasonably well anchored.

## Appendix B. Robustness Checks

To check the robustness of our headline empirical results, we estimated several alternative models. The baseline results are not sensitive to the alternative models as summarized below.

**Variable Ordering.** In our baseline panel VAR model, the inflation uncertainty is ordered first. In this way, we assume that inflation uncertainty shock is independent of the shocks that are ordered later within a month (or a quarter). In order to test the sensitivities of the impulse responses to the ordering, the models are tested by placing the uncertainty last or by comparing them with the generalized impulse response functions (not shown here). As shown in panel A of Figure C.2, the responses of variables to inflation uncertainty shocks are largely similar to those of baseline models, both in terms of direction and magnitude.

**Additional Control Variables.** To examine whether our empirical results are driven by any omitted variables—such as those reflecting common global shocks—we test the alternative models which augment the CBOE Volatility Index (VIX) or the Economic Policy Uncertainty Index (EPU) as exogenous variables. In the baseline model, the level of inflation uncertainty measure is employed. Although the inflation uncertainty is found to be stationary over the sample period, it can be potentially cointegrated with other uncertainty measures specifically driven by global factors, such as the VIX and the EPU.[37] In our robustness check, we additionally use either the VIX or the global EPU index, which is a GDP-weighted average of national EPU indices for 20 countries.

Figure C.3 reports the results from the test which employs VIX (panel A) or global EPU (panel B) as an exogenous variable. With VIX employed as an exogenous variable, the inflation uncertainty shock has significantly negative impacts on output and durable goods consumption while its impacts on non-durable goods consumption are largely insignificant. Partly reflecting the correlations between VIX and inflation uncertainty—in particular, around global

[37]The VIX is calculated using real-time, mid-quote prices of S&P 500 Index call and put options and is one of the most widely used measures of volatility in the global financial market. The EPU is a normalized index constructed from three different sources, including the newspaper, the number of federal tax code provisions set to expire, and disagreement among economic forecasters.

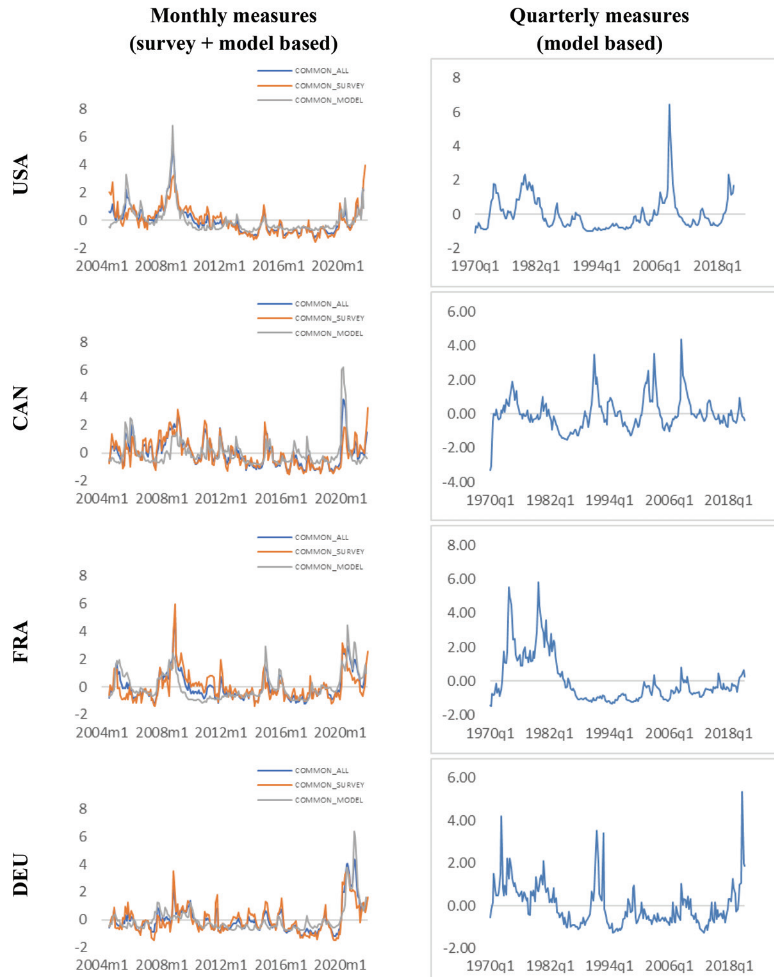
events—the impacts become somewhat more muted and less significant after controlling for VIX. Including global EPU as exogenous variables gives us similar significant results to those of baseline.

**Global Averages and the United States.** Instead of our baseline panel VAR, we iterate the estimation using country-specific SVAR models and compute the results based on the cross-country averages. We also report the result for the United States only as a representative country. As shown in Figure C.4, on an inflation uncertainty shock, global averages respond in the same direction as our baseline model while the magnitude of the negative impacts on economic variables are relatively smaller than those of panel analysis. The results for the United States are also largely consistent with the baseline results, but with less statistical significance. The output level drops by 1 percentage point in the first two years and then becomes stable. The impact on inflation is negative but insignificant.

## Appendix C. Additional Tables and Figures

### Figure C.1. Inflation Uncertainty for Individual Countries

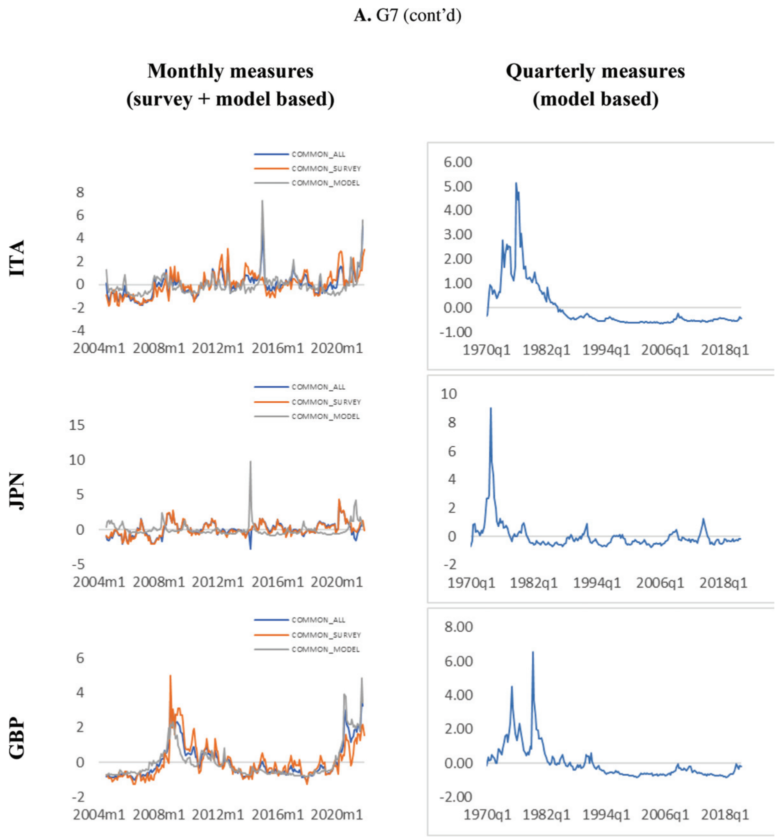
**A.** G7




**Note:** These figures show country-specific inflation uncertainty measures based on monthly (left) and quarterly (right) data. For monthly measures, blue, orange, and gray lines represent the common indicators, survey-based measure, and model-based measure of inflation uncertainty, respectively.

(*continued*)

**Figure C.1. (Continued)**

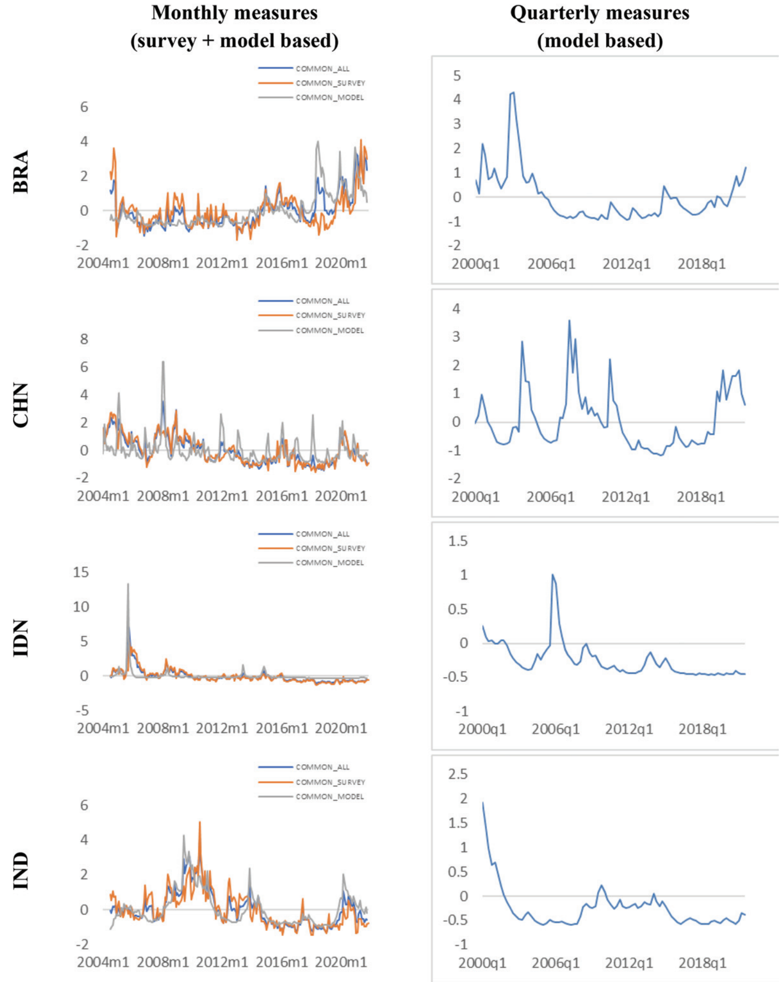



**Note:** These figures show country-specific inflation uncertainty measures based on monthly (left) and quarterly (right) data. For monthly measures, blue, orange, and gray lines represent the common indicators, survey-based measure, and model-based measure of inflation uncertainty, respectively.

(*continued*)

**Figure C.1. (Continued)**

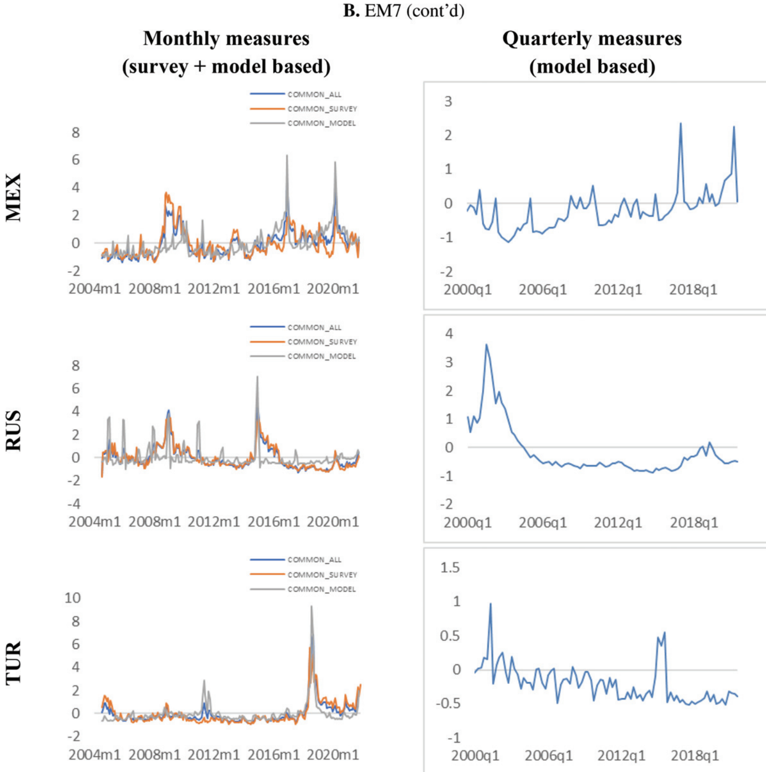
**B.** EM7




**Note:** These figures show country-specific inflation uncertainty measures based on monthly (left) and quarterly (right) data. For monthly measures, blue, orange, and gray lines represent the common indicators, survey-based measure, and model-based measure of inflation uncertainty, respectively.

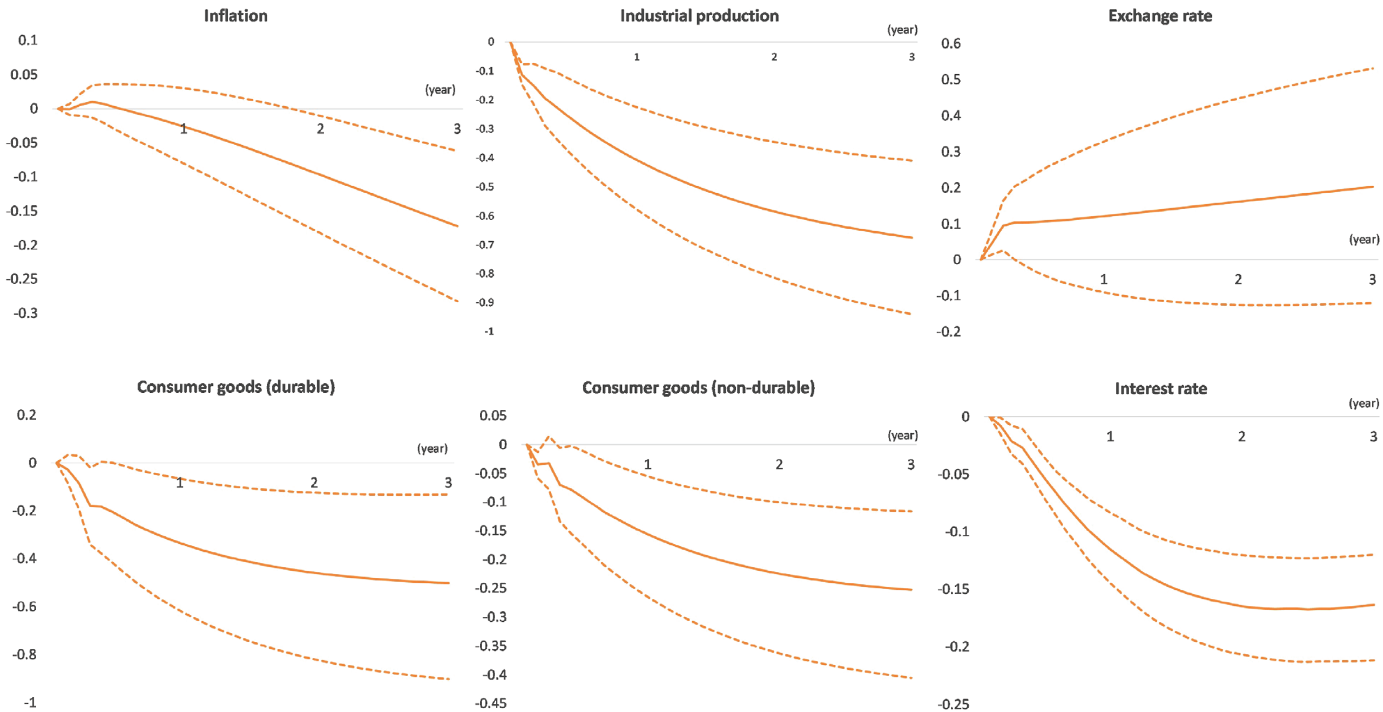
(*continued*)

## Figure C.1. (Continued)




**Note:** These figures show country-specific inflation uncertainty measures based on monthly (left) and quarterly (right) data. For monthly measures, blue, orange, and gray lines represent the common indicators, survey-based measure, and model-based measure of inflation uncertainty, respectively.

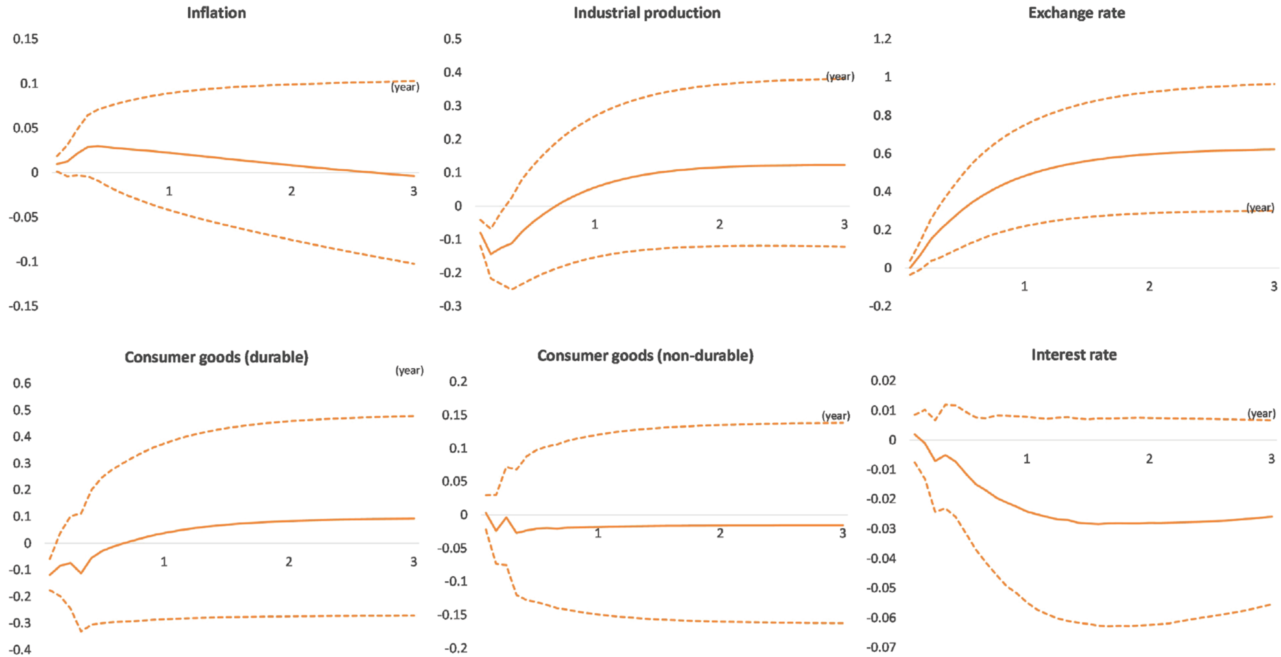
## Figure C.2. Robustness Check: VAR Ordering




**Note:** The figures present dynamic impulse responses of the variables following a positive one-standard-deviation increase in inflation uncertainty, based on the panel VAR model for G7 and EM7 countries where inflation uncertainty is ordered last. The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16–84 percentile confidence intervals.

## Figure C.3. Robustness Check: Exogenous Variables

**A.** VIX Employed as an Exogenous Variable

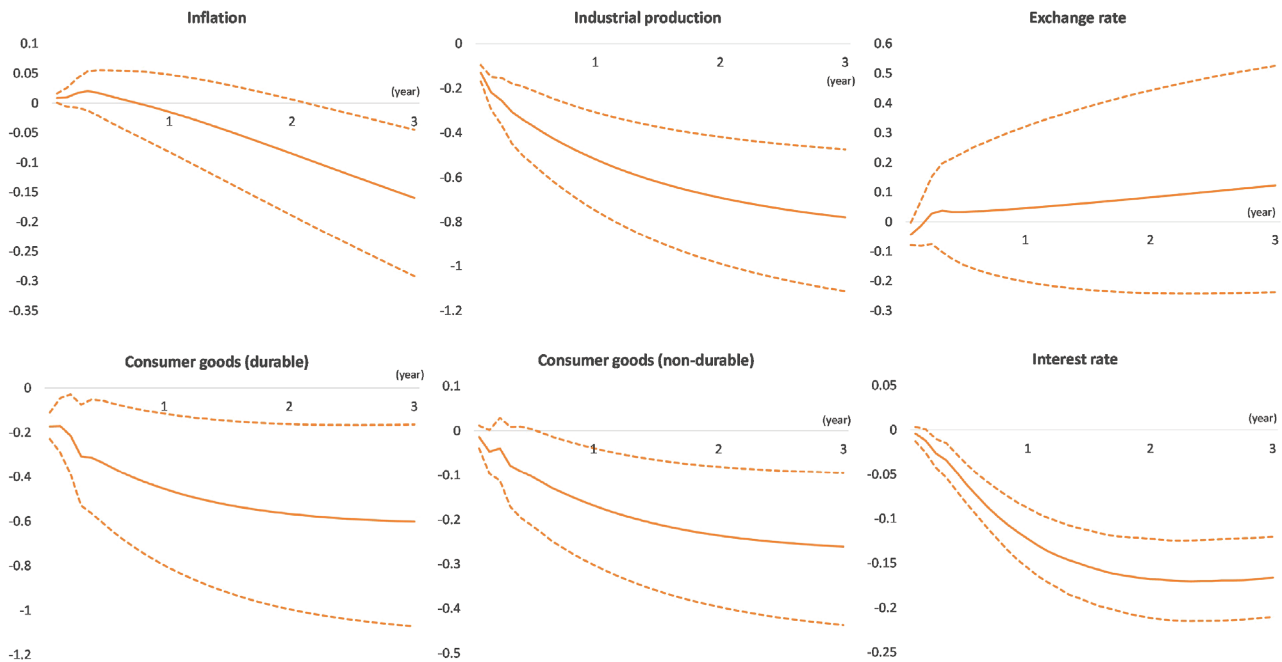



**Note:** The figures present dynamic impulse responses of the variables following a positive one-standard-deviation increase in inflation uncertainty, based on the panel VAR model for G7 and EM7 countries where VIX is included as a control variable. The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16–84 percentile confidence intervals.

*(continued)*

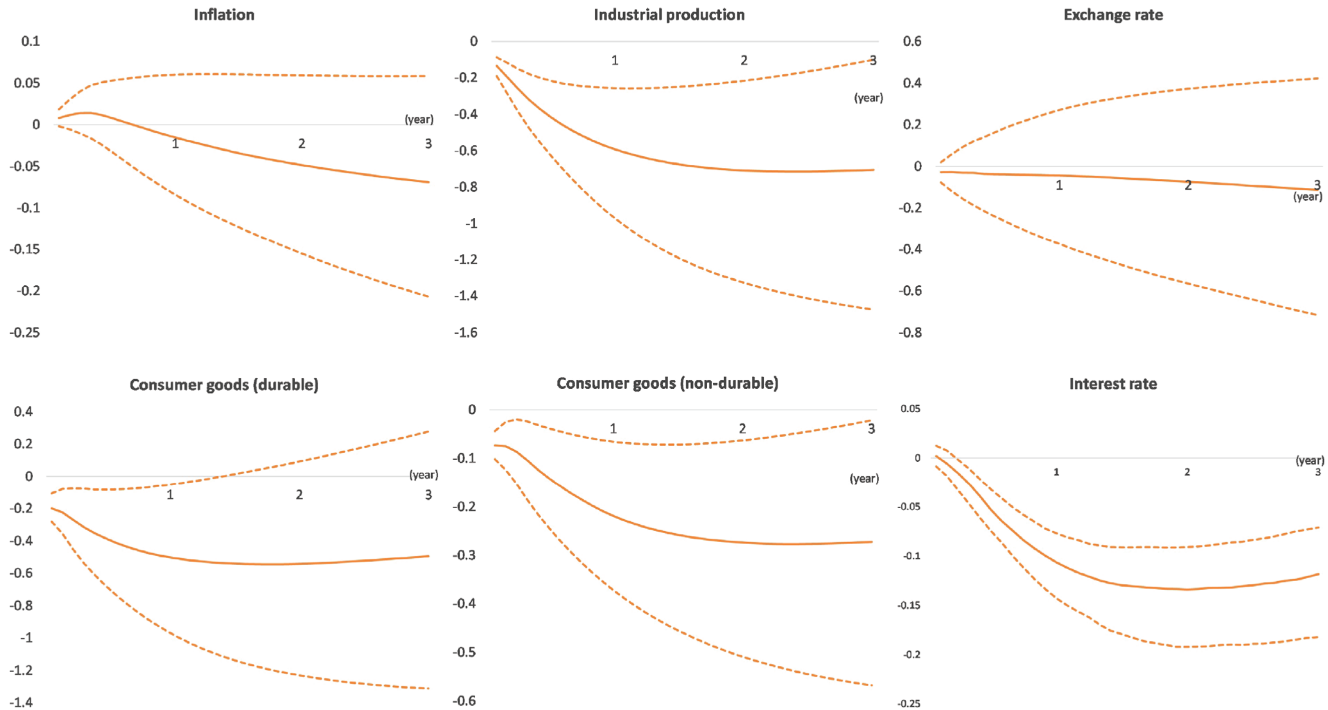
**Figure C.3. (Continued)**

**B.** EPU Employed as an Exogenous Variable



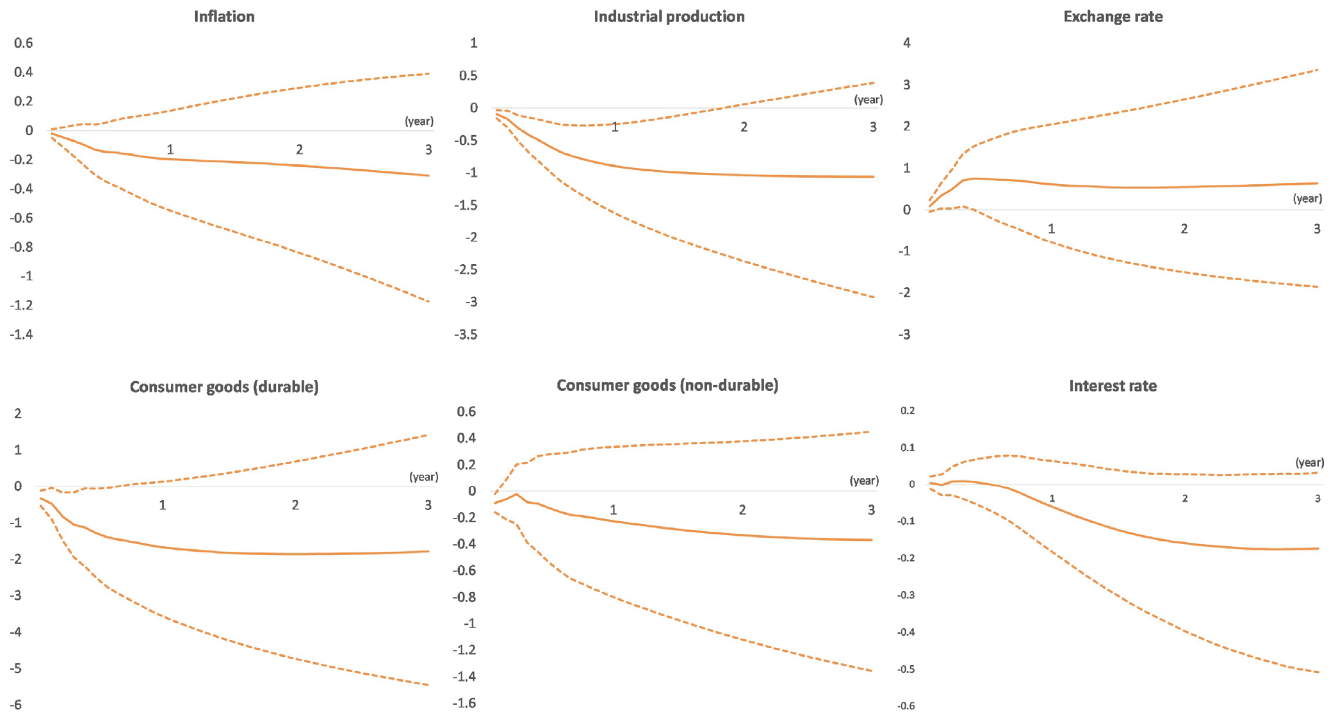

**Note:** The figures present dynamic impulse responses of the variables following a positive one-standard-deviation increase in inflation uncertainty, based on the panel VAR model for G7 and EM7 countries where global EPU is included as a control variable. The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16–84 percentile confidence intervals.

**Figure C.4. Robustness Check: SVAR with Global Average Data**




**Note:** The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16–84 percentile confidence intervals.

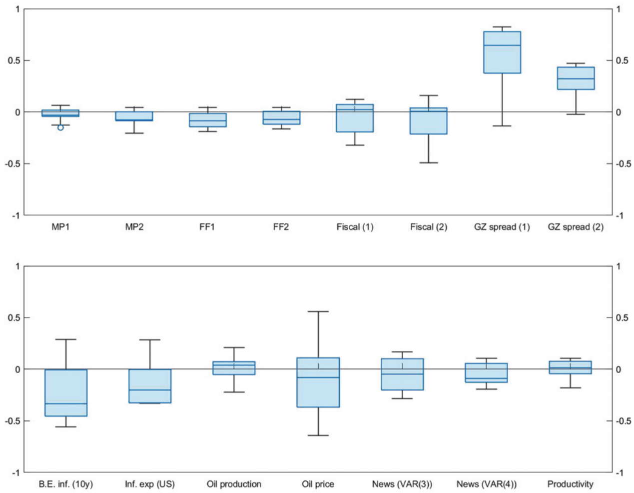
## Figure C.5. Robustness Check: SVAR of United States



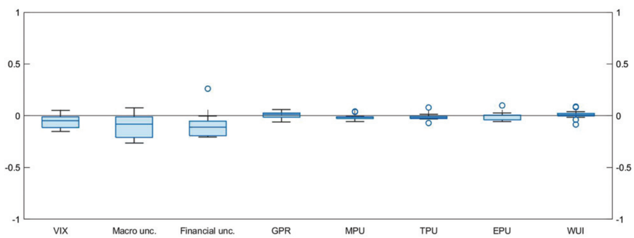

**Note:** The figures present the dynamic impulse responses of the variables following a positive one-standard-deviation increase in inflation uncertainty, based on the panel VAR model for the United States. The y-axis indicates percent (or percentage point for interest rate). The x-axis indicates years after shock. Broken lines are the 16–84 percentile confidence intervals.

## Figure C.6. Correlation Coefficients of Inflation Uncertainty with Other Shocks

**A.** Correlation between Inflation Uncertainty and Other Structural Shocks




**B.** Correlation between Inflation Uncertainty and Other Uncertainties




**Note:** The figures display the box plots of correlation coefficients of inflation uncertainty with other structural shocks and uncertainties. Each box and whisker is characterized by 14 (corresponding to G7 and EM7) correlation coefficients between inflation uncertainty in an individual country and other shocks. MP1, MP2, FF1, and FF2 indicate the monetary policy shocks identified using intraday movements of federal funds futures rates as suggested by Gertler and Karadi (2015). Fiscal (1) and (2) indicate exogenous tax changes and those based on the present value as identified by Romer and Romer (2010). GZ spread (1) and (2) are the predicted GZ credit spreads and those controlled for the term structure and interest effects, taken from Gilchrist and Zakrajšek (2012). News(VAR(3)) and (VAR(4)) are the news shocks identified by the three- and four-variable VAR frameworks following Barsky and Sims (2011) and Beaudry and Portier (2014), respectively. Productivity denotes productivity shocks, estimated frem the six-variable VAR as in Levchenko and Pandalai-Nayar (2020). Macro unc. and Financial unc. are three-month-ahead measures of macro and financial uncertainty taken from Jurado, Ludvigson, and Ng (2015). GPR, MPU, TPU, EPU, and WUI represent geopolitical risks (Caldara and Iacoviello 2022), monetary policy uncertainty (Husted, Rogers, and Sun 2020), trade policy uncertainty (Caldara et al. 2020), economic policy uncertainty (Baker, Bloom, and Davis 2016), and world uncertainty (Ahir, Bloom, and Furceri 2022), respectively.

**Table C.1. Regression Results of Inflation Uncertainty on Other Uncertainties and Structural Shocks[1]**

| Structural Shocks | | Country | Related Studies | $\beta$ | SE | *P*-value | Obs. | Sample |
|---|---|---|---|---|---|---|---|---|
| *A. G7* | | | | | | | | |
| Uncertainty | VIX | US | Bloom (2009) | 0.01 | 0.01 | 0.64 | 185 | 2004:M8–2019:M12 |
| | Macro Uncertainty ($h = 3$)[2] | US | Jurado, Ludvigson, and Ng (2015) | –0.03 | 0.24 | 0.90 | 185 | 2004:M8–2019:M12 |
| | Financial Uncertainty ($h = 3$)[2] | US | Jurado, Ludvigson,and Ng (2015) | –0.04 | 0.20 | 0.85 | 185 | 2004:M8–2019:M12 |
| | Geopolitical Risk | Global | Caldara and Iacoviello (2022) | –0.02 | 0.03 | 0.45 | 185 | 2004:M8–2019:M12 |
| | Monetary Policy Uncertainty | US | Husted, Rogers, and Sun (2020) | –0.03 | 0.03 | 0.33 | 185 | 2004:M8–2019:M12 |
| | Trade Policy Uncertainty | Global | Caldara et al. (2020) | –0.04 | 0.04 | 0.30 | 185 | 2004:M8–2019:M12 |
| | Economic Policy Uncertainty | Global | Baker, Bloom, and Davis (2016) | –0.02 | 0.03 | 0.45 | 185 | 2004:M8–2019:M12 |
| | World Uncertainty (Advanced Economies) | AEs | Ahir, Bloom, and Furceri (2022) | –0.03 | 0.01 | 0.06 | 120 | 1990:Q1–2019:Q4 |
| Monetary Policy[3] | MP1 | US | Gertler and Karadi (2015), Gürkaynak, Sack, and Swanson (2005) | –1.43 | 1.51 | 0.35 | 179 | 2004:M8–2019:M6 |
| | MP2 | | | –2.75 | 2.59 | 0.29 | 179 | 2004:M8–2019:M6 |
| | FF1 | | | –6.62 | 6.15 | 0.28 | 179 | 2004:M8–2019:M6 |
| | FF2 | | | –2.18 | 2.59 | 0.40 | 179 | 2004:M8–2019:M6 |
| Fiscal Policy[4] | Government Spending (1) | US | Romer and Romer (2010) | 0.00 | 0.00 | 0.19 | 72 | 1990:Q1–2007:Q4 |
| | Government Spending (2) | | | 0.00 | 0.00 | 0.86 | 72 | 1990:Q1–2007:Q4 |
| Financial[5] | GZ Spread (1) | US | Gilchrist and Zakrajšek (2012) | 0.19 | 0.10 | 0.06 | 74 | 2004:M8–2010:M9 |
| | GZ Spread (2) | | | 0.18 | 0.12 | 0.14 | 74 | 2004:M8–2010:M9 |
| Inflation | Breakeven Inflation (10-year) | US | Drakos, Konstantinou, and Thoma (2020), Kose et al. (2019) | –0.07 | 0.05 | 0.18 | 185 | 2004:M8–2019:M12 |
| | Inflation Expectation (Consensus Forecast, US) | | | –0.04 | 0.08 | 0.63 | 185 | 2004:M8–2019:M12 |

(*continued*)

**Table C.1. (Continued)**

| Structural Shocks | | Country | Related Studies | $\beta$ | SE | $P$-value | Obs. | Sample |
|---|---|---|---|---|---|---|---|---|
| *A. G7* | | | | | | | | |
| Oil Price | Oil Production | Global | Kilian (2008) | 0.00 | 0.01 | 0.99 | 41 | 2004:M8–2007:M12 |
| | Oil Price | Global | Ha, Kose, and Ohnsorge (2019) | 0.00 | 0.00 | 0.56 | 41 | 2004:M8–2007:M12 |
| News Shock | VAR(3) Residual | US | Barsky and Sims (2011) | –0.16 | 0.14 | 0.26 | 67 | 1996:Q1–2012:Q3 |
| | VAR(4) Residual | US | Beaudry and Portier (2014) | –0.07 | 0.11 | 0.52 | 67 | 1996:Q1–2012:Q3 |
| Productivity[6] | VAR(6) Residual | US | Levchenko and Pandalai-Nayar (2020) | –0.17 | 0.18 | 0.36 | 88 | 1996:Q1–2017:Q4 |
| *B. EM7* | | | | | | | | |
| Uncertainty | VIX | US | Bloom (2009) | 0.00 | 0.01 | 0.99 | 185 | 2004:M8–2019:M12 |
| | Macro Uncertainty ($h = 3$)[2] | US | Jurado, Ludvigson, and Ng (2015) | –0.11 | 0.19 | 0.54 | 185 | 2004:M8–2019:M12 |
| | Financial Uncertainty ($h = 3$)[2] | US | Jurado, Ludvigson, and Ng (2015) | –0.11 | 0.16 | 0.50 | 185 | 2005:M8–2019:M12 |
| | Geopolitical Risk | Global | Caldara and Iacoviello (2022) | –0.03 | 0.03 | 0.26 | 185 | 2004:M8–2019:M12 |
| | Monetary Policy Uncertainty | US | Husted, Rogers, and Sun (2020) | –0.04 | 0.03 | 0.18 | 185 | 2004:M8–2019:M12 |
| | Trade Policy Uncertainty | Global | Caldara et al. (2020) | –0.05 | 0.03 | 0.15 | 185 | 2004:M8–2019:M12 |
| | Economic Policy Uncertainty | Global | Baker, Bloom, and Davis (2016) | –0.03 | 0.03 | 0.21 | 185 | 2004:M8–2019:M12 |
| | World Uncertainty (Emerging Economies) | EMs | Ahir, Bloom, and Furceri (2022) | –0.02 | 0.01 | 0.20 | 80 | 2000:Q1–2019:Q4 |
| Monetary Policy[3] | MP1 | US | Gertler and Karadi (2015), Gürkaynak, Sack, and Swanson (2005) | –1.10 | 0.51 | 0.03 | 179 | 2004:M8–2019:M6 |
| | MP2 | | | –1.86 | 0.95 | 0.05 | 179 | 2004:M8–2019:M6 |
| | FF1 | | | –3.40 | 2.69 | 0.21 | 179 | 2004:M8–2019:M6 |
| | FF2 | | | –1.38 | 1.18 | 0.24 | 179 | 2004:M8–2019:M6 |

(*continued*)

## Table C.1. (Continued)

| Structural Shocks | | Country | Related Studies | $\beta$ | SE | $P$-value | Obs. | Sample |
|---|---|---|---|---|---|---|---|---|
| | | | *B. EM7* | | | | | |
| Fiscal Policy[4] | Government Spending (1) | US | Romer and Romer (2010) | 0.00 | 0.00 | 0.79 | 32 | 2000:Q1–2007:Q4 |
| | Government Spending (2) | | | 0.00 | 0.00 | 0.00 | 32 | 2000:Q1–2007:Q4 |
| Financial[5] | GZ Spread (1) | US | Gilchrist and Zakrajšek (2012) | 0.15 | 0.04 | 0.00 | 74 | 2004:M8–2010:M9 |
| | GZ Spread (2) | | | 0.19 | 0.08 | 0.01 | 74 | 2004:M8–2010:M9 |
| Inflation | Breakeven Inflation (10-Year) | US | Drakos, Konstantinou, and Thoma (2020), Kose et al. (2019) | –0.07 | 0.06 | 0.20 | 185 | 2004:M8–2019:M12 |
| | Inflation Expectation (Consensus Forecast, US) | | | –0.07 | 0.06 | 0.30 | 185 | 2004:M8–2019:M12 |
| Oil Price | Oil Production | Global | Kilian (2008) | 0.00 | 0.00 | 0.82 | 41 | 2004:M8–2007:M12 |
| | Oil Price | Global | Ha, Kose, and Ohnsorge (2019) | 0.00 | 0.00 | 0.80 | 41 | 2004:M8–2007:M12 |
| News Shock | VAR(3) Residual | US | Barsky and Sims (2011) | –0.03 | 0.04 | 0.38 | 51 | 2000:Q1–2012:Q3 |
| | VAR(4) Residual | US | Beaudry and Portier (2014) | 0.01 | 0.03 | 0.86 | 51 | 2000:Q1–2012:Q3 |
| Productivity[6] | VAR(6) Residual | US | Levchenko and Pandalai-Nayar (2020) | 0.12 | 0.08 | 0.17 | 72 | 2000:Q1–2017:Q4 |

**Note:** 1. This table reports the estimates ($\beta_i$) of regression (7). Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors are reported.
2. MP1, MP2, FF1, and FF2 indicate the monetary policy shocks identified using intraday movements of federal funds futures rates as suggested by Gertler and Karadi (2015).
3. Three-month-ahead measures of macro and financial uncertainty are taken from Jurado, Ludvigson, and Ng (2015).
4. Exogenous tax changes (1) and those based on the present value (2) are taken from Romer and Romer (2010).
5. Predicted GZ spreads (1) and those controlled for the term structure and interest effects (2) are taken from Gilchrist and Zakrajšek (2012).
6. Following Levchenko and Pandalai-Nayar (2020), residuals of labor productivity are regarded as a proxy for productivity, estimated in the six-variable VAR: labor productivity, real GDP, private consumption, investment, employment, and consumer price.

## Appendix D. The Details of the Model for Inflation Uncertainty

The model shares many features of the model of Basu and Bundick (2017), but substantially deviates from it by explicitly incorporating the inflation uncertainty process. The stochastic process related to the formation of inflation directly affects the inflation risk premium and the firm's adjustment cost. The process is governed by the second-moment shock, which is interpreted as the uncertainty about inflation.

A representative household maximizes the lifetime utility given Epstein-Zin preference by choosing consumption ($C_t$), labor ($N_t$), bonds ($B_t$) issued by intermediate goods firm, and equity share ($S_t$) for all periods:

$$V_t = \max \left[ a_t \left( C_t^{\eta} \left(1 - N_t\right)^{1-\eta} \right)^{\frac{(1-\sigma)}{\theta_V}} + \beta \left( E_t V_{t+1}^{1-\sigma} \right)^{\frac{1}{\theta_V}} \right]^{\frac{\theta_V}{(1-\sigma)}}$$

subject to the budget constraint

$$C_t + \frac{P_t^E}{P_t} S_{t+1} + \frac{1}{R_t^R} B_{t+1} \leq \frac{W_t}{P_t} N_t + \left( \frac{D_t^E}{P_t} + \frac{P_t^E}{P_t} \right) S_t + B_t,$$

where $\sigma, \theta_V$ denote the parameters for risk aversion and preference on the uncertainty resolution. Solving a household's problem yields the first-order conditions of labor supply and the Euler equations for equity shares and real bonds.

In addition, we assume that nominal bond rate ($R_t$) is affected by ex ante real rate ($R_t^R$), inflation ($\pi_t$), and premium compensated for inflation risk ($\Theta_t$). Hence, nominal bond rate can be rewritten with regard to inflation risk-free rate ($R_t^*$) and the premium ($\Theta_t$). $\Theta_t$ is assumed to be a linear function of an evolution of the stochastic process of $\Gamma_t (= E_t \left[ \Gamma_{t+1} / \Gamma_t \right])$.

$$R_t = R_t^* \Theta_{t+1} \tag{D.1}$$

Then, the Euler equation for a zero net supply of nominal bonds can be reexpressed in terms of inflation risk-hedged yield and the premium:

$$1 = R_t E_t \left[ \frac{M_{t+1}}{\Pi_{t+1}} \right] = R_t^* E_t \left[ \frac{M_{t+1}}{\Pi_{t+1}} \Theta_{t+1} \right]. \tag{D.2}$$

This also allows us to reformulate the conventional Taylor-type rule such that the central bank in the model adjusts $R_t^*$, additionally taking the evolution of inflation uncertainty into consideration.

$$\begin{aligned} log\left(R_t^*\right) = (1-\rho_{R^*}) \left[ log\left(R^*\right) + \rho_\Pi log\left(\frac{\Pi_t}{\Pi}\right) + \rho_Y log\left(\frac{Y_t}{Y_{t-1}}\right) \right] \\ + \rho_{R^*} log\left(R_{t-1}^*\right) - log\left(\Theta_{t+1}\right) \end{aligned} \tag{D.3}$$

Each intermediate goods producer $i$ employs labor $N_t(i)$ and produces intermediate goods $Y_t(i)$ according to the identical Cobb-Douglas type production function. Firm $i$ owns capital stocks $K_t(i)$ and faces the convex costs of capital adjustment. Also, the installed capital depreciates at the rate of $\delta$, which is affected by the rate of capital utilization $U_t(i)$. To reflect the influence of inflation uncertainty on the firm's pricing decision, the stochastic process of $\Gamma_t$ is assumed to determine the Rotemberg-type price adjustment cost. Taking these conditions into account together, each firm maximizes discounted cash flows $D_t(i)/P_t$

$$\max E_t \sum_{s=0}^{\infty} \left( \frac{\frac{\partial V_t}{\partial C_{t+s}}}{\frac{\partial V_t}{\partial C_t}} \right) \left[ \frac{D_{t+s}(i)}{P_{t+s}} \right],$$

where

$$\frac{D_t(i)}{P_t} = \left[ \frac{P_t(i)}{P_t} \right]^{-\theta_\mu} Y_t - \frac{W_t}{P_t} N_t(i) - I_t(i) - \frac{\phi_p}{2\Gamma_t} \left[ \frac{P_t\left(i\right)}{\Pi P_{t-1}\left(i\right)} - 1 \right]^2 Y_t \tag{D.4}$$

subject to the production function and the capital accumulation equation, which are given as

$$\left[ \frac{P_t(i)}{P_t} \right]^{-\theta_\mu} Y_t \leq \left[ K_t(i) U_t(i) \right]^{1-\alpha} - \Phi$$

and

$$K_{t+1}(i) = \left( 1 - \delta\left(U_t(i)\right) - \frac{\phi_K}{2} \left( \frac{I_t(i)}{K_t(i)} - \delta \right)^2 \right) K_t(i) + I_t(i),$$

where $\delta\left(U_t(i)\right)$ denotes a depreciation rate $\left(=\delta_0+\delta_1\left(U_t(i)-U\right)+\left(\frac{\delta_2}{2}\right)\left(U_t(i)-U\right)^2\right)$. The firm's optimization implies the first-order conditions with regard to the demands for labor and capital, and the price determination for goods (i.e., NKPC) and installed capital.

The final goods producer transforms intermediate goods $(Y_t(i))$ into final output $(Y_t)$. The producer maximizes the profits by selling final goods at price $P_t$ and buying intermediate goods at price $P_t(i)$:

$$P_tY_t-\int_0^1 P_t(i)Y_t(i)di$$

subject to the constant returns to scale technology

$$\left[\int_0^1 Y_t(i)^{\frac{(\theta_\mu-1)}{\theta_\mu}}di\right]^{\frac{\theta_\mu}{(\theta_\mu-1)}}\geq Y_t.$$

The first-order conditions for profit maximization results in

$$Y_t(i)=\left[\frac{P_t(i)}{P_t}\right]^{-\theta_\mu}Y_t \tag{D.5}$$

$$P_t=\left[\int_0^1 P_t(i)^{1-\theta_\mu}di\right]^{\frac{1}{(1-\theta_\mu)}}. \tag{D.6}$$

In addition to the demand $(a_t)$ and technology $(Z_t)$ shock processes as in Basu and Bundick (2017), we consider the process associated with inflation uncertainty evolution. It is parameterized as

$$\Gamma_t=\left(1-\rho_\Gamma\right)\Gamma+\rho_\Gamma\Gamma_{t-1}+\sigma_{t-1}^\Gamma\varepsilon_t^\Gamma \tag{D.7}$$

$$\sigma_t^\Gamma=\left(1-\rho_{\sigma^\Gamma}\right)\sigma^\Gamma+\rho_{\sigma^\Gamma}{\sigma^\Gamma}_{t-1}+\sigma^{\sigma^\Gamma}\varepsilon_t^{\sigma^\Gamma}, \tag{D.8}$$

where $\varepsilon_t^\Gamma$ and $\varepsilon_t^{\sigma^\Gamma}$ denote first- and second-moment shocks which capture innovations to the stochastic process for the level and the volatility of inflation uncertainty, respectively. Specifically, the second-moment shocks are referred to as the inflation uncertainty shock. All the stochastic shocks are orthogonal and follow a standard normal distribution. The rest of the features are identical to Basu and Bundick (2017).

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# The Macroeconomic Effects of Global Supply Chain Reorientation*

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Policymakers around the world are encouraging the local production of key inputs to reduce risks from excessive dependencies on foreign suppliers. We analyze the macroeconomic effects of supply chain reorientation through localization policies, using a global dynamic general equilibrium model. We proxy non-tariff measures, such as the stricter enforcement of regulatory standards, which reduce import quantity but do not directly alter costs and prices. These measures have, so far, been a key component of attempts to reshore production and are an increasingly popular trade policy instrument in general. Focusing on the euro area, we find that localization policies are inflationary, imply transition costs, and generally have a negative long-run effect on aggregate domestic output. The size (and sign) of the impact depends on whether these policies are implemented unilaterally or induce a retaliation from trade partners, and also the extent to which they reduce domestic competition and productivity. We provide some recommendations for policymakers considering implementing a localization agenda.

JEL Codes: F13, F41, F45, F62.

*We thank Keith Kuester (co-editor), Thomas Conefrey, Aydan Dogan (discussant), Sorcha Foster, Vahagn Galstyan, Pascal Jacquinot, Klaus Masuch, Martin O'Brien, Gerard O'Reilly, Dimitrios Papaoikonomou (discussant), and participants at the International Journal of Central Banking Annual Research Conference, the 29th International Conference for Computing in Economics and Finance, the 25th INFER Annual Conference, the ESCB Research Cluster 2 Annual Workshop, and Central Bank of Ireland and ECB seminars for comments. Matija Lozej provided invaluable advice throughout the project. These views are our own and do not necessarily reflect the views of the CBI, the ECB, or the OECD. Author e-mails: daragh.clancy@centralbank.ie; Donal.SMITH@oecd.org; vilem.valenta@ecb.europa.eu.

*European strategic autonomy is goal number one for our generation.*

— Charles Michel, President of the European Council

## 1. Introduction

The COVID-19 pandemic and heightened geopolitical tensions from events such as Brexit, U.S./China trade tensions, and the Russian invasion of Ukraine have increased concerns over the smooth functioning and security of global supply chains. European policymakers, like many others around the world, have introduced legislation to spur the local production of key manufacturing inputs and reduce "excessive dependencies" on external suppliers. These initiatives seek to help Europe achieve *Open Strategic Autonomy*, one of the key policy objectives of the von der Leyen European Commission.[1] Broadly speaking, this term refers to the European Union (EU)'s ability to protect its interests and adopt its preferred economic, defense, and foreign policy without depending heavily on foreign states.

While arguments about comparative advantage, the potential forgone benefits of international specialization, and industry- and product-specific disruptions are familiar, there is less analysis on the macroeconomic effects of supply chain changes resulting from localization policies. Recent supply chain shocks have had large effects, with disruptions in 2021 estimated to have reduced euro-area GDP by around 2 percent and doubled the rate of manufacturing producer inflation (Celasun et al. 2022). These disruptions contributed to the need for a large fiscal response—first to the COVID-19 pandemic, and later to the energy crisis.[2] The large sensitivity of the global

[1] In Appendix A, we discuss a specific piece of legislation that illustrates the concept of Open Strategic Autonomy: the European Chips Act. This legislation aims to bolster the supply of (strategically important) semiconductors and demonstrates the shift in emphasis towards the domestic production of some essential goods. Note that we use the euro area and Europe interchangeably throughout, and that we also use domestic, local, and regional as synonyms.

[2] European countries have allocated over €750 billion in support since the energy crisis erupted, according to a Bruegel database (Sgaravatti, Tagliapietra, and Zachmann 2022). To put this in context, German supports alone are equivalent to almost 7.5 percent of GDP.

economy to the smooth functioning of supply chains suggests that the international trade reconfiguration implied by localization policies could also have sizable impacts on key macroeconomic variables such as output, employment, and inflation.

To analyze this issue, we simulate a (partial) reshoring of production back to Europe in a global dynamic general equilibrium framework. Our model covers three regions: the euro area (EA), the United States (US), and the rest of the world (RW). These economies are linked through bilateral trade and participation in international financial markets, with region-specific calibration. We model the reshoring of production by (permanently) replacing a proportion of imported inputs used in the creation of export goods with locally produced inputs. Thus, localization focuses on the goods in our model most closely related to global supply chains.[3] We model reshoring through a direct change to the export goods' production-function parameters. Our approach is a proxy for non-tariff measures, such as the stricter enforcement of regulatory standards, which reduce import quantity but do not directly alter costs and prices.

We start by analyzing the effects of the EA *unilaterally* reshoring part of its production. In a basic scenario, whereby there is no impact from reshoring on local competition and productivity and no retaliation by trade partners, aggregate output in the economy increases by around 0.5 percent in the *long run*. An important aspect of this economic expansion is the reaction of foreign firms, who *drop* their prices in response to the anticipated fall in demand. Since the reshoring is only partial, the cost savings on remaining imported inputs boosts the competitiveness of EA exporters and allows them to export more. This is despite a real effective exchange rate appreciation from the rise in domestic costs and prices, due to increased demand for factor inputs. The positive wealth effect from increased export earnings facilitates a rise in consumption and a decrease in work effort, with increased investment required for the capital-intensive rise in production.

[3]Our exercise looks at reshoring the production of goods that are solely intended for export. This captures only one component of trade, and production that ends in domestic use may still use foreign inputs in the same way as before. This means that imports that are at the end of the supply chain remain unaffected. Our results, available upon request, are robust to the reshoring of imported final goods.

Another crucial aspect of these long-run results is the rise in foreign demand for EA exports. This occurs because of the reduction in a source of inefficiency: the market power of export firms, which enables them to set a markup over marginal costs. At each stage of the supply chain, producers charge markups (assumed, for now, to be constant over time). Since reshoring effectively shortens the supply chain, the sum of markups along the chain falls. These cost savings facilitate the expansion in demand in all three regions and are key to our finding of increased aggregate output in this basic scenario.

A value-added of our framework is that we can analyze the *medium-term* adjustment process following a decision to reshore. We find that aggregate economic output is lower and inflation is higher initially, while the economy adjusts. Increased costs and prices result in a (real effective) exchange rate appreciation that worsens external competitiveness and leads to a shift in resources from tradable to non-tradable production. Gradually, as lower import prices feed into lower export prices, the effect of the appreciation is fully offset and demand for EA exports rises. This, and the increase in domestic demand for tradable goods (from the decision to reshore), results in a need for greater tradable production, and the transition towards the new steady state is set in motion.

In the basic scenario we have described so far, reshoring leads to higher economic activity in the long run at the cost of increased prices. However, there are several reasons why reshoring might be less benign for local economic activity. We analyze three such scenarios and find that the size (and sign) of the impact of unilateral reshoring on aggregate output depends on the extent to which it results in (i) a (permanent) rise in local firm price markups (from increased market power), (ii) a fall in local firm productivity (from the use of lower-quality local inputs), and (iii) a retaliation by trade partners. We find that the adverse impacts of the markup and productivity shocks resulting from reshoring would likely more than offset the positive impact from moving production back home, resulting in permanently lower domestic aggregate output. Finally, if Europe's trade partners *retaliate* by also reshoring (a symmetric amount of) production, the increase in EA economic activity and inflation is attenuated by a less pronounced wealth effect and, in contrast to the unilateral scenarios, global trade declines.

***Related Literature.*** Our analysis sits within the broad literature examining the role of global supply chains as a mechanism for the propagation and amplification of shocks (e.g., Carvalho et al. 2021). In particular, our work relates to papers examining the potential for countries to reduce their exposure to global supply chains. Rodrik (1998) and Giovanni and Levchenko (2009) find that greater openness increases an economy's exposure to external shocks. In contrast, Caselli et al. (2020) show that international trade reduced volatility in most countries and Bonadio et al. (2021) demonstrate that reduced reliance on foreign inputs does not mitigate pandemic-induced contractions in labor supply. D'Aguanno et al. (2021) find no evidence of a relationship between global value chain integration and macroeconomic volatility.

The onset of the COVID-19 pandemic and the severe supply chain issues seen in many countries has fostered a narrative that countries and regions could be better off reducing their exposure to foreign shocks that propagate into their economies through trade in intermediate goods. Baldwin and Freeman (2021) provide a comprehensive discussion of proposals to reduce this exposure, such as decoupling from global supply chains through greater use of domestic inputs, shortening value chains, and through further diversification of input sources. Additionally, the rising global tensions following Russia's invasion of Ukraine suggests that a more fragmented international system could replace previous norms of ever more open markets and increasing globalization. In particular, strategic geopolitical rivalries may decrease the weight on economic gains from trade. This dynamic, along with factors such as natural disasters, climate-change-induced volatility, and terrorism mean that supply chain disruptions could be a new normal (Grossman, Helpman, and Lhuillier 2021).

Our work fits within the literature providing dynamic general equilibrium analyses of protectionist policies, in particular those using global macroeconomic models to quantify trade policy changes. Faruqee et al. (2008) analyze the effect of a rise in protectionism in response to rising global trade imbalances. They find that imposing import tariffs does not help reduce these imbalances. Lindé and Pescatori (2019) find that although the macroeconomic costs of a trade war are substantial, a fully symmetric retaliation is the best response. Cappariello et al. (2020) consider a rich input-output structure and demonstrate that closer integration amplifies the adverse effects of protectionist trade policies. Other papers to analyze trade policy issues using the EAGLE model framework include Pisani and Vergara Caffarelli (2018), Bolt, Mavromatis, and van Wijnbergen (2019), and Jacquinot, Lozej, and Pisani (2022).

Several recent studies have also examined the economic effects of a global trade fragmentation. Góes and Bekkers (2022) find that Europe could suffer substantial welfare losses from a split into a two-bloc world along geopolitical lines. The size of the effect depends crucially on the extent to which this decoupling reduces the cross-border diffusion of ideas and therefore innovation. A common finding is that distortions to trade from geopolitical fragmentation generally entail higher prices and lower welfare (Javorcik et al. 2022; Attinasi, Boeckelmann, and Meunier 2023; Campos et al. 2023; Felbermayr, Mahlkow, and Sandkamp 2023).[4] More localization may also increase vulnerability to (external and domestic) shocks (OECD 2020).

We contribute to this literature in a number of ways. First, we modify a dynamic general equilibrium model of the global economy in order to analyze the transmission of localization policies. This allows for a comprehensive treatment of cross-border macroeconomic interdependences and spillovers between the different regions.

Second, we are able to assess both long-run effects and the transition dynamics of localization policies. We believe that the short- to medium-run effects are crucial from a policy perspective. Our model contains a detailed monetary block and captures inflation dynamics, which is a key concern for supply chain reorientation. These important macroeconomic features are typically highly stylized, or omitted, from static international trade models.

Third, our approach permits an analysis of non-tariff measures (NTMs), which are so far dominating the localization agenda. The generic nature of our shock means it is a suitable proxy for a broad range of NTMs, including potential future new measures. Another

[4]There is, however, substantial cross-country heterogeneity in terms of impact, with small open economies (SOEs) reliant on global supply chains more affected. Clancy, Smith, and Valenta (2023) analyze spillovers to SOEs from the localization policies of (much) larger trade partners and examine the use of fiscal policy instruments to reshore production. See Aiyar et al. (2023) and Ioannou et al. (2023) for comprehensive discussions of the wider economic implications of the changing geopolitical environment.

advantage of our approach is that implementing reshoring through NTMs means that a rise in inflation and an output loss is not a predetermined outcome, as is the case when modeling reshoring through import tariffs and/or a rise in (iceberg) trade costs.

The main limitations of our approach, compared to international trade models, are the lack of differentiation between essential and non-essential productions and less granularity in modeling cross-border linkages.[5] The generic nature of our reshoring shock also does not allow for an analysis of specific policy measures.

Overall, our paper contains a careful analysis of the key aspects of the localization debate, including effects of localization on domestic competition and efficiency. The outline of the paper is as follows. Section 2 provides a brief overview of the model, the modifications to examine global supply chain reorientation, some key details on the calibration, and a brief discussion of the nature of our exercise. We present the results of our simulations of the unilateral reshoring scenarios in Section 3 and the retaliation scenario in Section 4. Finally, in Section 5, we summarize our findings and discuss their policy implications.

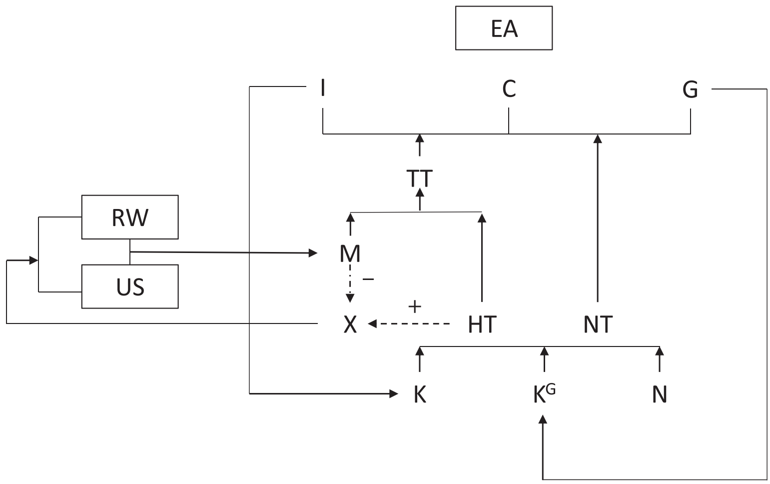
## 2. Model Overview

We conduct our analysis using an extended version of the EAGLE, a dynamic general equilibrium model. This framework permits the implementation of counterfactual exercises and avoids issues of causal identification faced by empirical studies. Here we only provide an overview of the model, with the reader referred to Gomes, Jacquinot, and Pisani (2012) for details on the original model; Brzoza-Brzezina, Jacquinot, and Kolasa (2014) for the import content of exports component; and Clancy, Jacquinot, and Lozej (2016) for government imports.[6]

[5]See Hunt et al. (2020) and Smith, Kowalski, and van Tongeren (2020) for discussions of the relative strengths and weaknesses of trade and macroeconomic models in assessing large economic shocks.

[6]Further extensions of the EAGLE have added search and matching frictions in the labor market (Jacquinot, Lozej, and Pisani 2018), financial frictions in (country-specific) banking sectors (Bokan et al. 2018), and import tariffs (Jacquinot, Lozej, and Pisani 2022).

**Figure 1. Model Structure**




**Note:** This figure shows the structure of our model. We model reshoring through a change to the export goods' production-function parameters. The dashed arrows indicate this *direct* channel of reshoring. However, by affecting the relative price of all goods produced in the economy, and therefore their quantity demanded and supplied, there are considerable *indirect* effects captured by our general equilibrium framework. For conciseness, the figure focuses on the euro-area (EA) economy. The structure of each regional economy is symmetric. US represents the United States, while RW is the rest of the world. M denotes imports, X exports, K private capital, $K^G$ public capital (i.e., infrastructure), N labor, NT nontradable goods, HT domestically produced tradable goods, TT total tradable goods, I investment, C consumption, and G government spending (which has both current expenditure and capital expenditure components).

We model three regions of the global economy: the euro area (EA), the United States (US), and the rest of the world (RW). The structure of each economy is symmetric and linked with each other through bilateral trade and participation in international financial markets, with bloc-specific calibration. This allows for a comprehensive treatment of cross-border macroeconomic interdependences and spillovers between the different regions. We include a number of real and nominal rigidities in order to match the sluggish reaction of prices and wages found in macroeconomic data. We display the structure of the model in Figure 1.

Each economy features both Ricardian and liquidity-constrained households, firms, and monetary and fiscal authorities. The (infinitely lived) households consume final goods, allocate time between work and leisure, and offer imperfectly substitutable labor services to domestic firms. They use their market power to set wages with a markup over the marginal rate of substitution between labor and consumption. Households own domestic firms and the capital stock, which they rent to firms in a fully competitive market.

Firms produce non-tradable final goods, tradable and non-tradable intermediate goods, and provide intermediation services. Non-tradable final goods are produced by perfectly competitive firms and include consumption goods, investment goods, and public goods. Tradable goods are an aggregate of domestically produced and imported goods. Final goods are produced using domestic tradable and non-tradable intermediate goods and imported goods, combined according to a constant elasticity of substitution technology. Different varieties of intermediate goods are imperfect substitutes, produced under monopolistic competition. This market power allows firms to set nominal prices with a markup over marginal costs. Each intermediate good is produced using domestic and (internationally immobile) labor and capital that are combined according to a Cobb–Douglas technology. Intermediate goods are sold both in the domestic and in the export market. Importantly for our analysis, this implies that there are five types of imports in the model: imports of intermediate goods for private consumption and investment, for government consumption and investment, and for exports.

The monetary authority sets the short-term nominal interest rate according to a standard Taylor-type rule, by reacting to changes in consumer inflation and real output. The fiscal authority sets government consumption and investment expenditures (contributing to domestic capital stock) with an explicit imported component. On the revenue side, the government (exogenously) sets labor income tax rates, and social contributions, capital income tax rates, and consumption tax rates. Public debt is stabilized through a fiscal rule that induces an endogenous adjustment through lump-sum taxes.

### *2.1 Supply Chain Reorientation*

Our analysis focuses on imported inputs used to produce goods for export, as the introduction of localization policies is in response to recent disruptions to global supply chains. These are a composite of imports from the other regions of the world, with the quantity and price of bilateral imports a function of preference shares and the elasticity of substitution from different trading partners. Imported inputs are then combined with domestic tradable inputs, produced using domestic capital and labor. Depending on demand, which is a function of preferences and relative prices, these goods are either packaged with locally produced non-tradables as final goods for private and public consumption and investment or exported for use in other countries' production. More formally, exports in our model are a combination of locally produced tradable inputs and intermediate imports (Armington 1969):

$$X_t(h) = \left[\nu_{X,t}^{\frac{1}{\mu_X}} HT_t^X(h)^{\frac{\mu_X-1}{\mu_X}} + (1-\nu_{X,t})^{\frac{1}{\mu_X}} IM_t^X(h)^{\frac{\mu_X-1}{\mu_X}}\right]^{\frac{\mu_X}{\mu_X-1}}, \tag{1}$$

where $X_t(h)$ denotes exports of the tradable intermediate good produced by firm $h$, $HT_t^X$ denotes locally produced tradable goods, $IM_t^X$ denotes intermediate imports destined for re-export, and $\mu_X$ represents the intertemporal elasticity of substitution between local tradable goods and imported inputs. In order to examine the macroeconomic effect of supply chain reorientation, we introduce *time-varying* weights of local inputs $\nu_{X,t}$ in the export good bundle:

$$\nu_{X,t} = (1-\rho_{\nu_X})\overline{\nu_X} + \rho_{\nu_X}\nu_{X,t-1} + \epsilon_{\nu_{X,t}}, \tag{2}$$

allowing us to simulate (permanent or temporary) changes in these weights. One can think of these weights as preferences, formed due to historical linkages, shared language/culture, geographical distance, quality of products, and ease of procurement (such as the existence and/or extent of non-tariff barriers), for example.[7]

In our simulations, we increase the value of $\overline{\nu_X}$, thereby *permanently* increasing the home bias of export firms and causing them to use a greater proportion of local inputs in production. The modeling of this variable as an autoregressive process means that this change is implemented gradually (i.e., the transition speed is dictated by

[7] Our use of these weights to pin down the steady-state import content of exports means they represent a region's revealed (trade) preference.

the size of the parameter $\rho_{\nu_X}$). As we employ a general equilibrium framework, this change will affect costs, prices, and demand for all other goods in the economy. We provide some more details on how this change propagates through the model system in Appendix B.

As our framework does not have internationally mobile firms, we cannot endogenously capture the impact of reshoring on local competition and productivity. Since these are important considerations in the debate surrounding supply chain reorientation, we analyze these as separate scenarios by imposing an additional shock on top of the change in the weight in local inputs in export goods.

To model the potential effect of reduced local competition following a supply chain reorientation, we introduce a *time-varying* elasticity of substitution of tradable firms' goods to increase their market power:

$$HT_{t+k}(h) = \left(\frac{P_{t+k}(h)}{P_{HT,t+k}}\right)^{-\theta_{T_t}} HT_{t+k}, \qquad (3)$$

where $HT_t(h)$ is demand for tradable firm $h$'s goods sold in the domestic market, $P_t(h)$ is the firm-specific price of these goods, $P_{HT,t}$ is the aggregate price of tradable goods, $\theta_{T_t}$ is the elasticity of substitution for their brand, and $HT_t$ is aggregate demand for tradables (taken as given). Tradable-sector firms can also sell their differentiated output in foreign markets:

$$IM^{CO}_{t+k}(h) = \left(\frac{P_{X,t+k}}{P^{H,CO}_{X,t+k}}\right)^{-\theta_{T_t}} IM^{CO,H}_{t+k}, \qquad (4)$$

where $IM^{CO}_t(h)$ is demand for tradable firm $h$'s goods sold in the foreign market $CO$ (either the US or the RW), $P_{X,t}(h)$ is the firm-specific price of these goods, $P^{H,CO}_{X,t}$ is the aggregate price of tradable goods from the euro area (region $H$) in region $CO$, and $IM^{CO,H}_t$ is aggregate demand for tradables imports from the euro area in region $CO$ (again, taken as given). By reducing the elasticity of substitution, firms have greater market power and can charge a larger markup over their marginal cost. We model these time-varying elasticities of substitution in a similar way to the weights of local inputs in the export bundle (i.e., as an autoregressive process).

Finally, we also consider the potential side effect of having to use lower-quality goods in areas where Europe is not at the technological frontier. Returning to the example of semiconductors, Europe is substantially behind global leaders (such as South Korea and Taiwan) in terms of advanced chip manufacturing capabilities. To examine this aspect of the supply chain reorientation debate, we implement a shock to the total factor productivity term in the local tradable good firm's production function:

$$Y_{T,t}(h) = max\left\{z_T K_t(h)^{\alpha_T} N_t(h)^{1-\alpha_T} - \psi_T, 0\right\}, \tag{5}$$

where $Y_{T,t}$ is the output of tradable firm $h$, $K_t^D$ and $N_t^D$ are the firm's capital and labor, the parameter $\alpha_T$ represents the share of capital used in the production of tradable goods, the parameter $\psi_T$ represents fixed costs of production (calibrated to ensure zero profits in the steady state and therefore ruling out an incentive for other firms to enter the market in the long run), and $z_{T,t}$ are (permanent or temporary) sector-specific productivity shocks. As with the other shocks, we model productivity as an autoregressive process to facilitate a gradual transition to the permanent change.

## *2.2 Calibration*

To get a sense of the euro area's trade relationships in the model, we detail the key steady-state ratios and bilateral trade partners in Table C.1. The most important dimension of our analysis relates to international trade. The euro area is the smallest and most open region. Arriola et al. (2020) note that countries that tend to rely more on foreign inputs and ship larger portions of their production to foreign markets are more exposed to global value chain disruptions. Unsurprisingly, given the relative size of the regions, the RW is the EA's largest trading partner for all types of imports. The value of parameters in the model (Tables C.2–C.7) are either based on region-specific empirical evidence, where available, or kept consistent with the original model which uses standard values, prevalent in the literature. See Gomes, Jacquinot, and Pisani (2012) and Clancy, Jacquinot, and Lozej (2016) for details.

It is worth highlighting that we follow the principle that the elasticity of substitution between tradable and non-tradable goods is substantially lower than the elasticity of substitution between different types of tradable goods. We set the (long-run) elasticity of substitution between tradable goods to 2.5 and the (long-run) elasticity of substitution between tradable and non-tradable goods to 0.5. These values come from Faruqee et al. (2008) and are in line with the literature.[8] The elasticities of substitution between local tradable goods and imports (of 2.5) are closer to the macroeconomic literature than the trade literature, which often uses higher values (see, for example, Imbs and Mejean 2015).

Regarding the focus of our study, the value for $\nu_X$ is greatest for the US (where only 15 percent of exports contain imported components) and lowest for the RW (where over one-third of exports are composed of imported inputs). The EA lies closer to the middle of this range, with an import content of exports of around one-fifth. The $\mu_X$ for each region is set at 1.5, meaning that intermediate imports used in the creation of exports are substitutes and not complements.

Finally, price and wage markups are generally larger in the EA, indicating a somewhat less competitive economy than in the other regions.[9] Markups in the non-traded sector are larger than for the tradable and export sectors in all regions, as they are less exposed to foreign competition. We assume that nominal (price and wage) rigidities are the same across regions.

### *2.3 Nature of the Exercise*

Our approach to modeling localization involves a permanent change to the export goods' production-function parameters. This change in international trade structure is not the endogenous result of an explicit policy decision in the model. As such, this change is efficient, in the sense that it does not impose any deadweight loss, as

[8] Note that because of adjustment costs on bilateral imports, actual *short-run* elasticities in the model are smaller, in line with the empirical evidence (Peter and Ruane 2023). Drozd, Kolbin, and Nosal (2021) model a dynamic elasticity, which is low in the short run but high in the long run, by imposing a convex adjustment cost on trade shares. This represents an interesting avenue for future research within our framework.

[9] Our results are not dependent on this region-specific calibration. We verified this by also assessing the effects of reshoring production in a fully symmetric model, with all regions being of equal size and having the same calibrated values.

would occur if we modeled reshoring using import tariffs, subsidies or through iceberg trade costs for example.[10]

However, we believe that our approach is a useful proxy of a generic rise in non-tariff measures (NTMs). Examples of NTMs include the imposition of local content requirements, stricter quality standards, and alterations in national procurement rules to favor local sellers and promote strategic sectors. Fugazza (2013) provides a comprehensive discussion of these policy instruments. We focus on NTMs, as these are becoming the dominant instrument of trade protectionism (Niu et al. 2018) and are a likely policy tool through which countries may attempt to reshore production (Kratz, Vest, and Oertel 2022). They are also extremely flexible. Grundke and Moser (2019) provide empirical evidence that the stricter enforcement of product standards, a typical form of an NTM, is countercyclical and reacts to business cycle developments. Since NTMs are often de facto, rather than de jure, policy changes, they are less likely to draw attention from trade partners and thereby risk retaliation.[11]

An additional advantage of implementing reshoring with these policy instruments is that changes in prices and output are not a pre-determined outcome. For example, modeling reshoring through import tariffs and/or a rise in (iceberg) trade costs imposes a rise in import prices. Instead, modeling localization measures directly through a change in trade shares does not presuppose a particular response in costs and prices (and, therefore, demand for and production of affected goods). Directly altering trade shares, without imposing cost and price increases, is therefore a close proxy of a localization policy driven by local content, quota, and other legally based trade *volume* distorting NTMs.

These instruments are not barriers that exporters can overcome through price adjustments. They lock out a share of, or all, imports of a product. Other non-tariff barriers can have a similar effect through a prohibitively high cost of compliance. For example, the European Communities (EC) health restrictions on beef imports in

[10]Obstfeld and Rogoff (2000) note that imposing home bias is isomorphic to the effects of trade costs. The size of such costs depend on the elasticity of substitution. Future research could seek to ascertain the value for the elasticity of substitution for which our approach to modeling reshoring becomes inefficient.

[11]Moral suasion is another channel through which governments can encourage desired behavioral changes (Ongena, Popov, and Van Horen 2019).

1989 led to an immediate alteration of trade shares due to the collapse in US beef exports to the EC (Johnson 2017). The change in EC standards meant that US industry would have had to completely restructure to meet the new criteria, an infeasible adjustment for producers. In this case, the NTM essentially ruled out price and cost adjustments to regain trade shares, and US producers in these industries were essentially blocked from the market.

## 3. Unilateral Reshoring

We utilize scenario analysis to examine the effects of Europe reshoring production. For now, we assume that this is unilateral (i.e., the other regions do not retaliate by also reshoring production). This basic, and arguably simplistic, scenario allows us to explore the main mechanisms through which reshoring policies affect the economy, but without the additional complications resulting from simultaneous changes in the production structure of the other regions.[12]

We model reshoring by increasing the bias for locally produced inputs used in the creation of exports from the other regions in favor of locally produced inputs. We impose this change in the production structure by inducing a permanent 1 percent of GDP decrease, relative to the initial steady state, in the EA's imported inputs used in the production of export goods. This transition occurs gradually, with almost all of the change complete after 10 years. As we solve our model using perfect foresight, all agents in the model are fully aware of the path the shock will take.[13]

[12] After describing the effects from this simple case, we examine more realistic scenarios that also affect local competition and productivity and a retaliation by trade partners. These additions could also capture other salient aspects of international trade that are not endogenous in our model. Feenstra (2018a) notes the particular importance of pro-competitive (i.e., reduced markups) and productivity gains from trade, which he estimates account for roughly 30 and 40 percent, respectively, of total US gains.

[13] Our model is deterministic and is solved using a non-linear Newton-type algorithm in Dynare (see Adjemian et al. 2011 for details). Not having to linearize the model around a given steady state allows us to plot the transition dynamics between the initial and new steady state (i.e., after the supply chain reorientation).

**Table 1. Long-Term Effects of Reshoring (% deviation from initial steady state)**

| | **Unilateral** | **Markups** | **Productivity** | **Retaliation** |
|---|---|---|---|---|
| Imported Inputs for Exports (% of Aggregate Output) | –1.0 | –1.0 | –1.0 | –1.0 |
| Aggregate Output | 0.5 | –0.3 | –0.4 | 0.3 |
| Tradable Output | 0.5 | –1.4 | –1.1 | 0.5 |
| Non-tradable Output | 0.5 | 0.6 | 0.2 | 0.1 |
| Consumption | 1.4 | 1.2 | 0.6 | 0.4 |
| Investment | 1.9 | 0.0 | 0.8 | 0.9 |
| Hours Worked | –0.1 | –0.3 | 0.0 | 0.0 |
| Real Effective Exchange Rate | –1.9 | –2.3 | –1.6 | –1.0 |
| Effective Terms of Trade | 0.3 | 0.9 | –0.1 | 1.3 |
| Imports | 0.7 | 1.6 | –0.1 | –1.6 |
| Exports | 1.0 | 2.5 | –0.2 | –0.2 |
| Tradable Marginal Costs | 0.7 | 0.1 | 1.5 | 0.2 |
| Imports for Re-export Prices | –2.1 | –2.1 | –1.5 | –0.8 |
| Export Prices | –2.5 | –3.0 | –1.5 | –2.3 |
| Domestic Debt | –1.8 | –0.4 | –0.8 | –0.7 |

**Note:** This table compares the initial steady-state values to those following a permanent 1 percent of aggregate output reduction in imported inputs used in the production of export goods. "Unilateral" examines the case where the EA enacts this reshoring on its own. "Markups" adds an increase in EA tradable firms' price markups to the unilateral scenario. "Productivity" adds a decrease in EA tradable firms' productivity to the unilateral scenario. "Retaliation" adds a symmetric reduction (i.e., scaled by region size) in the imported content of exports-to-output ratio in both the RW and US regions to the unilateral scenario. All variables are in percentage deviations from the initial steady state, except for the imported inputs for exports (i.e., the reshoring shock), which is in percentage-point deviations.

We first discuss the long-term implications of reshoring. This facilitates a comparison of our results with international trade models, which generally focus on comparative statics. We display these long-term results in the second column of Table 1.

This shock raises aggregate output in the economy by around 0.5 percent in the long run.[14] Increasing the share of local inputs used

[14]The quantitative size of this effect is similar for a unilateral 1 percent of GDP reshoring of imported inputs for export goods in both the RW and US regions (an increase in aggregate output of around 0.3 percent). The underlying transmission channel is also the same. These results are available from the authors upon request.

to produce exports decreases demand for the imported component of these goods. Foreign exports firms react to this drop in demand by reducing the price of these goods.[15] Since the reshoring is only partial, the cost savings on remaining imported inputs results in a fall in the marginal cost for EA exporters. This is despite the higher demand for factor inputs feeding through into higher costs, with local tradable good prices rising as a result. The reduction in overall costs allows export firms to reduce their prices, boosting their competitiveness and leading to an increase in foreign demand for their goods. There is a decline in the terms of trade as export prices fall by more than import prices.

The increased demand for local inputs results in an increase in tradable-sector production. Higher domestic demand, and therefore costs and prices, induces a real effective exchange rate (REER) appreciation. There is a positive wealth effect from the REER appreciation and increased export earnings, boosting domestic households' consumption of both imported (consumption and investment) and domestic non-tradable goods. The boost in domestic demand requires an increase in non-tradable production, further boosting aggregate production. Investment also increases, as the positive wealth effect reduces work effort (resulting in higher wages) and the rise in tradable production is driven by increases in capital usage (reducing the rental cost of capital). Domestic debt falls as increased economic activity boosts tax revenue.

A crucial aspect of these long-run results is the rise in foreign demand for EA exports. Why does this occur, when, all else being equal, the reduction in demand for some of their exports to the EA should have a negative effect on the RW and US? The reason all regions benefit in this basic scenario is due to the reduction of a source of inefficiency: the market power of export firms, which enables them to set a markup over marginal costs. At each stage of the supply chain, producers charge markups (assumed, for now, to be constant over time). Since reshoring effectively shortens the supply chain, the sum of markups along the chain falls. This means that

[15] Khalil and Strobel (2021) provide empirical evidence that cuts to tariff import prices as a result of (trade-policy induced) exchange rate appreciations largely offset tariff price increases.

less resources are lost due to inefficiencies from markups.[16] These cost savings facilitate the expansion in demand in all three regions and are key to our finding of increased aggregate output in the basic scenario.

Importantly, despite engaging in unilateral reshoring, these savings are not entirely captured by the EA. This is clear from the roughly 0.5 percent increase in aggregate production in the EA following the reshoring of 1 percent additional output. The RW and US also benefit through the endogenous response of prices and reallocation of production that boosts EA demand for other types of imports and lowers the price of EA exports. The RW and US increase production to meet increased EA demand, and can do so at lower prices due to the cost savings passed on from EA production being less subject to inefficient distortions from firm market power.

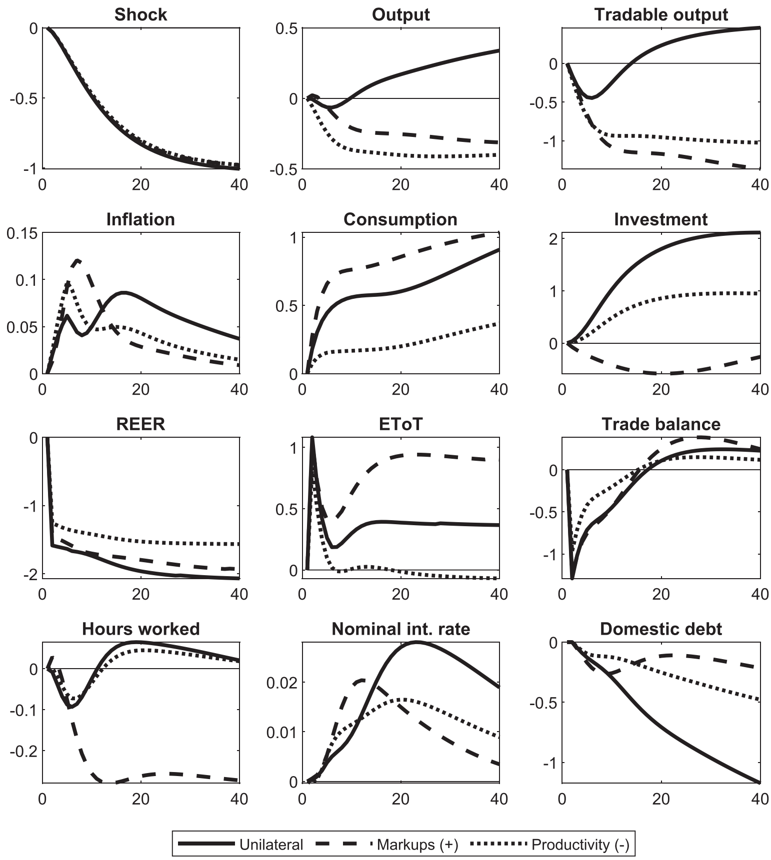
A value added of our framework is the ability to analyze the dynamic response. For policymakers, it is essential to understand the adjustment process. There are some important considerations from the short- to medium-term responses to reshoring production. We display these results (solid line) in Figure 2.

In adjusting to this change, inflation rises by roughly 10 basis points on impact. This effect is highly persistent, with inflation elevated for over a decade. The anticipated rise in production, and therefore factor input costs and prices, results in an expected interest rate differential and an immediate jump in the exchange rate. This appreciation boosts demand for other (i.e., untargeted for localization) imports, and results in a trade deficit. There is local currency pricing, which means the change in exchange rate is not fully passed through to exports (i.e., the appreciation of the euro does not result in an immediate large increase in the price charged in foreign markets). As a result, the increased demand for exports takes some time to materialize, and this weighs on tradable production in the short run. Indeed, this reduction in tradable production is sufficiently large to result in a decrease of aggregate production.

Gradually, as lower import prices (from foreign firms reacting to reduced demand for their goods in EA) feed into lower export prices

[16]In a model where product variety is endogenously determined by firm entry, Bilbiie, Ghironi, and Melitz (2019) demonstrate that markups (and the profits they provide) can be welfare enhancing.

## Figure 2. Unilateral Reshoring




**Note:** This figure shows the effect on the euro area (EA) of a permanent increase in EA-only preferences for domestically produced inputs for export goods (i.e., a partial reshoring of production). We analyze three scenarios: (i) a "unilateral" reshoring; (ii) unilateral plus reduced local competition ("markup"); and (iii) unilateral plus reduced local "productivity." The plotted lines represent transition dynamics between the initial and new steady state. We scale the shock such that the import content of exports-to-output ratio decreases by 1 percentage point in the long run, with almost all of this adjustment complete after 10 years. All variables are in percentage deviations from the initial steady state, except for the imported inputs for exports (i.e., the reshoring shock), consumer price inflation, and the nominal interest rate, which are in percentage-point deviations. Domestic debt is expressed as a nominal value (not as a ratio of GDP). For context, debt is 60 percent of GDP in the initial steady state.

(by reducing their marginal costs), the effect of the appreciation is fully offset and demand for EA exports rises. This, and the increase in domestic demand for tradable goods, results in a need for greater tradable production and the transition towards the new steady state is set in motion.

### *3.1 Increased Firm Market Power*

Greater economic openness exposes local firms to foreign competition. However, efforts to boost local production would likely reduce existing producers' exposure to foreign competition. The large setup costs involved in global supply chains, as well as relaxations in EU state aid rules aimed at facilitating greater public support for existing firms, make it more difficult for new entrants. By signaling a clear increase in preference for local intermediate inputs, localization policies could (unintentionally) increase market power of domestic firms in supported sectors and allow them to increase their price markups.

We now amend our simplified unilateral reshoring scenario to include an additional (permanent) shock to EA tradable-good firms' market power. In the absence of conclusive evidence of what the size of this increase in market power would likely be, we scale this shock to induce a 0.5 percentage point increase in tradable-good price markups (from 30 percent to 30.5 percent). Given the uncertainty as regards the size of this effect, we emphasize that this is a scenario and is largely for illustrative purposes.[17] We nevertheless believe that this calibration is within a plausible range. This increase in markups is similar to increases documented in the literature for typical fluctuations in markups due to business cycle shocks (Nekarda and Ramey 2021).

As before, the shock occurs gradually and is almost fully absorbed after 10 years. We display the results (dashed line) in Figure 2. As in the basic scenario, we first describe the long-run effects. The long-run effect on euro-area output is negative in this

[17] There are a wide range of estimates of the pro-competitive gains from trade. Feenstra (2018b) estimates the US gains from trade (between 1992 and 2005) at just over 1 percent of GDP, of which he ascribes approximately 0.4 percent to decreased markups. However, Costinot and Rodríguez-Clare (2018) estimate gains from trade for the US over a similar period (1995 to 2011) at between 2 and 8 percent of GDP.

scenario, as losses from lower competition more than offset gains from bringing production back home (third column of Table 1). The underlying mechanism is similar to the basic scenario. A decrease in demand for imported inputs in the production of exports results in foreign firms reducing their prices. This boosts the competitiveness of EA exporters, and therefore exports rise despite the REER appreciation. A positive wealth effect spurs consumption and non-tradable-sector production, while lowering work effort.

What is different to the basic scenario is that the greater market power of tradable firms allows them to increase their prices by far more. This reduces demand for tradable goods and therefore tradable sector output falls (while there is an increase in the production of the local input for export goods, these are only one component of overall tradable production). Demand for factor inputs is lower, with investment falling in line with reduced aggregate production.

In terms of the adjustment process, the rise in inflation is much larger than in the basic scenario. This reduces the real interest rate, spurring consumption and resulting in a stronger, but shorter-lived, monetary policy response. Reduced domestic demand due to higher tradable good prices means that investment and employment both decline sharply over the short to medium term. Accordingly, the improvement in public finances is mitigated in this scenario.

### *3.2 Reduced Firm Productivity*

Reshoring production weakens the interaction of the domestic economy with global supply chains. Openness affects growth positively, as economies that are more open have a greater ability to absorb technological advances generated elsewhere (Barro and Sala-i Martin 1997). Global value chains have important implications for productivity and innovation.[18] Increased competition from foreign

[18]Trade in our model is motivated by the Armington assumption that countries produce unique goods and consumers have a love of variety. However, this setup is silent on potentially important implications of localization policies, such as shift patterns of specialization driving by comparative advantage. Given Arkolakis, Costinot, and Rodríguez-Clare (2012)'s equivalence result for different classes of quantitative trade models, it is unclear whether incorporating such changes in specialization would affect our aggregate results. This represents an important avenue for future research.

suppliers can induce improvements in domestic firms. Firms can have potential gains through specializing in their most productive tasks and from utilizing a wider array of new varieties and higher-quality foreign goods, services, and intangible inputs. Further to these effects, engagement with global firms provides an opportunity for knowledge spillovers to local firms (Criscuolo and Timmis 2017). Reshoring could potentially weaken all of these transmission channels, resulting in the use of lower-quality locally produced inputs.

We next amend our simplified unilateral reshoring scenario to include an additional (permanent) shock to tradable good firms' productivity. Again, in the absence of definitive evidence of how big this shock might be, we induce a 0.5 percent decrease in tradable good productivity for illustrative purposes.[19] As before, the shock occurs gradually and is almost fully absorbed after 10 years. We display the long-term results in the fourth column of Table 1.

We find that reshoring has a negative effect on EA output in this scenario. As in the basic scenario, there is an increase in non-tradable output, consumption, and investment as well as an appreciation of the REER. However, the less efficient use of factor inputs means that the marginal cost of producing tradable goods increases substantially. Export prices fall, but by less than import prices and therefore exports are lower (and the terms of trade improve). Imports are also lower, despite the REER appreciation, because there is no longer a positive wealth effect from increased competitiveness.

The adjustment process is quite similar to the basic scenario, with a key difference being the lower beneficial effect of reshoring on consumption, investment, public finances, and the REER appreciation (results displayed using the dotted line in Figure 2). The main differences largely emerge in the medium term, where the more rapid rise in marginal costs means that exports and tradable production remain lower as external competitiveness is weaker. While the response of inflation is initially larger, the muted effect on domestic demand means that the monetary policy response can also be weaker.

[19]Feenstra (2018b) estimates that productivity account for around 30 percent of the total US gains (1.1 percent of GDP) from trade between 1992 and 2005.

## 4. Retaliation by Trade Partners

Our analysis has thus far focused on the case of Europe unilaterally reshoring production. In reality, such developments would almost certainly induce retaliation from trade partners.[20] In our framework, retaliation is not endogenous and we model it as an exogenous change. More specifically, we analyze a symmetric form of retaliation. This means that we need to take into account the differential size of the regions. To match the 1 percent of GDP reshoring in the EA, we implement a respective 0.4 percent and 0.65 percent of GDP reductions in RW and US imports of tradable goods for re-export. This ensures the reduction of the same quantity of imports in each region. As before, these changes occur gradually and take roughly 10 years to implement.[21] We display the long-term results in the fifth column of Table 1.

Following a partial reshoring of production by all regions, the long-term effects on the EA economy are quite similar to the unilateral scenario. Indeed, the response of almost all variables has the same sign in the medium to long run, with the prominent exception of foreign trade, which declines in the retaliation scenario. Magnitudes also differ, along with the short-term response of inflation and nominal interest rates. We focus our discussion on the variables that now have an opposite-signed response to the unilateral scenario.

The positive wealth effect from the increase in exports, despite the appreciated exchange rate, reduced work effort in the unilateral scenario. When the other regions retaliate, this effect is no longer present and hours worked no longer decrease. The less pronounced wealth effect also means that imports fall as the rise in domestic demand is dampened. Exports now decrease, despite the reduction

[20]Martin and Vergote (2008) show that retaliation is a necessary feature of an efficient equilibrium in trade agreements. This is because governments do not, or cannot, compensate trade partners for terms-of-trade externalities.

[21]We abstract from analyzing potential knock-on effects on local competition and productivity in this scenario, as this would require us making assumptions regarding differential impacts of decreased competition and productivity across the three regions. Of course, even if technically feasible, the imposition of multiple simultaneous region-specific shocks would raise important concerns over interpretation. Therefore, this scenario is essentially the global equivalent of the basic scenario analyzed in Section 3.

in the marginal cost of producing these goods, due to lower foreign demand for imported inputs for export goods. The increase in economic activity facilitates a fall in domestic debt, with consumption rising from higher labor income (wages and hours worked increase). Investment increases to facilitate the expansion in production in both the tradable and non-tradable sectors.

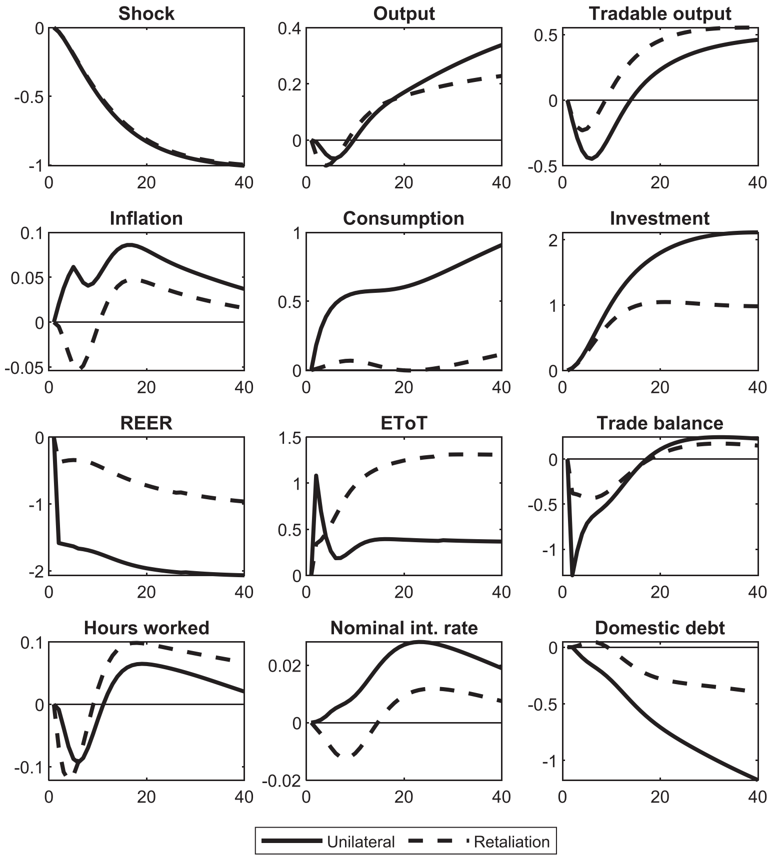
As with the unilateral scenarios, there are some useful insights from analyzing the adjustment process (we display the results from this scenario using the dashed line in Figure 3). On impact, the REER appreciates due to the anticipated rise in factor input costs and therefore prices associated with increased tradable good production. However, this process takes time to play out, and in the short run the reduction in tradable output means there is an initial decline in inflation and nominal interest rates. The decline in exports is sharper than for imports, and a trade deficit opens. As production gradually ramps up, prices and inflation rise and induce a tightening of monetary policy. Domestic debt remains relatively stable initially, before declining once aggregate output begins to increase.

Overall, our analysis shows that retaliation attenuates the positive effect of reshoring on domestic economic activity. However, the savings from the reduction of inefficient distortions remain sufficient for an increase in aggregate production in the EA. However, this result does not include the likely detrimental effects on local competition and productivity (as analyzed in Sections 3.1 and 3.2). Another concern is that international trade decreases in this scenario, with imports and exports in all three regions lower. This fragmentation of the global economy runs counter to the EU's aim to achieve *Open* Strategic Autonomy.

## 5. Conclusion

The Open Strategic Autonomy agenda is rooted in concerns over and beyond economics. However, European policymakers should consider the economic trade-offs related to the implementation of localization policies and understand the main transmission channels through which these policies affect the economy. We find that a unilateral reshoring of some production by the euro area is inflationary, implies transition costs, and generally has a negative long-run effect on

**Figure 3. Symmetric Retaliation**




**Note:** This figure shows the effect on the euro area (EA) of a permanent increase in EA-only preferences for domestically produced inputs for export goods (i.e., a partial reshoring of production). In addition to the "unilateral" reshoring scenario, we now also examine a (symmetric) "retaliation" by trade partners. The plotted lines represent transition dynamics between the initial and new steady state. We scale the shock such that the import content of exports-to-output ratio decreases by 1 percentage point in the long run, with almost all of this adjustment complete after 10 years. All variables are in percentage deviations from the initial steady state, except for the imported inputs for exports (i.e., the reshoring shock), consumer price inflation, and the nominal interest rate, which are in percentage-point deviations. Domestic debt is expressed as a nominal value (not as a ratio of GDP). For context, debt is 60 percent of GDP in the initial steady state.

aggregate domestic output, considering plausible detrimental effects on local competition and productivity. A symmetric retaliation by trade partners also results in persistently higher EA inflation (following the initial decline), although less pronounced than in the unilateral scenario. Retaliation also attenuates any positive effects from reshoring on output and implies a reduction in the volume of overall international trade.

To counter the inflationary pressures of reshoring, it is essential to minimize the crowding out of resources (i.e., capital and labor) that pushes up costs and prices in our simulations. This finding calls for limiting the scope of reshoring, such as by focusing on vital goods that are most susceptible to supply chain disruptions.

Another important finding is that if local tradable firms use their greater market power to increase their markups, this likely negates a positive effect of reshoring on domestic output and amplifies inflationary pressures. Therefore, policymakers should avoid excessively weakening Europe's long-established state aid rules and competition laws, as reduced foreign competition will ultimately undermine the local economy. It could also lead to demands for support in other industries, which are not the focus of reshoring initiatives.[22]

Our results also indicate that if locally produced inputs are inferior to their imported counterparts, reduced productivity amplifies the economic costs of reshoring. As such, policymakers should focus localization policies on goods where there is already an existing comparative advantage in production (or, at least, where the distance from the technological frontier is not too large). Either that, or the economic costs are considered a worthwhile trade-off for an increase in security of supply.

We believe there are several other interesting avenues for future research on this topic using our modeling approach. An important aspect, given our finding that localization policies are inflationary, is the monetary policy response. In our simulations, all regions have the same calibrated values in their Taylor rules. Making these values region specific would allow one to analyze how monetary policy

[22]Experience with past initiatives, such as the Common Agricultural Policy, demonstrates that industries can become reliant on public support (Kazukauskas et al. 2013).

could affect the adjustment following localization initiatives. Our model framework is also capable of analyzing other forms of supply chain reorientation. For example, reorientation of production towards "trusted partners" (friendshoring) could be approximated by increasing their share in intermediate good imports from one region at the expense of another.

## Appendix A. The European Chips Act

Public policy choices emphasizing security considerations over cost minimization, foreshadowing a less-integrated global economy with shorter supply chains, are already apparent in the sectors providing critical intermediate inputs. As an essential component of electronic devices, semiconductors are vital for the global economy. Post-pandemic shortages forced production slowdowns, and even shutdowns, in many parts of the world and exposed global reliance on a small number of producers in a small number of countries. These few and geographically concentrated production locations must operate at close to full capacity in order to cover the very high capital investment costs, leaving little capacity to accommodate demand volatility.

European policymakers have identified securing the supply of the most advanced chips as an economic and geopolitical priority, with industrial automation equipment highly dependent on their supply. As an example of the disruption due to the global chips shortage, Europe produced over 11 million fewer cars in 2021, a substantial shock that brought production back to 1975 levels (European Commission 2022).

The European Chips Act aims to double Europe's semiconductor global market share, to 20 percent from less than 10 percent currently, by 2030. This requires the mobilization of substantial public and private investment in this industry. Given the high entry barriers and the capital intensity of the sector, the European Commission will allow greater than usually permitted (under state aid rules) public support for chips manufacturing. Through the Important Project of Common European Interest on Microelectronics and Communication Technologies, approval of state aid is possible for facilities where the economic benefit outweighs the potentially negative impact on trade and competition. The legislation also contains mechanisms for greater cooperation and coordination amongst EU member states to provide early warnings of, and reaction to, supply chain bottlenecks.

However, Europe is not alone in seeking to enhance the resilience of its semiconductor supply. In China, a series of initiatives, such as "Made in China 2025," will provide substantial financing to boost this industry. Planned public support, through tax incentives and investment, is orders of magnitude larger again in South Korea and Taiwan, the global leaders in the production of the most advanced semiconductor chips. In the United States, the CHIPs and Science Act has a similar set of aims to the European Chips Act and goes a step further by explicitly stating a partial motivation is to "counter China."

Such legislation marks an important turning point in European industrial policy.[23] After decades of emphasis on reducing costs and maintaining competition, policymakers are beginning to reconsider the efficiency versus resilience trade-off. Since strategic autonomy as a whole is too broad a concept to analyze, we consider the European Chips Act as a proxy for the types of initiatives that policymakers may implement to meet this objective.

## Appendix B. Locally Produced Intermediate Inputs

In this appendix, we provide some more details on how changes in the share of imported inputs used in the production of exports can affect the prices and quantities of other goods in the economy.[24] Imported inputs are a composite of tradable goods produced in other regions of the world:

[23]Of course, such a change is not necessarily an improvement. See Tagliapietra, Veugelers, and Zettelmayer (2023) for a critique of the Net Zero Industry Act, which is essentially the EU's response to the U.S. Inflation Reduction Act.

[24]Here we only provide the aspects of the model most directly related to our analysis. We refer the interested reader to Gomes, Jacquinot, and Pisani (2012) for details on the original EAGLE model, Brzoza-Brzezina, Jacquinot, and Kolasa (2014) for the import content of exports component, and Clancy, Jacquinot, and Lozej (2016) for the fiscal extension. These papers also provide detailed discussion on the calibration choices documented in Appendix C.

$$IM_t^X(h) = \left[\sum_{CO \neq H} \left(\nu_{IM^X}^{H,CO}\right)^{\frac{1}{\mu_{IM^X}}} \left(IM_t^{X,H,CO}(h)\left(1-\gamma_{IM^X}^{H,CO}(h)\right)\right)^{\frac{\mu_{IM^X}-1}{\mu_{IM^X}}}\right]^{\frac{\mu_{IM^X}}{\mu_{IM^X}-1}}, \tag{B.1}$$

where $IM_t^X$ denotes imported inputs used by firm $h$ to produce export goods, $\nu_{IM^X}$ represents the share of imports from each region in total imports (and so must sum to one), $\mu_{IM^X}$ is the intertemporal elasticity of substitution between imports from different trading partners, and $\gamma_{IM^X}^{H,CO}$ are (quadratic) adjustment costs on bilateral imported inputs for export goods of firm $h$. Firm $h$ then combines these intermediate-good imports with local (i.e., regional) tradable inputs, produced using regional capital $K_t$ and labor $L_t$ subject to productivity shocks $z_T$ and fixed costs $\psi_T$:

$$Y_{T,t}(h) = max\left\{z_T K_t(h)^{\alpha_T} N_t(h)^{1-\alpha_T} - \psi_T, 0\right\} \tag{B.2}$$

to produce exports goods $X_t$:

$$X_t(h) = \left[\nu_{X,t}^{\frac{1}{\mu_X}} HT_t^X(h)^{\frac{\mu_X-1}{\mu_X}} + (1-\nu_{X,t})^{\frac{1}{\mu_X}} IM_t^X(h)^{\frac{\mu_X-1}{\mu_X}}\right]^{\frac{\mu_X}{\mu_X-1}} \tag{B.3}$$

that are in turn used as inputs in other countries' production of (public and private) consumption, investment, and export goods. Importantly for our analysis, $\nu_{X,t}$ represents the time-varying weight of local goods $HT_t^X$ in the export good bundle and $\mu_X$ represents the intertemporal elasticity of substitution between local and foreign tradable goods. The marginal cost $MC_{T,t}$ of producing regional intermediate tradable goods is

$$MC_{T,t} = \frac{1}{z_{T,t} K_{G,t}^{\alpha_G} (\alpha_T)^{\alpha_T} (1-\alpha_T)^{1-\alpha_T}} \left(R_t^K\right)^{\alpha_T} \left((1+\tau_t^{W_f})W_t\right)^{1-\alpha_T}, \tag{B.4}$$

where $\alpha_T$ is the capital share in the tradable sector; $\alpha_G$ determines the productivity of public capital $K_{G,t}$; $\tau_t^{W_f}$ is the labor tax rate paid by firms; $W_t$ are wages; and $R_t^K$ is the rental cost of capital. The marginal cost of producing export goods $MC_{X,t}$ is therefore

$$MC_{X,t} = \left[\nu_{X,t}[MC_{T,t}]^{1-\mu_X} + 1 - \nu_{X,t}[P_{IM^X,t}]^{1-\mu_{X,t}}\right]^{\frac{1}{1-\mu_{X,t}}}, \tag{B.5}$$

where the aggregate price of imported inputs for re-export is

$$P_{IM^X_{,}t} = \left[\sum_{CO \neq H} \nu_{IM^X}^{H,CO} \left(\frac{P_{IM,t}^{H,CO}}{\gamma_{IM^X}^{H,CO,\dagger}(h)}\right)^{1-\mu_{IM^X}}\right]^{\frac{1}{1-\mu_{IM^X}}}, \tag{B.6}$$

where $P_{IM,t}^{H,CO}$ is the price of imports in region $H$ produced by firms in region $CO$ and $\gamma_{IM^X}^{H,CO,\dagger}$ is the derivative of bilateral import adjustment costs. Demand for local tradables produced by firm $h$ is then

$$HT_t^X(h) = \nu_{X,t}\left(\frac{MC_{T,t}}{MC_{X,t}}\right)^{-\mu_X} X_t, \tag{B.7}$$

where $X_t$ is aggregate demand for tradables (taken as given), while demand for imported inputs is

$$IM_t^X(h) = (1 - \nu_{X,t})\left(\frac{P_{IM^X,t}}{MC_{X,t}}\right)^{-\mu_X} X_t. \tag{B.8}$$

Firms producing tradable goods sell their (differentiated) output in the domestic and foreign markets, charging different prices (set in local currency) in each market. The price-setting process is analogous for the (domestic) tradable and non-tradable goods, so to save space we only provide details of pricing in foreign markets. In setting prices abroad, tradable firms use their monopoly power to set their prices with a markup over marginal costs:

$$\frac{\tilde{P}_{X,t}}{P_{X,t}} = \frac{\theta_X}{\theta_X - 1}\frac{f_{X,t}}{g_{X,t}} \tag{B.9}$$

$$f_{X,t} = X_t MC_{X,t} + \beta \xi_X E_t \left[ \frac{\Lambda_{I,t+1}}{\Lambda_I, t} \left( \frac{\Pi_{X,t+1}}{\Pi_{X,t+1}^{\chi_X} \bar{\Pi}^{(1-\chi_X)}} \right)^{\theta_X} f_{X,t+1} \right] \tag{B.10}$$

$$g_{X,t} = P_{X,t} X_t + \beta \xi_X E_t \left[ \frac{\Lambda_{I,t+1}}{\Lambda_I, t} \left( \frac{\Pi_{X,t+1}}{\Pi_{X,t+1}^{\chi_X} \bar{\Pi}^{(1-\chi_X)}} \right)^{\theta_X - 1} g_{X,t+1} \right], \tag{B.11}$$

where $\theta_X$ is the elasticity of substitution between different export brands and the ratio $f_{X,t}/g_{X,t}$ reflects the fact that only a fraction of export firms can change their prices in every period (i.e., some firms may be stuck with the same price for a number of periods). In this staggered framework (Calvo 1983) prices evolve according to

$$P_{X,t} = \left[ \Xi_X \left( \Pi_{X,t-1}^{\chi,X} \bar{\Pi}^{1-\Xi_X} P_{X,t-1} \right)^{1-\theta_X} \right.$$
$$\left. + (1-\chi_X) \left( \tilde{P}_{X,t} \right)^{1-\theta_X} \right]^{\frac{1}{1-\theta_X}}. \tag{B.12}$$

Adjusting the share of local inputs in export goods, of course, affects prices and quantities all along the supply chain. As an illustration, consider the effect of a change in preferences for local intermediate inputs on demand for (final) consumption goods $Q_t^C$. These are a bundle comprising tradables $TT_t^C$ and non-tradable $NT_t^C$ intermediates:

$$Q_t^C = \left[ \nu_C^{\frac{1}{\mu_C}} \left( TT_t^C \right)^{\frac{\mu_C - 1}{\mu_C}} + (1-\nu_C)^{\frac{1}{\mu_C}} \left( NT_t^C \right)^{\frac{\mu_C - 1}{\mu_C}} \right]^{\frac{\mu_C}{\mu_C - 1}}, \tag{B.13}$$

where $\nu_C$ represents the share of tradables in the final consumption good and $\mu_C$ represents the intertemporal elasticity of substitution between tradable and non-tradable goods. Tradables are themselves a bundle of locally produced $HT_t^C$ and imported $IM_t^C$ consumption goods:

$$TT_t^C = \left[ \nu_{TC}^{\frac{1}{\mu_{TC}}} \left( HT_t^C \right)^{\frac{\mu_{TC} - 1}{\mu_{TC}}} + (1-\nu_{TC})^{\frac{1}{\mu_{TC}}} \left( IM_t^C \right)^{\frac{\mu_{TC} - 1}{\mu_{TC}}} \right]^{\frac{\mu_{TC}}{\mu_{TC} - 1}}, \tag{B.14}$$

where $\nu_{TC}$ represents the share of local inputs in the tradable consumption good and $\mu_{TC}$ represents the intertemporal elasticity of substitution between local tradable consumption goods and imported consumption goods. Demand for local tradables used for consumption goods is

$$HT_t^C = \nu_{TC} \left( \frac{P_{HT,t}}{P_{TTC,t}} \right)^{-\mu_{TC}} TT_t^C, \tag{B.15}$$

where $P_{HT,t}$ is the price of the local tradable input and $P_{TT,t}$ is the aggregate price of tradable consumption goods. The price of the latter is

$$P_{TT^C,t} = \left[ \nu_{TC} [P_{HT,t}]^{1-\mu_{TC}} + 1 - \nu_{TC} [P_{IM^C,t}]^{1-\mu_{TC}} \right]^{\frac{1}{1-\mu_{TC}}}, \tag{B.16}$$

which in turn affects the price of final consumption goods $P_{C,t}$:

$$P_{C,t} = \left[ \nu_C [P_{TT^C,t}]^{1-\mu_C} + 1 - \nu_C [P_{NT^C,t}]^{1-\mu_C} \right]^{\frac{1}{1-\mu_C}}. \tag{B.17}$$

Finally, the market clearing condition for locally produced tradable good $h$ is

$$\begin{aligned} Y_{T,t}(h) = {} & HT_t^C(h) + HT_t^I(h) + HT_t^{GC}(h) + HT_t^{GI}(h) \\ & + \sum_{CO \neq H} HT_t^{X,H,CO}(h), \end{aligned} \tag{B.18}$$

which therefore implies that a change in preference for local inputs in export goods will affect demand for tradable and final consumption goods by changing $P_{HT,t}$.

## Appendix C. Model Calibration

### Table C.1. Key Steady-State Ratios (as a % of aggregate output)

| | EA | RW | US |
|---|---|---|---|
| ***Domestic Demand*** | | | |
| Private Consumption | 58.5 | 58.6 | 65.9 |
| Public Consumption | 20.5 | 16.6 | 14.7 |
| Private Investment | 17.0 | 21.0 | 15.0 |
| Public Investment | 4.0 | 4.0 | 4.0 |
| ***Trade*** | | | |
| Total Imports | 27.9 | 11.3 | 17.1 |
| Private Consumption Goods | 14.0 | 2.6 | 6.9 |
| Public Consumption Goods | 1.2 | 1.0 | 0.9 |
| Private Investment Goods | 8.6 | 4.1 | 7.2 |
| Public Investment Goods | 0.4 | 0.4 | 0.4 |
| Import Content of Exports | 3.7 | 3.2 | 1.8 |
| ***Bilateral Trade*** | | | |
| Imported Consumption Goods | 14.0 | 2.6 | 6.9 |
| From EA | — | 1.1 | 1.3 |
| From RW | 13.2 | — | 5.6 |
| From US | 0.7 | 1.5 | — |
| Imported Investment Goods | 8.6 | 4.1 | 7.2 |
| From EA | — | 1.4 | 1.2 |
| From RW | 5.7 | — | 6.0 |
| From US | 2.8 | 2.7 | — |
| Imported Goods for Re-exports | 3.7 | 3.2 | 1.8 |
| From EA | — | 1.3 | 0.4 |
| From RW | 3.2 | — | 1.4 |
| From US | 0.4 | 1.9 | — |
| Size of Region (% of World Output) | 20.0 | 49.0 | 31.0 |

**Note:** Euro area (EA), rest of the world (RW), and the United States of America (US). Rounding may affect totals.

**Table C.2. Household and Firm Behavior**

| | **EA** | **RW** | **US** |
|---|---|---|---|
| ***Households*** | | | |
| Subjective Discount Factor | $1.03^{\frac{1}{4}}$ | $1.03^{\frac{1}{4}}$ | $1.03^{\frac{1}{4}}$ |
| Depreciation Rate (Private Capital) | 0.025 | 0.025 | 0.025 |
| Int. Elasticity of Substitution | 1.00 | 1.00 | 1.00 |
| Habit Formation | 0.70 | 0.70 | 0.70 |
| Frisch Elasticity of Labor (Inverse) | 2.00 | 2.00 | 2.00 |
| ***Intermediate-Goods Firms*** | | | |
| Tradable—Bias toward Capital | 0.30 | 0.30 | 0.30 |
| Non-tradable—Bias toward Capital | 0.30 | 0.30 | 0.30 |
| ***Final Consumption Goods*** | | | |
| Subst. btw. Local and Imported | 2.50 | 2.50 | 2.50 |
| Subst. Imported | 2.50 | 2.50 | 2.50 |
| Bias toward Local Tradables | 0.24 | 0.92 | 0.56 |
| Subst. btw. Tradable and Non-tradable | 0.50 | 0.50 | 0.50 |
| Bias toward Tradables | 0.35 | 0.35 | 0.35 |
| ***Final Investment Goods*** | | | |
| Subst. btw. Local and Imported | 2.50 | 2.50 | 2.50 |
| Subst. Imported | 2.50 | 2.50 | 2.50 |
| Bias toward Local Tradables | 0.25 | 0.83 | 0.24 |
| Subst. btw. Tradable and Non-tradable | 0.50 | 0.50 | 0.50 |
| Bias toward Tradable | 0.75 | 0.75 | 0.75 |
| ***Export Goods*** | | | |
| Subst. btw. Local and Imported | 1.50 | 1.50 | 1.50 |
| Subst. Imported | 2.50 | 2.50 | 2.50 |
| Bias toward Local Tradables | 0.80 | 0.65 | 0.85 |

**Table C.3. Government Behavior**

| | EA | RW | US |
|---|---|---|---|
| ***Consumption Expenditure*** | | | |
| Domestic Consumption Goods (% of Output) | 20.5 | 16.6 | 14.7 |
| Imported Consumption Goods (% of Output) | 1.2 | 0.9 | 1.0 |
| Quasi-Share of Govt. Cons. | 0.75 | 0.80 | 0.80 |
| Complementarity of Consumption | 0.29 | 0.33 | 0.33 |
| Subst. btw. Local and Imported | 2.50 | 2.50 | 2.50 |
| Subst. Imported | 2.50 | 2.50 | 2.50 |
| Bias toward Local | 0.73 | 0.80 | 0.66 |
| Subst. btw. Tradable and Non-tradable | 0.50 | 0.50 | 0.50 |
| Bias toward Tradable | 0.80 | 0.80 | 0.80 |
| ***Investment Expenditure*** | | | |
| Domestic Investment Goods (% of Output) | 4.0 | 4.0 | 4.0 |
| Imported Investment Goods (% of Output) | 0.4 | 0.4 | 0.4 |
| Subst. btw. Local and Imported | 2.50 | 2.50 | 2.50 |
| Subst. Imported | 2.50 | 2.50 | 2.50 |
| Bias toward Local | 0.54 | 0.60 | 0.46 |
| Subst. btw. Tradable and Non-tradable | 0.50 | 0.50 | 0.50 |
| Bias toward Tradable | 0.80 | 0.80 | 0.80 |
| Depreciation Rate (Public Capital) | 0.025 | 0.025 | 0.025 |
| ***Taxation*** | | | |
| Consumption Tax Rate | 0.183 | 0.077 | 0.077 |
| Labor Income Tax Rate | 0.122 | 0.154 | 0.154 |
| Capital Tax Rate | 0.19 | 0.16 | 0.16 |
| SSC Rate Paid by Firms | 0.219 | 0.071 | 0.071 |
| SSC Rate Paid by Households | 0.118 | 0.071 | 0.071 |
| ***Fiscal Rule*** | | | |
| Target Public Debt (% of Annual Output) | 60.0 | 60.0 | 60.0 |
| Sensitivity of Lump-Sum Taxes to Debt | 0.1 | 0.1 | 0.1 |

**Table C.4. Monetary Policy**

| | EA | RW | US |
|---|---|---|---|
| Inflation Target | 1.02 | 1.02 | 1.02 |
| Interest Rate Inertia | 0.87 | 0.87 | 0.87 |
| Sensitivity to Inflation Gap | 1.70 | 1.70 | 1.70 |
| Sensitivity to Output Growth | 0.10 | 0.10 | 0.10 |

## Table C.5. Real and Nominal Rigidities

| | EA | RW | US |
|---|---|---|---|
| ***Real Rigidities*** | | | |
| Investment Adjustment | 6.00 | 4.00 | 4.00 |
| Import Adjustment (Cons.) | 5.00 | 5.00 | 5.00 |
| Import Adjustment (Inv.) | 2.00 | 2.00 | 2.00 |
| Import Adjustment (Inter.) | 2.00 | 2.00 | 2.00 |
| ***Nominal Rigidities*** | | | |
| Wage Stickiness | 0.75 | 0.75 | 0.75 |
| Wage Indexation | 0.75 | 0.75 | 0.75 |
| Price Stickiness (Local) | 0.75 | 0.75 | 0.75 |
| Price Indexation (Local) | 0.50 | 0.50 | 0.50 |
| Price Stickiness (Imported) | 0.75 | 0.75 | 0.75 |
| Price Indexation (Imported) | 0.50 | 0.50 | 0.50 |
| Price Stickiness (Services) | 0.75 | 0.75 | 0.75 |
| Price Indexation (Services) | 0.50 | 0.50 | 0.50 |

## Table C.6. Price and Wage Markups (implied elasticity of substitution)

| | EA | RW | US |
|---|---|---|---|
| Tradables | 1.30 (4.3) | 1.20 (6.0) | 1.20 (6.0) |
| Non-tradables | 1.50 (3.0) | 1.30 (4.3) | 1.30 (4.3) |
| Exports | 1.30 (4.3) | 1.20 (6.0) | 1.20 (6.0) |
| Wages | 1.30 (4.3) | 1.16 (7.3) | 1.16 (7.3) |

## Table C.7. Bilateral Trade Relations (% of category total)

| | EA | RW | US |
|---|---|---|---|
| ***Imported Consumption Goods*** | | | |
| From REA | — | 42.3 | 18.8 |
| From RW | 94.3 | — | 5.6 |
| From US | 5.7 | 57.7 | — |
| ***Imported Investment Goods*** | | | |
| From REA | — | 34.1 | 16.7 |
| From RW | 66.3 | — | 83.3 |
| From US | 33.7 | 65.9 | — |

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# Supply Chain Disruption and Energy Supply Shocks: Impact on Euro-Area Output and Prices*

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We identify jointly supply chain disruptions shocks and energy supply shocks together with demand shocks using a structural Bayesian vector autoregression (BVAR) with narrative restrictions. The impact of adverse supply chain disruption shocks on inflation expectations and core HICP is strong and rather persistent, while the impact is small and transitory after energy supply shocks. Supply chain disruption shocks and favorable demand shocks explain the large faction of output fluctuations in the 2020–22 period. The dynamics of core prices and inflation expectations are instead mostly explained by supply chain disruption shocks and to a lesser extent by adverse energy supply shocks.

JEL Codes: C32, E32.

## 1. Introduction

After a prolonged period of low inflation rates, core Harmonised Index of Consumer Prices (HICP) and the two-year-ahead inflation expectations of the Survey of Professional Forecasters (SPF) rose sharply from the beginning of 2021. This prompted the European Central Bank to tighten its policy stance by lifting sharply the interest rates and discontinuing their asset purchases in 2022.

*I would like to thank Maarten Dossche, Robert Kelly, Beatrice Pierluigi, Michaela Elfsbacka Schmöller, Peter Tillmann, and a referee of the International Journal of Central Banking for helpful comments and Johannes Gareis for providing the interpolated monthly GDP. The views expressed in this paper are those of the authors and do not necessarily reflect those of the European Central Bank or the Eurosystem.The author declares that he has no relevant or material financial interests that relate to the research described in this paper. Author contact: European Central Bank, Sonnemannstrasse 20, 60314 Frankfurt am Main, Germany. E-mail: roberto.de_santis@ecb.europa.eu; tel.: +49 69 1344 6611.

Supply shocks to supply chains and energy markets might have adversely affected economic activity and caused elevated inflation in the euro area. Are real GDP, core prices, and medium-term expected inflation persistently affected by such supply shocks? To answer this question, we identify jointly supply chain disruption shocks and retail energy supply shocks together with demand shocks using a Bayesian structural vector autoregression (SVAR) model with sign and narrative restrictions.

We show that the impact of adverse supply chain disruption shocks on inflation expectations and core HICP is strong and rather persistent, while the impact of energy supply shocks is small and transitory. GDP instead drops immediately after a supply chain disruption shock and in the medium term after a retail energy supply shock.

Motor vehicle output in the euro area was strongly affected by disruptions in global supply chains. It is a critical sector and, across sectors, it is characterized by the longest supply chain (Boranova et al. 2022). Therefore, to identify supply chain disruption shocks, we use the suppliers' delivery times in the motor vehicle sector, which captures the extent of supply chain delays in such sector.

Typically, the 2020 period is shut down in empirical models through dummies (Finck and Tillmann 2022) or handled through methods addressing heteroskedasticity (Lenza and Primiceri 2022). In this study instead, after having shown that the stochastic trends remain stable over the entire 1999–2022 sample period, the extreme volatility characterizing March–May 2020, with automotive production essentially halting in April, is used to identify the supply chain disruption shocks. Macroeconomic shocks are better identified when they are relatively large (Rigobon 2003). Specifically, we assume that the forecast errors of the suppliers' delivery times in March–April (May) 2020 are primarily driven by positive (negative) supply chain disruption shocks. This assumption is corroborated by microeconometric evidence: by using the difference-in-difference approach, Lebastard, Matani, and Serafini (2023) found that the performance of French firms more exposed to global supply chains was much worse than simple exporters in March–April 2020, while the opposite was true with the recovery in May 2020.

Gas supplies from Russia to the European Union (EU) were cut significantly at the beginning of autumn 2021, contributing to the slow replenishment of gas inventories in Europe ahead of the winter season, and at the end of February 2022 Russia invaded Ukraine. Both historical episodes caused a sudden surge in energy prices. To disentangle demand from supply shocks, we assume that the forecast errors of energy prices in October–November 2021 and March 2022 are driven primary by energy supply shocks.

These sets of narrative restrictions are sufficient to identify the specific supply shocks. In the baseline model, sign restrictions are added only to sharpen the identification. The response of the other three main variables of the structural model—medium-term expected inflation, HICP excluding food and energy (core HICP), and real GDP—is always left unrestricted also on impact. This allows us to be completely agnostic about the impact of the two supply shocks on the key variables of the business cycle.

We show that both supply chain disruptions shocks and energy supply shocks were key drivers over this period, but the former played the larger role. Cumulatively, between January 2020 and September 2022, they explain about 60 percent of the increase in inflation expectations and core HICP. Conversely, demand shocks played a smaller role.

Supply chain disruption shocks played a key role when the pandemic hit, explaining about 35 percent of the drop in GDP in March–April 2020. The reorganization of the supply chains was rather fast in the summer 2020, but such shocks hit activity again in the autumn 2020. With the collapse of world trade in April 2020, cargo ships were not able to run at full capacity and many containers were left to pile up in western countries' ports due to the lockdowns. After the summer of 2020, once global demand had picked up again, the lack of containers to transport these goods from Asia to the United States and Europe, as well as numerous vessels arriving at their destinations well outside of schedule (exacerbated by the massive container ship that blocked the Suez Canal), led to considerable supply bottlenecks, affecting primarily the manufacturing sector. Energy supply shocks also caused a marginal decline in real GDP since October 2021, affecting however primarily the manufacturing sector. The energy crunch played a far limited role because 70–80 percent of euro-area value-added is produced by the less energy-intensive service sector. Also demand shocks contributed to the dynamics of real GDP. They explain about 25 percent of the drop in GDP in

March–April 2020. The demand recovery was fast and steady. The contribution of demand forces was particularly strong after the first round of vaccination from COVID in the spring 2021.

The literature on global value chains is large (see for a review Antràs and Chor 2022), studying the optimal allocation of ownership rights along the value chain (Antràs and Chor 2013) and investigating the effects of demand (Alfaro et al. 2019), interest rate (Antràs 2023), financing conditions (Kim and Shin 2023), and risk (Ersahin, Giannetti, and Huang 2023). However, the identification of supply chain disruptions shocks and retail energy supply shocks is at its infancy and, to the best of our knowledge, nobody has studied the impact of these shocks on expected inflation, core prices, and real GDP and nobody has identified these two supply shocks jointly. Supply chain disruption shocks have been identified using sign and narrative restrictions (De Santis 2021; Celasun et al. 2022; Finck and Tillmann 2022; Kabaca and Tuzcuoglu 2023; Kemp, Portillo, and Santoro 2023). di Giovanni et al (2022) instead study the propagation of shocks through interconnected sectors defining the supply chain disruptions as labor shortages. Other studies analyze the impact of rising shipping costs on inflation, finding a positive statistical significant effect (Herriford et al. 2016; Carrière-Swallow et al. 2023). As for the retail energy supply shocks, De Santis et al. (2022) and De Santis and Tornese (2023) use sign and narrative restrictions on retail energy prices and the energy-intensive sector. Another strand of the literature for the United States looks at gasoline prices (Edelstein and Kilian 2009; Kilian and Zhou 2022a).[1]

From a methodological point of view, we use the techniques devised by Antolín-Díaz and Rubio-Ramírez (2018), but we deviate from it along three dimensions: (i) Antolín-Díaz and Rubio-Ramírez (2018) impose narrative restrictions on top of an already fully self-identified system, in order to sharpen the identification of some specific shocks. In our setting, the narrative restrictions are the identifying assumptions and sign restrictions are intended to

[1]Knotek and Zaman (2021) assess the asymmetric responses of consumer spending to energy prices, but ordering energy inflation first in the Cholesky factorization followed by core inflation and real consumption growth and therefore using the reduced-form residuals for the analysis.

sharpen the identification. (ii) We refrain from applying the importance resampling scheme as suggested by Giacomini, Kitagawa, and Read (2020). (iii) We remove the restriction on the relative sizes of the various shocks on the dates in which we impose narrative shock restrictions, as suggested by De Santis and Van der Weken (2022).[2]

The paper is structured as follows. Section 2 describes the shock identification strategy and the data set. Section 3 presents the key results. Section 4 studies the impact on headline HICP. Section 5 compares our shocks with those estimated in the literature. Section 6 provides some robustness checks. Section 7 concludes.

## 2. Framework and Identification

### *2.1 Supply Chains and Energy Prices*

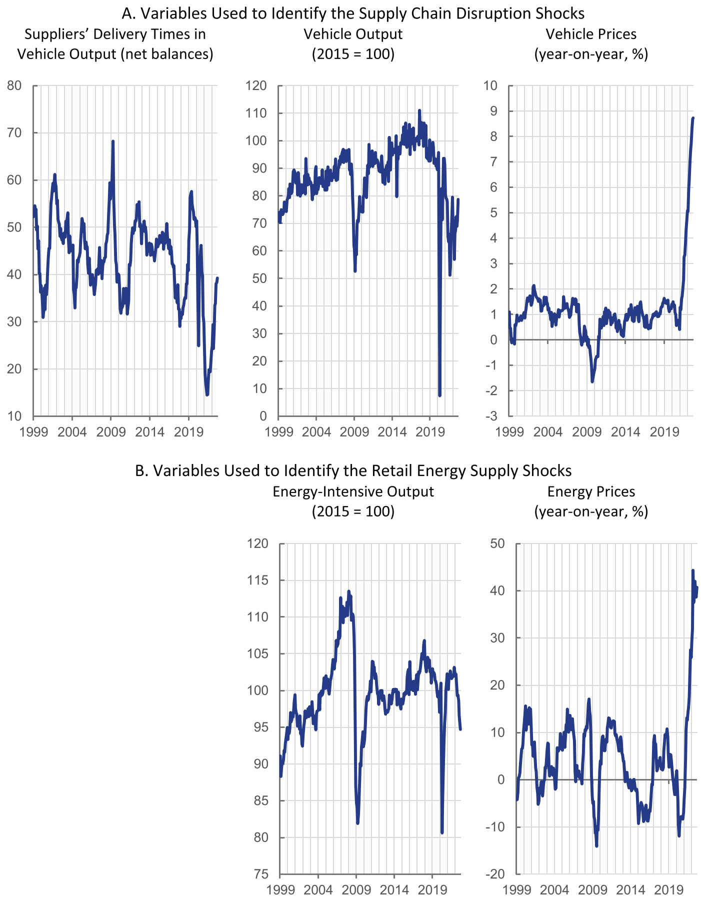
We provide in this section information on the variables used to identify the supply shocks. Panel A of Figure 1 shows the variables used to identify the supply chain disruption shocks. Panel B shows the variables used to identify the energy supply shocks.

The motor vehicle industry is present in several euro-area countries covering 93.6 percent of euro-area GDP in 2021 and, therefore, making the sector a good proxy for the analysis.[3] The lengthening of the motor vehicle suppliers' delivery times in March and

[2]Baumeister and Hamilton (2015) raised some concern about the undesired effect of uniformly distributed (Haar) priors for generation the rotation matrix. In this context, Baumeister and Hamilton (2015) warn that the uniform prior specified for the rotation matrix can translate into unintentionally informative conditional priors for objects of interests, such as impulse responses, that will drive the results even asymptotically. The key point is that posterior inference could be governed by the prior over the set of orthogonal matrices, which is assumed to be uniform. Arias, Rubio-Ramírez, and Waggoner (2022) show that the posterior medians and probability intervals tend to be quite different from the corresponding statistics based on the prior (see also Inoue and Kilian 2022). In addition, using the multiple-prior Bayesian approach described in Giacomini and Kitagawa (2021), Arias, Rubio-Ramírez, and Waggoner (2022) confirm that posterior inference about the mean of the impulse responses is robust to the uniform prior over the set of orthogonal matrices embedded in the conventional method.

[3]According to the European Automobile Manufacturers' Association, or ACEA, motor vehicles were produced in the following 12 euro-area countries: Austria, Belgium, Finland, France, Germany, Italy, Lithuania, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.

**Figure 1. Variables Used to Identify the Great Supply Shocks**




**Source:** Eurostat and S&P Global.

April 2020, its shortening in May 2020, and its lengthening again since autumn 2020 is noticeable. Vehicle production moved in tandem with the suppliers' delivery times, dropping after the pandemic restrictions, recovering immediately, but then dropping again in the autumn 2020. Vehicle prices started to rise sharply since the end of 2020. This suggests that supply chain disruption shocks played a key role in this period.

The remarkable drop in energy-intensive output together with the surge in energy prices since autumn 2021 suggest that energy supply shocks might have played a key role in the dynamics of the business cycle since then. The energy-intensive sector is defined by aggregating the production of chemicals, chemical products, and basic metals, as they are by far the largest-scale users of energy (e.g., Energy Information Administration 2021; Gunnella et al. 2022). We use time-varying weights provided by Eurostat to construct the index. These sub-sectors account on average for about 10 percent of euro-area industrial production.

Two key variables used to identify the supply shocks, the euro-area motor vehicle suppliers' delivery times and the euro-area retail energy prices, are less known and detailed information is provided next.

### *2.1.1 Suppliers' Delivery Times in the Vehicle Sector*

The suppliers' delivery times index from Standard and Poor's (S&P) global (previously IHS Markit's) Purchasing Managers' Index (PMI) business surveys captures the extent of supply chain delays in an economy, which in turn acts as a useful barometer of capacity constraints.[4]

Purchasing managers of the vehicle sector participating in business surveys are asked if it is taking their suppliers more or less time to provide inputs to their factories on average. The precise question wording is: "Are your suppliers' delivery times slower, faster or unchanged on average than one month ago?" The percentage of companies reporting an improvement, deterioration, or no change in delivery times is weighted to derive a "diffusion index" as follows: $\alpha + \beta/2$, where $\alpha$ and $\beta$ are the percentages of survey panel responding "Faster" and "Same," respectively. Hence readings of

[4]The aggregate manufacturing suppliers' delivery times index became widely watched in the 1990s by high-profile users such as U.S. Federal Reserve Chair Alan Greenspan, who cited the index (produced at the time by the National Association of Purchasing Management, or NAPM—now known as the Institute for Supply Management, or ISM) as his preferred leading indicator of inflation. According to the *Wall Street Journal* of April 6, 1996, "Mr. Greenspan, speaking in congressional testimony, said that suppliers' deliveries are 'far more relevant than the Fed's own capacity utilization figures at gauging price pressures in the economy'."

50 indicate no change in delivery times on the prior month, readings above 50 indicate that delivery times have improved (become shorter, or faster), and readings below 50 indicate that delivery times have deteriorated (become longer, or slower).[5]

In each euro-area country, the panel of companies is carefully selected to accurately represent the true structure of the chosen sector of the economy as determined by official data. A weighting system is also incorporated into the survey database that weights each response according to the workforce size.

Because of their just-in-time strategy, highly personalized car configurations, and stringent safety demands requiring specific chips, the shortage has made delivery planning harder for car makers. A shortage of chips and other components needed to assemble new motor vehicles implied an unprecedented reduction in supply in the 2020–22 period.

On the supply side, container vessel activity sustained a major shock because of the pandemic. The global misallocation of containers as a result of the collapse of world trade in March and April 2020 and the rescheduling of numerous cargo vessels arriving late at their destinations led to considerable supply bottlenecks.[6] The disruptions in the cargo activity affected all manufacturing sectors and particularly those characterized by the longest supply chains, such as automotive. Another issue that exacerbated these supply bottlenecks was the renewed lockdown measures resulting from the spread of the delta variant in some countries of the Asia-Pacific region (e.g., Malaysia, Singapore, Thailand, and Vietnam), which are key to the semiconductor chip production generating a crisis in the supply of semiconductors.

Therefore, the use of suppliers' delivery times of the vehicle sector shown in Figure 1 is a suitable candidate to identify disruption in

[5]The index is seasonally adjusted to strip out normal variations in delivery performance for the time of year.

[6]According to the United Nations Conference on Trade and Development (UNCTAD), the average time spent by container vessels in ports in the first half of 2021 was 11 percent higher compared with the pre-pandemic average in 2018–19. In Europe, due to congestion, scheduling delays, and infrastructure constraints, German and French ports saw a very large increase in average port stays (e.g., 42 percent and 25 percent higher than their average in 2018 and 2019), thus standing even higher than those seen in the United States.

supply chains. Notice that the index rose during the global financial crisis in 2008–09 and the sovereign debt crisis in 2010–11 because they were driven by negative demand shocks, which tend to shorten the suppliers' delivery times, given that more resources are available to satisfy diminished demand. Instead, the index dropped in March and April 2020, jumped back in May 2020, and recovered in summer 2020 to drop again in autumn 2020. The sharp lengthening recorded after the pandemic hit in March 2020 can be exploited, because it was driven by supply considerations, as we can exclude the hypothesis that demand rose sharply in that period. Instead, the lengthening recorded in autumn 2020 can be driven either by the sharp recovery in demand (for work-related electronic equipment) or by adverse supply shocks to the supply chain. We exploit the extreme volatility during spring 2020 to identify the supply chain disruption shocks.

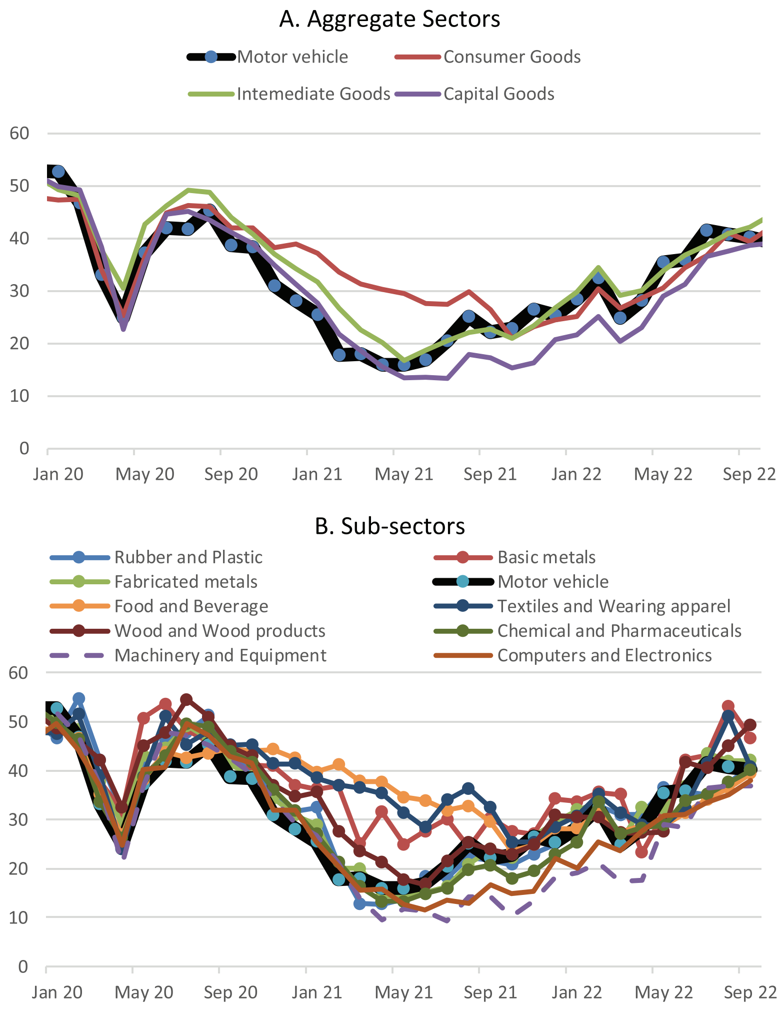
To demonstrate the additional sensitivity of the automotive industry to global supply chains, we show in Figure 2 the suppliers' delivery times in several sectors. Motor vehicle is part of the consumer goods and it features the largest drop in suppliers' delivery times until February 2021. Machinery and equipment remained flat for another nine months, while computers and electronics started to lift in summer 2021. It is well known that also these two sub-sectors suffered strongly from supply bottlenecks. However, the advantage of using the automotive industry for the identification of supply chain disruption shocks is that this sector is more homogeneous than machinery and equipment and computers and electronics. Therefore, the dynamics of the three variables used to identify the supply chain disruption shocks—suppliers' delivery times, vehicle output, and vehicle prices—are in principle more strongly related.

### *2.1.2 Energy Prices*

Energy supply shocks are typically studied through the global crude oil market.[7] However, the prices of other sources of energy are only

[7]Among others, see Kilian (2009); Baumeister and Peersman (2013); Kilian and Murphy (2014); Aastveit, Bjørnland, and Thorsrud (2015); Baumeister and Kilian (2016); Baumeister and Hamilton (2019); Caldara, Cavallo, and Iacoviello (2019); Aastveit, Bjørnland, and Cross (2021); Känzig (2021); and Kilian and Zhou (2022b).

**Figure 2. Suppliers' Delivery Times in Vehicle Output and Other Sectors (net balances)**




**Source:** Eurostat and S&P Global.

weakly correlated with oil prices. According to monthly data provided by the U.S. Energy Information Administration (EIA), available for a long period between January 1997 and December 2019, the correlation between the Henry Hub natural gas spot price and the West Texas Intermediate (WTI) spot price is 20 percent. Gas and renewable sources like wind, solar, geothermal, and hydropower have become important alternative sources in the last two decades for energy supplies' security motives and for environmental issues. Therefore, we employ the HICP category "Energy (ENRGY)" for goods and services, rather than oil prices, to identify energy shocks. The retail energy price includes electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment.

Energy price developments are shown in Figure 1. Unprecedentedly, energy prices rose by 62 percent cumulatively from the beginning of 2021 until September 2022. In order to identify the retail energy supply shocks, we exploit the extreme volatility in October and November 2021, when HICP energy rose by 8.7 percent due to the initial gas supply cuts from Russia, and in March 2022, when energy prices surge by 12.2 percent due to the Russian invasion of Ukraine.

### *2.2 Model Specification*

The reduced-form VAR is given by

$$x_t = a_0 + \sum_{k=1}^{K} A_k x_{t-k} + u_t, \tag{1}$$

$$\mathbf{u}_t = B\varepsilon_t \sim N(0, \mathbf{\Omega}), \tag{2}$$

where $x_t$ denotes the vector of endogenous variables, $a_0$ is a vector of constants, $A_k$ captures the dynamic relations (lag order $K = 6$), $u_t$ the reduced-form errors, $\varepsilon_t$ are uncorrelated structural shocks, and the impact matrix $B$ comprises the contemporaneous responses of the variables to all shocks. The model is estimated with Bayesian techniques. We assume natural conjugate normal-inverse-Wishart (N-IW) priors. The IW priors for $\Omega$ have $n+2$ degrees of freedom and diagonal scale matrix with the i-th diagonal elements equal to the mean squared error from estimating an AR(1) for the i-th variable. Conditional on $\Omega$, the priors for $A_k$ are normal with Minnesota-type mean and variance (Doan, Litterman, and Sims 1984), and complemented with a dummy-initial observation prior (Sims 1993) that is consistent with the assumption of cointegration.[8] The sample spans the monthly period from January 1999 to September 2022. The interpolation of GDP to a monthly frequency is carried out using the Chow and Lin (1971) method employing industrial production excluding construction, construction production, and service production. Therefore, it is a coincident indicator of economic activity. Narrative identification is more accurate at higher frequency.

The vector $\mathbf{x}_t = [\pi^e_t, p_t, p^v_t, p^e_t, y_t, y^v_t, y^e_t, s^v_t]'$ defines the eight variables of the SVAR, where $\pi^e_t$ denotes the SPF two-year inflation expectations,[9] $p_t$ core HICP, $p^v_t$ the vehicle producer price, $p^e_t$ the energy price, $y_t$ real GDP, $y^v_t$ the vehicle output, $y^e_t$ the output of the energy-intensive sector, and $s^v_t$ the suppliers' delivery times of the vehicle sector. All variables, except $s^v_t$ and $\pi^e_t$, are defined in logs.

The impulse response functions (IRFs) that trace out the dynamic effects of the structural shocks $\varepsilon_t$ can be obtained by inverting the VAR in Equation (1) into a moving-average (MA) process $x_t = \phi_0 + \sum_{k=1}^{\infty} \Phi_k B \varepsilon_{t-k}$. They are, however, not uniquely identified, as any orthogonal rotation of $B$ delivers a different MA process that is equally consistent with the data. In the following sections, we describe how this problem is solved by combining restrictions on $B$ with narrative information in the likelihood function.

The set of permissible impact matrices is infinite and the impact matrices cannot be identified uniquely from the data. Shocks are identified using the narrative identification method of Antolín-Díaz and Rubio-Ramírez (2018) with less restrictive signed contribution restrictions suggested by De Santis and Van der Weken (2022) and refraining from applying the importance weighting step as suggested by Giacomini, Kitagawa, and Read (2020).

[8]The hyperparameters take standard values from the literature. The hyperparameter which determines the tightness of the Minnesota prior is set equal to 0.2. The parameter which governs the variance decay with increasing lag order is set equal to 2. The hyperparameter which determines the tightness of the "dummy-initial-observation" prior is set equal to 1, a value recommended by Sims and Zha (1998).

[9]The European Central Bank's SPF collects information on the expected rates of inflation in the euro area at several horizons, ranging from the current year to the longer term. The SPF began in 1999. The aggregate results and microdata are published four times a year. The quarterly observations are linearly interporlated to obtain the monthly frequency.

### 2.3 Narrative Sign Restrictions

Antolín-Díaz and Rubio-Ramírez (2018) impose narrative restrictions on top of an already fully self-identified system, in order to sharpen the identification of some specific shocks. We instead rely on two kinds of narrative restrictions, the "narrative sign restrictions" and the "signed contribution restrictions," to obtain orthogonal shocks. Sign restrictions are used only to sharpen identification. The baseline model contains sign and narrative restrictions. A comparison with a model using only narrative restrictions is also provided.

**Narrative Sign Restrictions.** As in Antolín-Díaz and Rubio-Ramírez (2018), a narrative sign restriction on a structural shock imposes that the value of the identified structural shock $i$ on a specific date $t$ is either positive or negative:

$$\varepsilon_{i,t} > 0 \textit{ or } \varepsilon_{i,t} < 0 \textit{ at a given } t. \tag{3}$$

The signs in panel A of Table 1 indicate whether the shock is positive or negative in the correspondent dates.

In March and April 2020, the economy froze due to the restrictions introduced by the governments to contain the pandemic. Intermediate goods could not be supplied timely and the demand of goods and services dropped because people were forced to stayed at home. Therefore, we assume that both the supply chain disruption shocks were positive and the demand shocks were negative in March and April 2020. The sharp fall in economic activity was followed by a dramatic rise in May 2020. In order to characterize the V-shaped recovery, we assume that in May 2020 supply chain disruption shocks were negative and demand shocks were positive.

In autumn 2021 and again in March 2002, euro-area energy prices rose sharply, as a result of the cut in Russian gas supplies to Europe via the Yamal-Europe pipeline and in the aftermath of the Russian invasion of Ukraine. Almost 30 percent of the EU crude oil imports, 40 percent of the EU natural gas imports, and 50 percent of EU solid fossil fuel (mostly coal) imports originated from Russia. By keeping deliveries to Europe deliberately tight, Russia engineered an energy crunch and the ballooning of gas prices. Over the same period, the production of the energy-intensive sector (chemicals and basic

**Table 1. Sign and Narrative Restrictions**

| | **Supply Chain Disruption** | **Energy Supply** | **Demand** |
|---|---|---|---|
| *A. Narrative Sign and Signed Contribution Restrictions* | | | |
| **Dates** | | | |
| 03/20–04/20 | +, Delivery Times ↓ | | – |
| 05/20 | –, Delivery Times ↑ | | + |
| 10/21–11/21 | | +, Energy Prices ↑ | |
| 03/22 | | +, Energy Prices ↑ | |
| 03/21 | | | + |
| 06/21 | | | + |
| 05/22 | | | + |
| *B. Sign Restrictions on the Impact Matrix $A_0^{-1}$* | | | |
| **Variables** | | | |
| Expected Inflation Two Years Ahead | | | |
| Core HICP | | | + |
| Real GDP | | | + |
| Vehicle Prices | + | | |
| Vehicle Output | – | | |
| Vehicle Suppliers' Delivery Times | – | | – |
| Energy Prices | | + | + |
| Energy-Intensive Industrial Production | | – | |

**Note:** The sign restriction on vehicle output and energy-intensive output after supply chain disruption shocks and energy supply shocks holds for three consecutive periods.

metals) dropped. We assume that energy supply shocks are positive in these three months.

The aggregate demand shocks should be fully captured by the sign restrictions, including the discretionary reaction of fiscal policy, which has been rather significant over the period 2020–22. However, there are some effects of reopening that can be captured only through narrative restrictions. We assume that all demand shocks were negative in March and April 2020, as households were constrained to consume, being forced to stay at home. At the same time, we assume that all demand shocks were positive in May 2020 with the partial reopening of the activities. The success of the vaccination program against COVID-19 allowed governments to lift the restrictions in March 2021. In Germany, for example, hairdressers were allowed to reopen on March 1, 2021. Subsequently, Germany announced the reopening to tourists on June 15. In March and June 2021, euro-area monthly real GDP growth rose by 2.5 percent and 2.1 percent month-on-month, respectively.[10] Finally, we assume that the demand shocks were positive in May 2022, as output rose strongly in that month, despite the war in Ukraine. Most of the unexpectedly robust growth was due to strong activity in the services sector following the lifting of most pandemic-related restrictions (see European Central Bank 2022). We assume that all demand shocks in these three months are positive. Nevertheless, we will show that the results are robust to such assumptions.

**Signed Contribution Restrictions.** We also impose, on key restricted dates, that the supply-disruption shocks and the energy supply shocks are the most important contributor to the one-step-ahead forecast error of the vehicle suppliers' delivery times and energy prices, respectively. This assumption is made in March–May 2020 for the vehicle output suppliers' delivery times and in October 2021, November 2021, and March 2022 for energy prices (see panel A of Table 1). The sharp drop of the vehicle suppliers' delivery times recorded after the pandemic hit in March 2020 can be exploited to identify the supply chain disruption shocks, because we can exclude the hypothesis that demand rose sharply in that period. Following De Santis and Van der Weken (2022), the identification is less restrictive than Antolín-Díaz and Rubio-Ramírez (2018), as we allow the unrestricted shocks to have an even larger contribution to the one-step-ahead forecast error of the vehicle output suppliers' delivery times and energy prices, if the contribution of that unrestricted shock moves such forecast errors in the opposite direction.

**Sign Restrictions.** To refine the identification of the supply chain disruption shocks, we assume that they reduce vehicle output for three months consecutively, decrease the suppliers' delivery

[10]In March and June 2021, retail sales rose by 3.9 percent and 2.5 percent month-on-month, and service production rose by 3.5 percent and 3.7 percent, respectively, mainly due to higher demand for high-contact-intensive services, such as hotels, restaurant, arts, entertainment, and transport.

times instantaneously, and increase motor vehicle prices at impact. By imposing sign restrictions on the vehicle output on impact and for the following two periods, we reduce the probability of confounding supply chain disruption shocks with the frequent and temporary output adjustments that characterize this sector.

To refine the identification of the retail energy price shocks, we assume that they rise retail energy prices at impact and reduce the output of the energy-intensive sector, also in this case for three months to reduce the probability of confounding energy supply shocks with the frequent and temporary output adjustments that characterize this sector.

For demand shocks, we assume that at impact the one-step-ahead forecast errors of HICP, HICP energy, and GDP move in the same direction, while that of the suppliers' delivery times moves in the opposite direction as capacity constraints can limit the production expansion required to satisfy the increased demand. These restrictions are listed in panel B of Table 1.

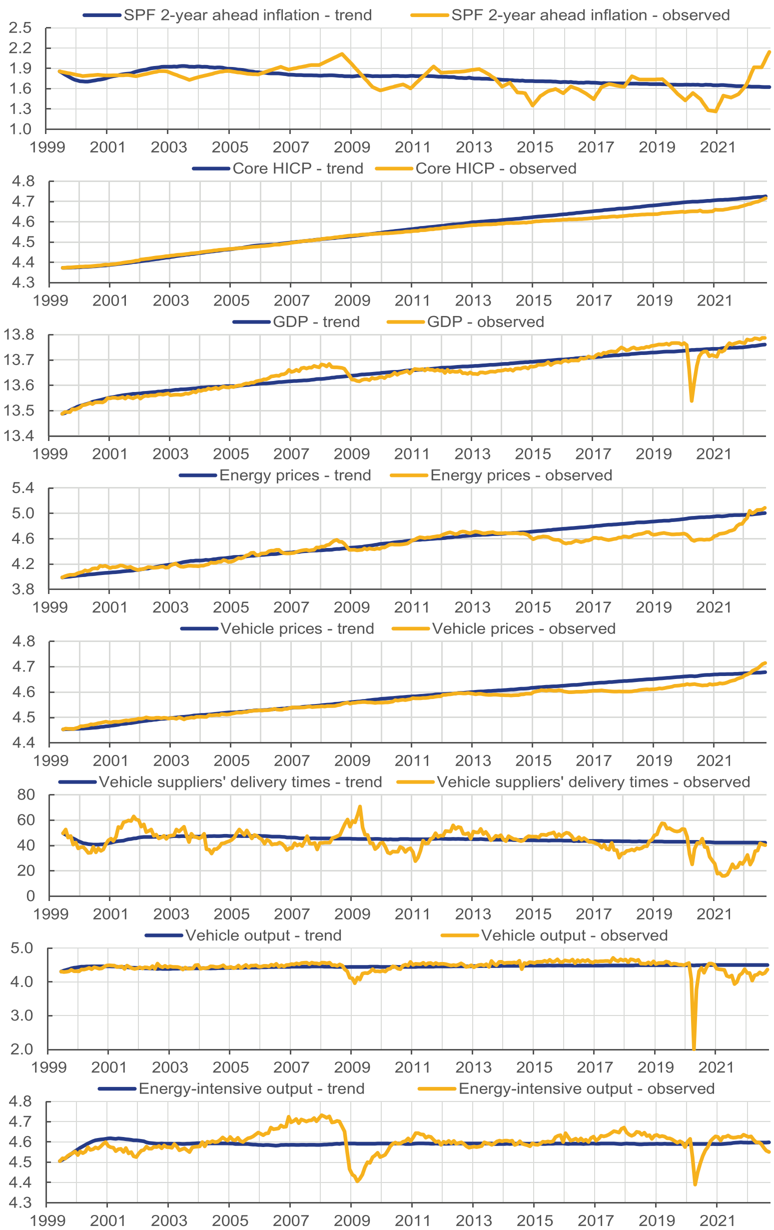
## 3. Business Cycle Response to Economic Shocks

### *3.1 Stochastic Trends*

Given that the identification makes use of the extraordinary volatility during the COVID-19 period, we need to ensure that there are no relevant structural breaks in 2020. A visual inspection of the stochastic trend of all variables, estimated simulating the Bayesian VAR forward in absence of shocks, indicates without any doubt that the extreme variation of some variables did not distort the trend relations characterizing the BVAR (see Figure 3).

Formally, we test a potential structural break using the Chow forecast test before and after March 2020. We compute both the F-statistic, which compares the residual sum of squares of the restricted and unrestricted models, and the log-likelihood ratio statistic, which is based on the comparison of the restricted and unrestricted maximum of the Gaussian log-likelihood function. Neither of the forecast test statistics reject the null hypothesis of no structural change in any of the variables before and after March 2020 (see Table 2).

**Figure 3. Observed Variables and Stochastic Trends (indices, net balance and %)**




**Note:** The stochastic trends provide the model simulation of each variable in absence of shocks. All variables except SPF inflation two years ahead and motor vehicle suppliers' delivery times are in natural logarithm. SPF inflation two years ahead is in percent and year-on-year growth rate. Motor vehicle suppliers' delivery times is in net balances.

**Table 2. Stability of the Stochastic Trends Before and After March 2020**

| | F-statistics | Likelihood Ratio |
|---|---|---|
| Expected Inflation Two Years Ahead | 1.000 | 1.000 |
| Core HICP | 1.000 | 1.000 |
| Real GDP | 0.092 | 0.051 |
| Vehicle Prices | 1.000 | 1.000 |
| Vehicle Output | 1.000 | 1.000 |
| Vehicle Suppliers' Delivery Times | 1.000 | 1.000 |
| Energy Prices | 0.997 | 0.994 |
| Energy-Intensive Industrial Production | 1.000 | 1.000 |

**Note:** This table shows the P-value of the F-statistics and the log-likelihood ratio statistics of the Chow forecast test before and after March 2020, under the $H_0$ of no structural change. The equation takes the following specification: $\Delta x_t = \alpha + \beta x_{t-1} + \gamma_1 D + \gamma_2 D x_{t-1} + u_t$, where $x_t$ denotes the stochastic trend of each of the variables of the VAR; $D$ a dummy variable, which takes the value of 1 after March 2020 and 0 otherwise; and $u_t$ the OLS residuals. Under the assumption of no structural change, $H_0 : \gamma_1 = 0, \gamma_2 = 0$.

The difference between the observed values and their stochastic trend can be explained by macroeconomic shocks, which we need to identify.

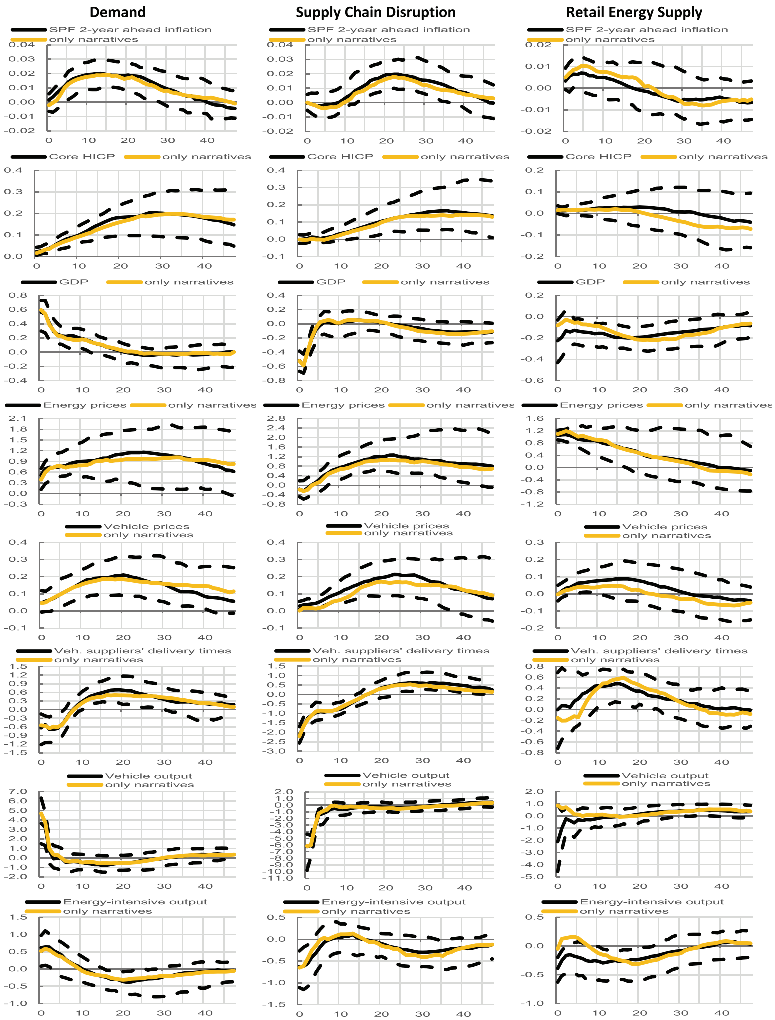
### *3.2 Response Functions, Shocks, and Contributions*

We identify the shocks as described in Table 1, using narrative and signed contribution restriction. The IRFs are displayed in Figure 4. Each panel shows the median IRFs (solid black line) and the corresponding posterior 68 percent pointwise credible sets (dashed lines). The yellow line is the median of the model with only narrative restrictions to identify the supply chain disruption shocks and energy supply shocks.[11]

The results suggest that both supply chain disruption shocks and retail energy supply shocks behave like cost-push shocks, but their

[11]The acceptance rate in the share of rotations that satisfy the restrictions imposed amounts to 0.163‰ in the benchmark model and to 0.484‰ in the model with only narrative restrictions, three times as large.

**Figure 4. Impulse Response Functions (IRFs) (impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)**




**Note:** The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68 percent pointwise credible sets (dashed lines). The orange line is the median of the model with only narrative restrictions to identify the supply chain disruption shocks and energy supply shocks.

transmission is very different. The professional forecasters' two-year inflation expectations and core HICP rise in response to positive demand shocks and to adverse supply chain disruption shocks, while the impact is small and transitory after energy supply shocks. The impact of supply chain disruption shocks is very persistent. Particularly, the impact on the SPF's two-year inflation expectations and core prices of supply chain disruption shocks becomes economically relevant after about 10 months and gets stronger over time, reaching the peak after 24 and 36 months, respectively. Correspondingly, GDP drops after the adverse supply shocks and rises after the favorable demand shocks. Particularly the impact on GDP is on average much stronger in the short term after a supply chain disruption shock and in the medium term after a retail energy supply shock. Given that these three variables are left unrestricted, the identified IRFs are very informative.

As for the other variables, vehicle and energy prices tend to increase after both adverse supply shocks. While a supply chain disruption shock causes a drop in vehicle output and energy-intensive sector output, an energy supply shock causes a drop in the energy-intensive sector and on average it reduces vehicle output, but the credible set includes zero. Therefore, the impact of energy shocks on vehicle output is more uncertain.

It is worth emphasizing that the suppliers' delivery times are driven by both demand and supply forces. First, demand shocks have a strong negative impact on the vehicle output suppliers' delivery times and the lengthening of the supply chain lasts about nine months. Then, the dynamics mean-reverts fully, with a shortening of the delivery times, reaching the peak after 20 months. The vehicle output suppliers' delivery times returns to its equilibrium prior to the demand shock after two and a half years. Second, supply chain disruption shocks also lengthen the delivery time of material and equipment and the delay of the supply chain lasts about 15 months. Then, the dynamics mean-reverts, with a shortening of the delivery times reaching the peak after 30 months. The vehicle output suppliers' delivery times returns to its equilibrium prior to the supply shock after four years. Interestingly, energy supply shocks are accompanied by a shortening of the supply chain. Possibly, firms tend to gain production efficiency in order to offset the rise in firms' energy costs.

Demand shocks tend also to increase the production of vehicles and energy-intensive sectors, as well as vehicle prices, which are left unrestricted also at impact.

We have been arguing that sign restrictions used to identify the supply shocks are redundant and that only narrative restrictions are fundamental to orthogonalize the macroeconomic system. The macroeconomic responses of the model where the two supply shocks are identified only using narrative restrictions have similar median responses across all variables (see orange line in Figure 4). The sign restrictions tend to narrow the credible set on some variables subject to such restrictions, such as vehicle prices after a supply chain disruption shock and energy-intensive output after an energy supply shock; but they also have an implication on the response of GDP and automotive production after an energy supply shock (see Figure 5).

Finally, Figure 6 shows the 90 percent pointwise credible sets of the baseline model, and the conclusions that can be drawn are the same.

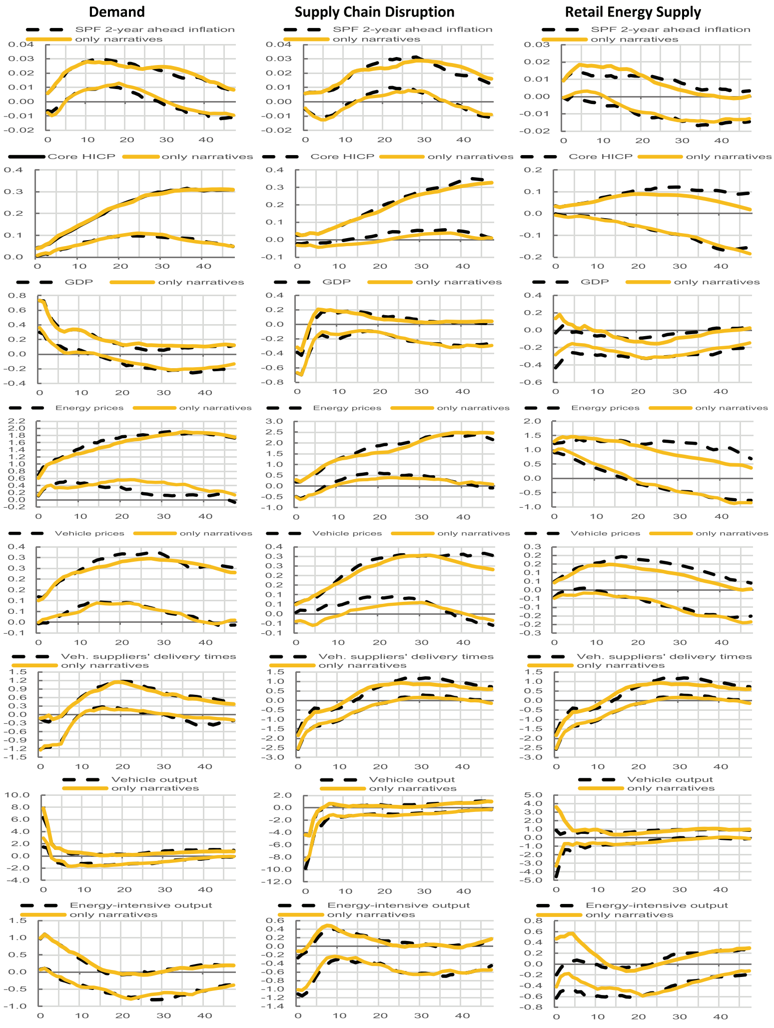
The three identified shocks are shown in Figure 7. Demand shocks were strongly negative (four standard deviations) when the COVID-19 pandemic hit in March 2020 for two consecutive months. Similarly, supply chain disruption shocks were strongly adverse in these two months (four to six standard deviations). Instead, in line with the existing narrative, energy supply shocks did not play any role in that period. In the course of 2021 and 2022, a number of adverse supply chain disruption shocks continue to hit the economy. Energy supply shocks began to be an important driver of the macroeconomy after summer 2021 with the gas rationing from Russia and then after the invasion of Ukraine in February 2022.

### *3.3 The Drivers in the 2020–22 Period*

The historical decomposition of the shocks allows to quantify the role of each driver on each macroeconomic variable. Through the lenses of our model, we can look at the economic forces at play during the 2020–22 period (see Figure 8).

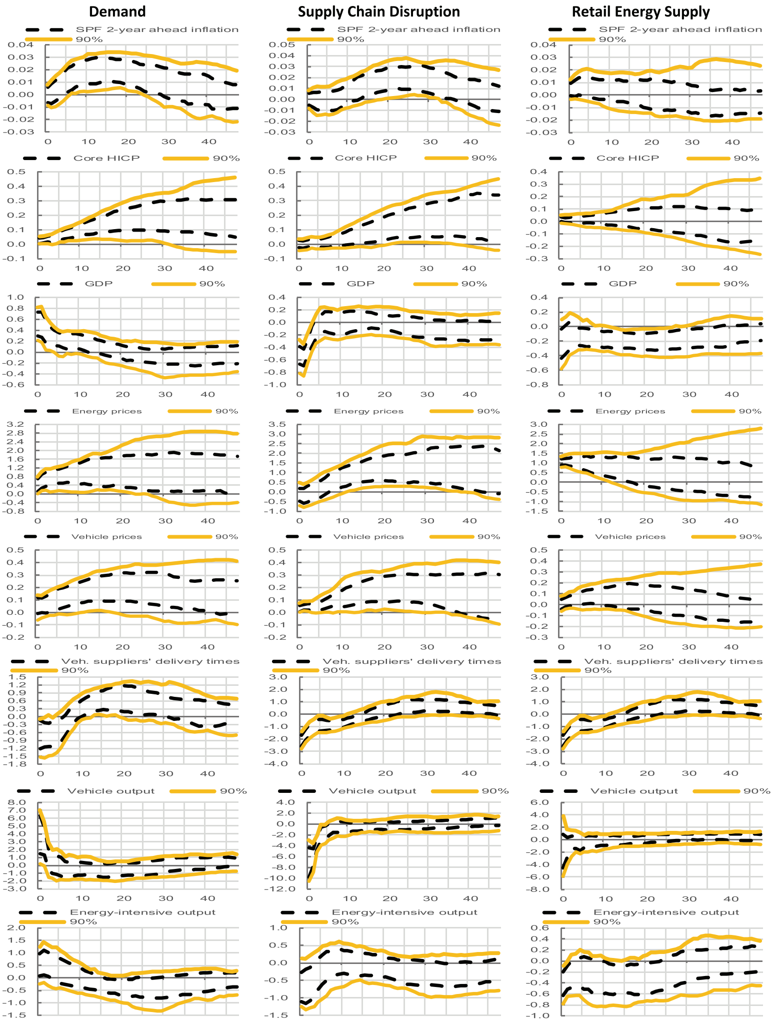
Looking first at the nominal side, aggregate core consumer prices and two-year inflation expectations were marginally affected in the initial phases of the pandemic in line with the hump-shaped IRFs

**Figure 5. IRFs' Credible Sets: Baseline vs. Only Narrative Restrictions (impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)**




**Note:** The identifying assumptions are collected in Table 1. Each panel shows the IRFs' posterior 68 percent pointwise credible sets. The black dashed lines are the 16 percent and 84 percent posteriors of the baseline model. The orange lines are the 16 percent and 84 percent posteriors of the model with only narrative restrictions to identify the supply chain disruption shocks and energy supply shocks.

**Figure 6. IRFs' Credible Sets: Baseline with 68 Percent vs. 90 Percent Pointwise Credible Sets (impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)**

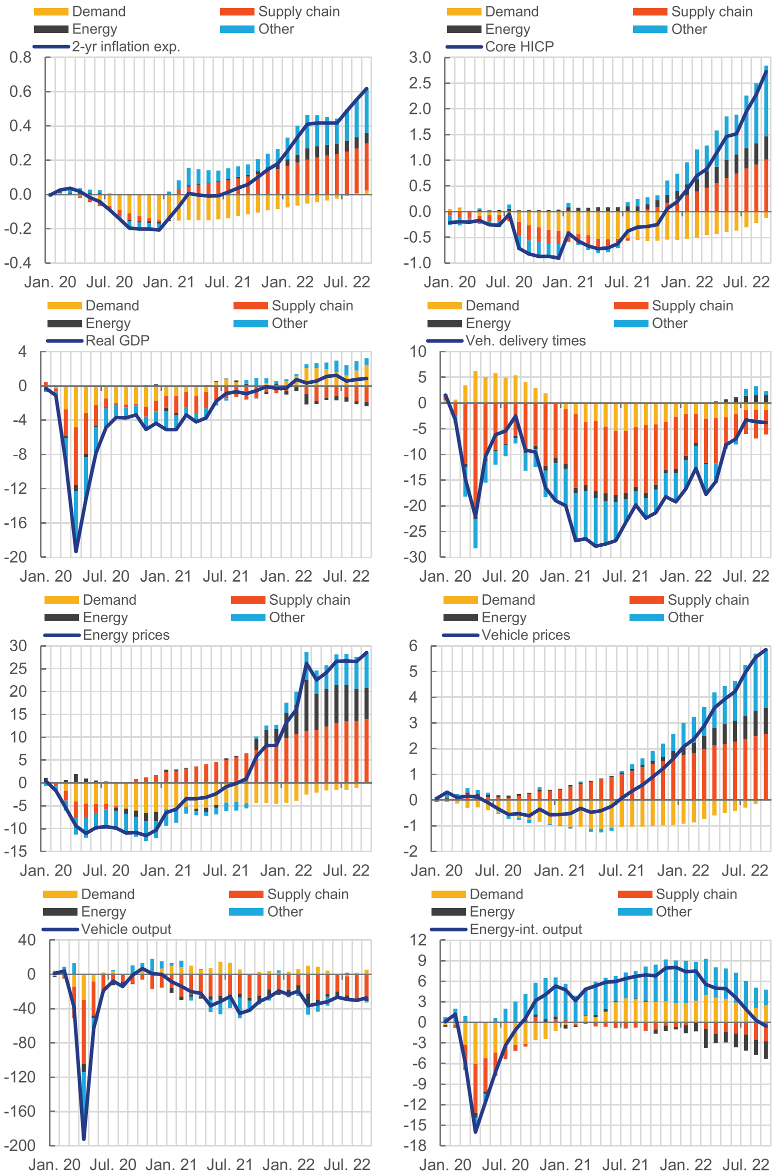



**Note:** The identifying assumptions are collected in Table 1. Each panel shows the IRFs' posterior 68 percent and 90 percent pointwise credible sets. The black dashed lines are the 16 percent and 84 percent posteriors of the baseline model. The orange lines are the 5 percent and 95 percent posteriors of the baseline model.

**Figure 7. Demand and Supply Structural Shocks (standard deviations)**


**Note:** The identifying assumptions are collected in Table 1. Each panel shows the median structural shocks.

**Figure 8. Historical Decomposition of Shocks during the Pandemic Period (percent, percentage points, deviation from stochastic trend)**




**Note:** All contributions are cumulated from December 2019.

and the limited response at impact. The role of adverse demand shocks started to become relevant in the second half of 2020, causing a 0.1–0.2 percentage point decline in expected inflation. The situation reverted dramatically since the beginning of 2021, when initially large adverse supply chain disruption shocks and, since summer 2021, large adverse energy supply shocks caused a surge in core HICP and expected inflation. Since January 2021 and by the end of the sample period in September 2022, supply chain disruption shocks contributed to about 35 percent of the increase in both core HICP and expected inflation, respectively, while retail energy supply shocks contributed to 12 percent and 9 percent, respectively. In aggregate, the great supply shocks since the beginning of 2020 account for about 55 percent of the 2.7 percent increase in core HICP and about 60 percent of the 0.6 percentage point increase in two-year inflation expectations. These findings are not very dissimilar from the results of di Giovanni et al. (2022), who found that sectoral labor shortages, their proxy of supply chain "bottlenecks," explain around half of the observed inflation in the euro area. Since the partial reopening of the economy in summer 2021, only about 10 percent of the 3.4 percent increase in core HICP and about 20 percent of the 0.6 percent increase in two-year-ahead inflation expectations are attributed to demand shocks.[12]

Similar relative dynamics are recorded in vehicle and energy prices, despite the fact that the former is used to identify supply

[12]Gonçalves and Koester (2022) adopt a disaggregated approach to analyzing the role of supply and demand factors in each core HICP component, exploiting the fact that a supply shock affects activity and inflation in opposite directions while a demand shock affects them in the same direction. Based on this approach suggested by Shapiro (2022), for each month each core price category can then be labeled as predominantly demand driven, as predominantly supply driven, or as ambiguous. Their decomposition suggests that supply and demand factors have played broadly similar roles in core inflation. We instead find that demand shocks have played a smaller role in the dynamic of core prices. These differences can be explained by three main reasons. First, Shapiro's approach assumes that the decomposition is static, as shocks affect core HICP only at impact. Second, the immediate response of core HICP (e.g., the impact matrix implicitly) is not estimated, but it is equal to the weight of each sector in the core HICP basket. Third, our approach leaves unidentified the sectoral shocks associated with the automotive production and energy-intensive sector, which instead Gonçalves and Koester (2022) would attribute either to supply or to demand shocks. Therefore, the full comparison across the two methods is not possible.

chain disruption shocks and the latter is employed to identify energy supply shocks.

Looking at the real GDP, the results suggest that supply chain disruption shocks played a key role in the output dynamics recorded in March and April 2020, explaining 35 percent of the 19 percent drop in April 2020 since the beginning of the year. Similar results are found also for the two manufacturing sectors. Also demand forces played a negative role in March and April 2020 with a 25 percent contribution. Given that we do not impose any supply chain disruption restrictions on GDP, this result corroborates the role of supply chain disruption shocks as a key driver of the business cycle, when the COVID-19 pandemic shocked the global economy.

Between May 2020 and September 2020, positive supply chain disruption shocks and demand shocks helped the output recovery, with the supply shocks again playing a key role. The situation changed substantially since autumn 2020, as demand forces continued to remain favorable, while supply chain disruption shocks pull down GDP. The lack of semiconductors and memory chips, plus the misallocation of containers globally and the stop at the ports of cargo ships due to COVID-19 restriction policies in key Asian countries, lengthened the delivery times of key intermediate inputs, stopping part of the production in the euro area. Between January 2020 and September 2022, we estimate that real GDP would have been 1.9 percent higher in absence of supply chain disruption shocks. The contribution of demand forces was particularly strong after the first round of vaccination against COVID in spring 2021. Since the beginning of 2020, our model suggests that the real GDP would have been 2.4 percent lower in absence of demand shocks. Expansionary fiscal policies, directed in particular to protect employment through job-retention schemes, but also to fund increased health spending, plus the use of households' accumulated savings fully counteracted the negative effects from the adverse supply shocks.

The situation has been volatile since October 2021 because adverse energy supply shocks started to cause a reduction in output, as the energy crunch intensified in the euro area, culminating in the war of Russia against Ukraine. However, energy supply shocks have only marginally affected real GDP also because fiscal policy was employed to limit the rise in energy prices. In contrast, the output of the energy-intensive sector has been mostly adversely affected.

Manufacturing production of motor vehicle and energy-intensive sectors was strongly affected by supply chain disruption shocks. The dynamics of sectoral industrial production suggests that their output was heavily affected by supply chain disruption shocks in the course of the entire 2020–22 period. Relative to the beginning of 2020, by September 2022, in absence of supply chain disruption shocks, vehicle output and the production of the energy-intensive sector would have been 27.4 percent and 2.8 percent higher, respectively. Therefore, the impact on automotive has been heavily disruptive.

The energy-intensive sector has been heavily affected by the energy supply disruptions. It lost 2.8 percent of production since September 2021 amid the gas shortages.

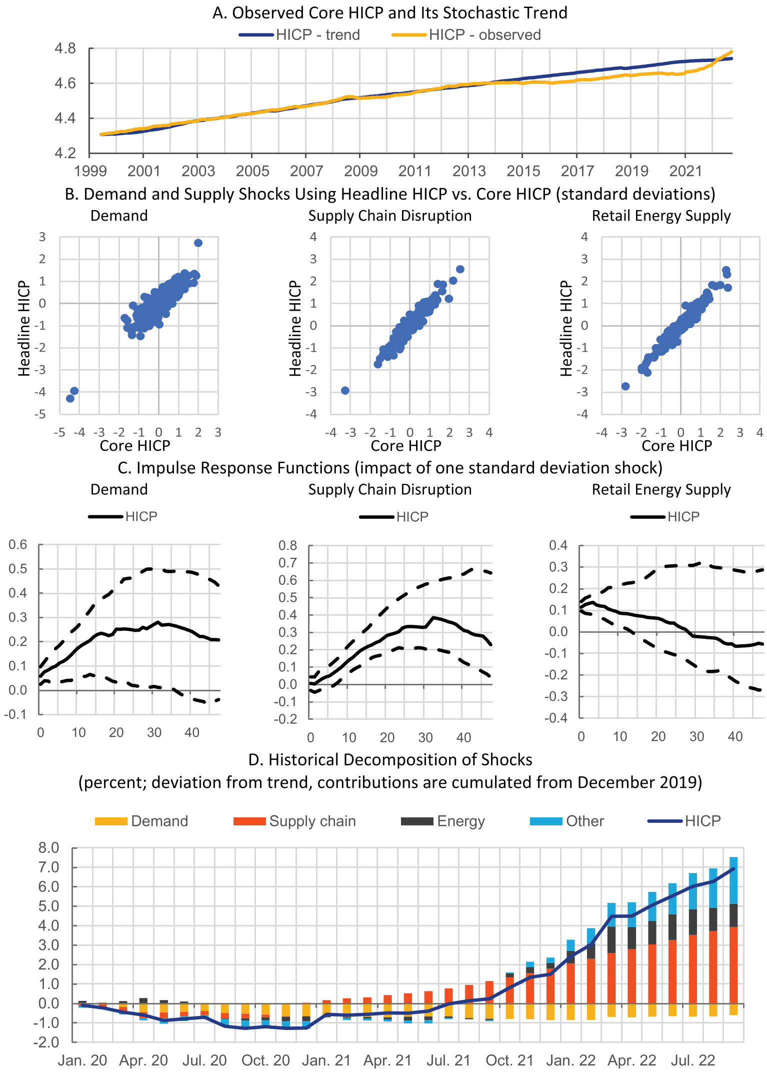
Finally, the decomposition of the suppliers' delivery times is informative because it disentangles the supply chain disruption shocks from the demand forces. When the pandemic hit, the adverse demand shocks shortened the delivery of intermediate inputs, while the supply chain disruption shocks lengthened such delivery, causing important supply constraints. The shift to remote working during the pandemic increased the demand for electronic equipment (work related as well as for home appliances), further pushing up the demand for semiconductors. This phenomenon become relevant in fall 2020, when favorable demand forces contributed to the lengthening of the suppliers' delivery times. However, the major contributor remained the adverse supply forces, associated with the global pandemic restrictions and the disruption in global logistics. They are identified as the main drivers of the lengthening of the suppliers' delivery times since fall 2020.

## 4. Using Headline HICP

How would the shocks be modified if using headline HICP instead of core HICP? What is the impact of demand and supply shocks on headline HICP? We substitute core HICP with headline HICP in the BVAR and run in this section the same empirical exercises carried out earlier. A summary of key findings is shown in Figure 9.

First, the results confirm that the extreme variation of macroeconomic variables recorded in 2020 did not create a worrying break in the stochastic trend of headline HICP (see panel A), a conclusion corroborated by the Chow forecast test before and after March 2020.

**Figure 9. Impact of Demand and Supply Shocks on Headline HICP (percent)**




**Note:** The represented SVAR contains eight variables: the two-year inflation expectations, headline HICP, the vehicle output price, the energy price, real GDP, the vehicle output, the output of the energy-intensive sector, and the suppliers' delivery times of the vehicle sector. The identifying assumptions are collected in Table 1.

Second, the three identified shocks using the two versions of the BVAR, one with core HICP and one with headline HICP, are well aligned on the 45-degree line (see panel B). This suggests that similar shocks are identified using headline HICP and the IRFs and the historical decomposition across common variables are very similar.[13]

Third, supply shocks do affect headline HICP (see panel C). Headline HICP rises in the first two and a half years and then gradually declines after a supply chain disruption shock. The impact of a retail energy supply shock on headline HICP is much stronger at impact in line with the 10 percent weight of HICP energy in the HICP basket, but it is transitory, as the impact remains stable for about a year and then declines.

Finally, looking at the historical decomposition of the shocks in the 2020–22 period (see panel D), negative demand shocks reduced headline HICP in the initial phases of the pandemic. From the beginning of 2021, the rise in HICP was driven by supply chain disruption shocks and by autumn 2021 the surge in goods prices was also caused by the energy supply shocks. Cumulatively, between January 2020 and September 2022, supply chain disruption shocks and retail energy supply shocks contributed to 41 percent and 26 percent of the increase in headline HICP, respectively.

## 5. Cross-Checking with Other Measures

How does the euro-area vehicle supply chain versus global supply chain pressure index vary? Similarly, are the identified euro-area retail energy supply shocks correlated with oil market developments? Despite the regional dimension of our identified shocks, one could still expect a positive correlation with the global gauges.

### *5.1 Euro-Area versus Global Supply Chain Pressure Index*

Although the supply chain disruption shocks are estimated using euro-area vehicle data, the global competition and the length of the supply chain characterizing the automotive sector allow to compare the identified regional shock with the Global Supply Chain

[13] All comparisons are available upon request.

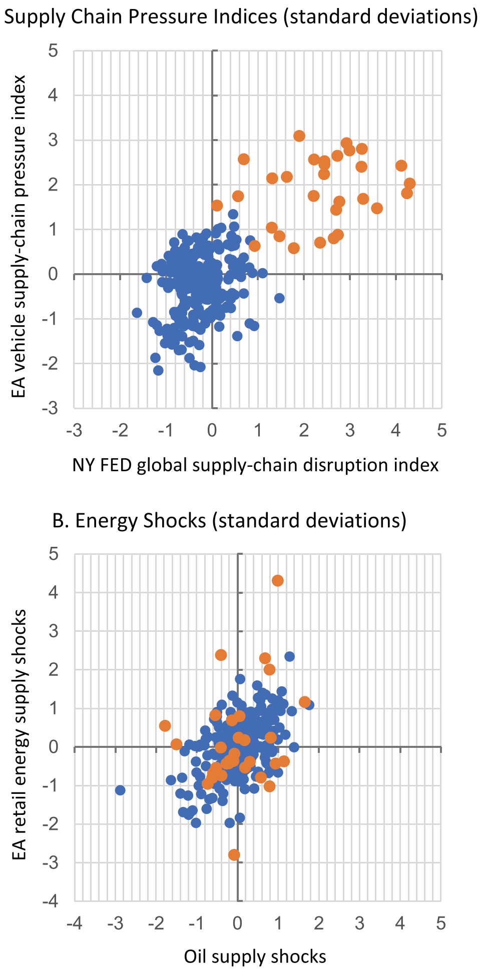
Pressure Index (GSCPI) proposed by Benigno et al. (2022). It is a parsimonious global measure designed to capture supply chain disruptions using a range of indicators. They use measures of transportation costs, associated with shipping and airfreight costs, and subcomponents of country-level manufacturing data from the PMI surveys, covering the euro area, China, Japan, South Korea, Taiwan, the United Kingdom, and the United States, such as the suppliers' delivery times; "backlogs," which quantifies the volume of orders that firms have received but have yet to either start working on or complete; and "purchased stocks," which measures the extent of inventory accumulation by firms in the economy.

To isolate the supply-side drivers of each data series, they regress delivery time, backlogs, and purchased stocks against the "new orders" PMI subcomponent, which captures the extent of customer demand for firms' products; and they regress the global transport cost measures against a GDP-weighted average of the aforementioned "new orders" PMI subcomponents as well as a similarly weighted average of the "quantities purchased" PMI subcomponents for their seven economies. The residuals from these regressions for each country are used as inputs in constructing the global supply chain pressure index through a principal component analysis.

Our definition of euro-area supply chain pressure index is the historical contribution of supply chain disruption shocks on the euro-area vehicle output suppliers' delivery times. Despite the fact that the two approaches are very different, the correlation reported in panel A of Figure 10 is positive (e.g., the blue dots refer to the period between July 1990 and December 2019; the red dots refer to the period between January 2020 and September 2022).[14] The statistical significance of these relations is shown in Table 3. The contemporaneous relation between the Federal Reserve Bank of New York's Global Supply Chain Pressure Index and the euro-area motor vehicle supply chain pressure index is tight and depends on the 2020–22 period, given that the coefficient on the GSCPI is halved when an interacted dummy, which is equal to one after January 2020, is included in the regression.

[14]Given that the GSCPI is measured in standard deviation, we standardize the historical contributions.

**Figure 10. Supply Chain Pressure Indices and Energy Shocks**




**Source:** Benigno et al. (2022), Känzig (2021), and own calculations. The blue dots refer to the period between July 1990 and December 2019. The red dots refer to the period between January 2020 and September 2022. The identifying assumptions are collected in Table 1.

**Table 3. Correlation Between Euro-Area and Global Supply Chain and Energy Measures**

| | Euro-Area Supply Chain Pressure Index | Euro-Area Supply Chain Pressure Index | Euro-Area Retail Energy Shocks | Euro-Area Retail Energy Shocks |
|---|---|---|---|---|
| Global Supply Chain Index | 0.657*** | 0.322*** | | |
| | (0.044) | (0.093) | | |
| Global Supply Chain Index*Dummy | | 0.088 | | |
| | | (0.145) | | |
| Dummy | | 1.054*** | | |
| | | (0.299) | | |
| Oil Supply Shocks | | | 0.590*** | 0.626*** |
| | | | (0.070) | (0.077) |
| Oil Supply Shocks*Dummy | | | | –0.200 |
| | | | | (0.181) |
| Dummy | | | | 0.076 |
| | | | | (0.134) |
| Adj. R-squared | 0.447 | 0.492 | 0.203 | 0.202 |

**Note:** This table shows the OLS regression coefficients and in parentheses the standard errors. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively. "Dummy" is a dummy variable which takes the value of 1 from January 2020. The coefficients on the intercept are not shown. Sample period: July 1999–September 2022.

### *5.2 Retail Energy versus Crude Oil Supply Shocks*

Eurostat's HICP price index of energy goods includes various components, such as electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment. Therefore, the underlying retail energy supply shocks are in principle able to capture broader developments in the energy markets. We check this by comparing the median of our identified retail energy supply shocks with the median of the crude oil supply shocks estimated in Känzig (2021). Panel B of Figure 10 displays the cross-plot of the two shocks over the sample period. The contemporaneous relation between the oil supply shocks and the euro-area retail energy supply shocks is positive and does not depend on the 2020–22 period (see Table 3).

## 6. Model Validation

### *6.1 The Drivers during the Global Financial Crisis*

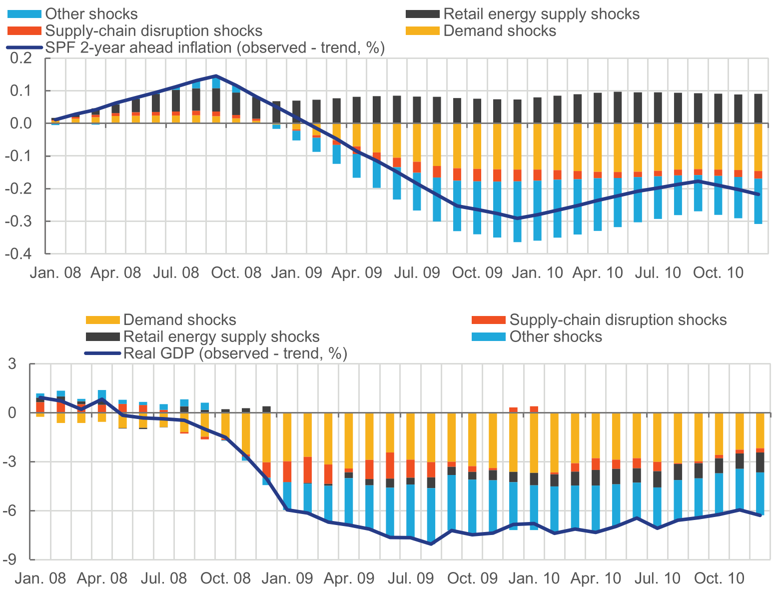
It could be argued that the model might fit well the identified supply shocks' narrative during the pandemic period, while failing in other key periods. For example, we should expect that demand shocks should be rather prominent during global financial crisis. The historical decomposition of shocks in the 2008–10 period suggests that this is the case (see Figure 11). Half of the drop in GDP is attributed to adverse demand shocks and the other half is attributed to other types of unidentified shocks. The same conclusions can be drawn looking at the decline in expected inflation after the collapse of Lehman Brothers in September 2008.

### *6.2 Robustness Checks*

The narrative restrictions on the demand shocks shown in Table 1 could be redundant, as the sign restrictions, together with the narrative restrictions for the other two supply shocks, are sufficient to select the IRFs characterizing the demand forces underlying the business cycle. The robustness check of the results consists of excluding all narrative restrictions underlying the demand shocks in the baseline. The new IRFs with the credible sets are shown in Figure 12 together with the median estimate of the baseline. The results are similar. The median estimates of the responses of GDP, vehicle output, and energy-intensive output are slightly smaller at impact after a demand shock. However, the credible sets of the two manufacturing sectors' responses include zero after the demand shocks. The results are invariant on all prices and on expected inflation. Therefore, the narrative restrictions to identify the demand shocks are useful for manufacturing.

In March 2021, the Suez Canal was totally blocked for six days by a 400-meter-long container ship. The obstruction created a massive traffic jam in the vital passage, straining supply chains already burdened by the coronavirus pandemic. Therefore, we assume that the supply chain disruption shocks were positive in that month, providing the largest contribution to the one-step-ahead forecast error of the suppliers' delivery times. A similar assumption is made by De Santis (2021), De Santis et al. (2022), and Finck and Tillmann

**Figure 11. Historical Decomposition of Shocks during the Global Financial Crisis (percent, percentage points, and net balances; deviation from trend)**

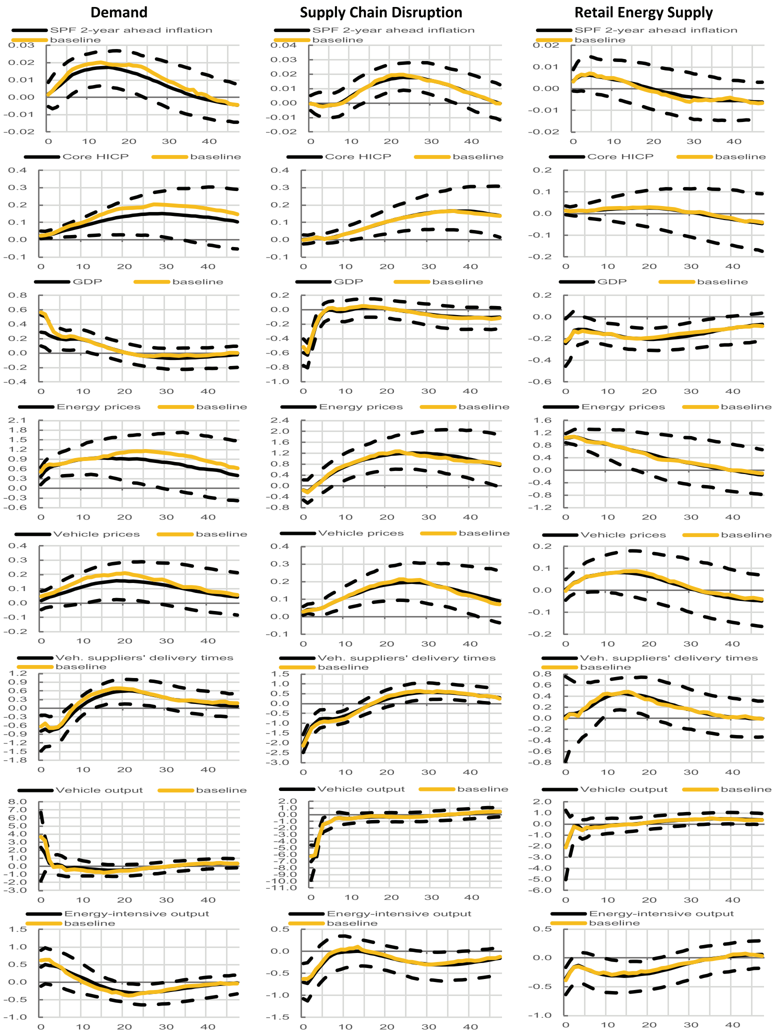



**Note:** The identifying assumptions are collected in Table 1. All contributions are cumulated from December 2007.

(2022), while Furceri et al. (2022) use the Suez Canal obstruction in March 2021 as an exogenous instrument for the identification of shipping shocks. The results displayed in Figure 13 are very similar to the baseline model, but the number of accepted draws declines somewhat.

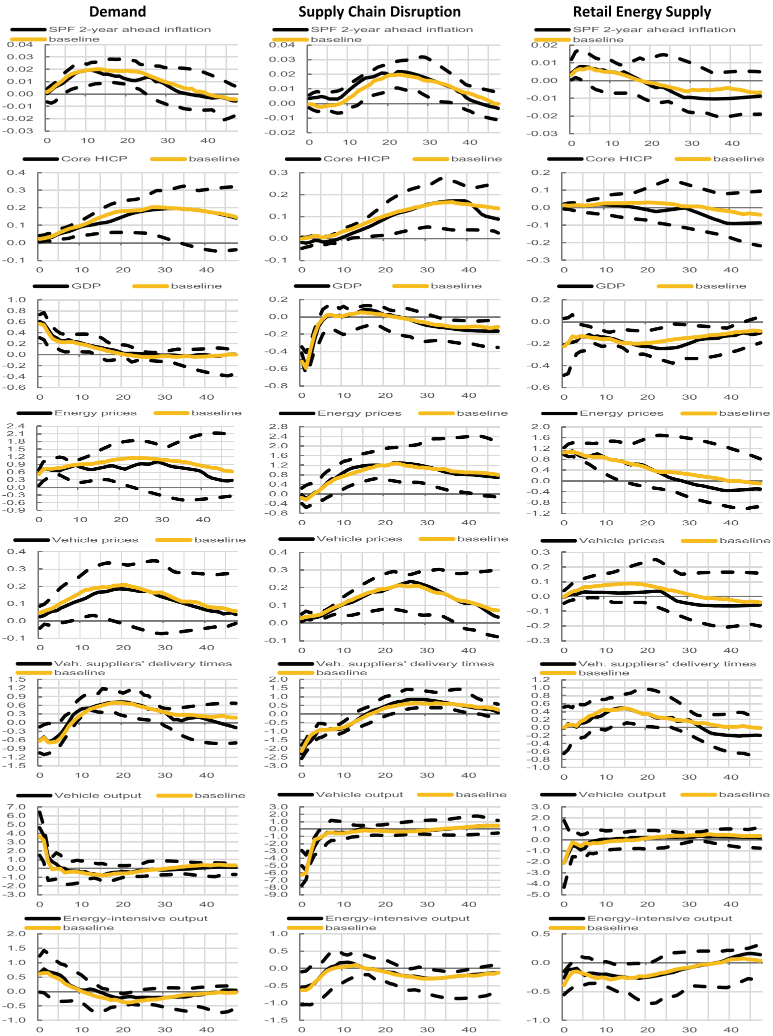
It could be argued that energy demand shocks could also lead to a decline in production in the energy-intensive sector (due to the higher cost of energy inputs). To consider this possibility, we assume that after a demand shock the energy-intensive sector declines at impact and for the subsequent two months. The results are provided in Figure 14. The responses of all variables to the supply chain disruption shocks and energy supply shocks remain invariant. The variables' responses to demand shocks are different in sign only for the energy-intensive output, which declines due to the underlying hypothesis.

**Figure 12. IRFs—Excluding the Narratives on the Demand Shocks (impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)**



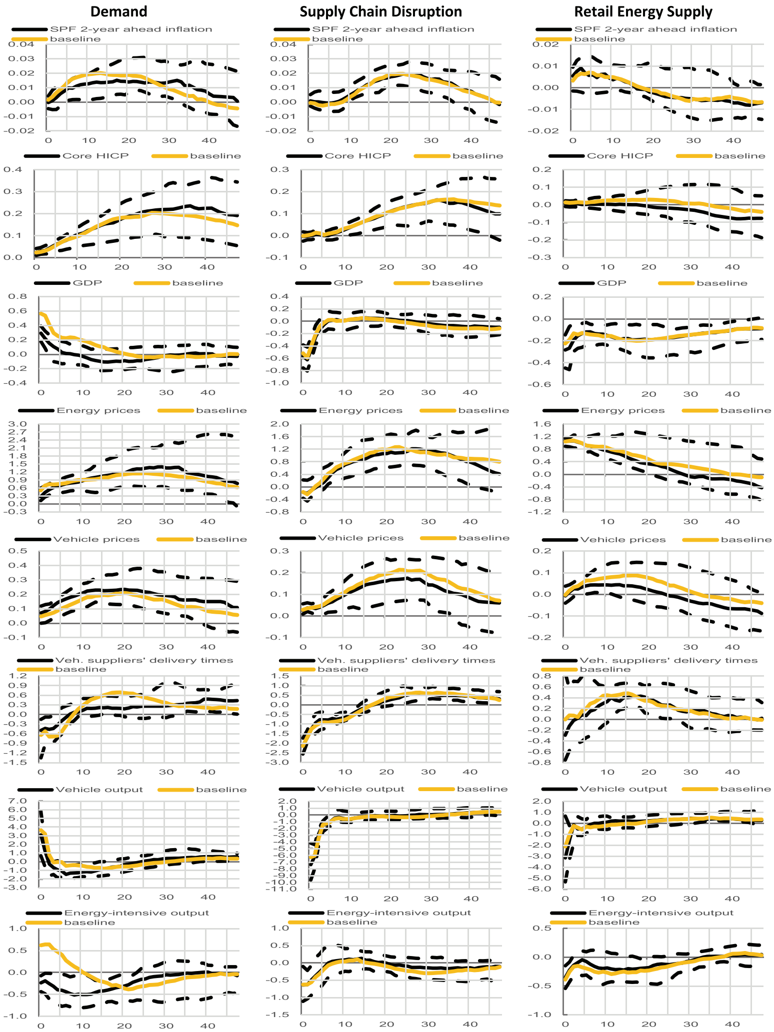

**Note:** The identifying assumptions for the baseline are collected in Table 1. The identifying assumptions for the alternative model are those of Table 1, excluding the narrative restrictions on the demand shocks. Each panel shows the median IRFs of the baseline model (orange), the median IRFs of the alternative model (black), and the corresponding posterior 68 percent pointwise credible sets (dashed lines).

**Figure 13. IRFs—Including March 2021 on the Supply Chain Disruption Shocks (impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)**




**Note:** The identifying assumptions for the baseline are collected in Table 1. The identifying assumptions for the alternative model are those of Table 1, including the March 2021 narrative restrictions on the supply chain disruption shocks. Each panel shows the median IRFs of the baseline model (yellow), the median IRFs of the alternative model (black), and the corresponding posterior 68 percent pointwise credible sets (dashed lines).

**Figure 14. IRFs—Including a Negative Response of the Energy-Intensive Sector Output after Demand Shocks (impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)**




**Note:** The identifying assumptions for the baseline are collected in Table 1. The identifying assumptions for the alternative model includes the negative response of the energy-intensive output for three consecutive months after demand shocks. Each panel shows the median IRFs of the baseline model (orange), the median IRFs of the alternative model (black), and the corresponding posterior 68 percent pointwise credible sets (dashed lines).

## 7. Conclusions

We investigate the transmission mechanism of supply chain disruption shocks and energy supply shocks on output and prices using a Bayesian SVAR with narrative restrictions, leaving unrestricted the impact on GDP, core prices, and expected inflation.

We show that the impact of adverse supply chain disruption shocks on inflation expectations and core HICP is strong and rather persistent, while the impact is small and transitory after energy supply shocks. GDP instead drops immediately after a supply chain disruption shock and in the medium term after a retail energy supply shock.

We find that supply chain disruption shocks and energy shocks played a key role in shaping core prices and expected inflation in the 2020–22 period, but the former contributed most, also because they are rather persistent. Conversely, the favorable demand shocks played a more negligible role. Real GDP was also negatively affected by supply chain disruption shocks and only marginally by the adverse retail energy supply shocks; instead GDP was strongly affected by demand shocks also in the post-pandemic recovery.

The lockdown was an extremely large and complex event and the war in Ukraine (and the preceding events) triggered not only energy price shocks but also a general increase in uncertainty. Since, from a set identification principle, distortions from other shocks are properly accounted for from wider credible sets, it can be argued that supply chain disruption shocks have implications on output and can be entrenched in core HICP and expected inflation for a prolonged period of time, and this would require more attention by policymakers.

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# Here Comes the Change: The Role of Global and Domestic Factors in Post-Pandemic Inflation in Europe*

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The world economy is currently grappling with an unprecedented inflation shock, comparable in magnitude to the 1970s, driven by a convergence of extraordinary factors. This surge raised global inflation to 8.1 percent in 2022, from 3.4 percent in 2020 and an average of 2.1 percent during 2010–20. The inflationary wave has posed a momentous challenge to developing nations and advanced economies historically accustomed to low and steady inflation rates. This paper disentangles the confluence of contributing factors to the post-pandemic rise in consumer price inflation, using monthly data and a battery of econometric methodologies covering a panel of 30 European countries over the period 2002–22. We find that while global

*The authors would like to thank the editor, Robin Lumsdaine, for insightful comments and suggestions that led to marked improvements in the paper. An earlier version of this article benefited from comments by Chris Jackson, Harri Kemp, Ting Lan, Rafael Portillo, Christopher Waller, James Bullard, Òscar Jordà, Jane Ihrig, and the participants of seminars at the European Department of the International Monetary Fund (IMF), the Bank of England, the 62nd Société Canadienne de Science Economique, and the conference on Global Supply Shocks, Trade Frictions, and Inflation organized by the Central Bank of Ireland and the International Journal of Central Banking. The views expressed in this paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The data that support the findings of this study are available at Eurostat, IMF, OECD, and the World Bank.

factors continue to shape inflation dynamics throughout Europe, country-specific factors, including monetary and fiscal policy responses to the crisis, have also gained greater prominence in determining consumer price inflation during the pandemic period. Coupled with increasing persistence in inflation, these structural shifts call for a significant and extended period of monetary tightening and fiscal realignment.

JEL Codes: C13, C32, C33, C53, E31, E32, E37, E58, F62.

*We now understand better how little we understand about inflation.*
—Jerome Powell
Chair, Board of Governors of the Federal Reserve System

## 1. Introduction

The world economy is amid the worst inflation shock since the 1970s due to a plethora of unprecedented developments. Global inflation soared to 8.1 percent in 2022, from 3.4 percent in 2020 and an average of 2.1 percent from 2010–20. The extent and pace of this surge are not just a recurring problem in developing countries, but have also threatened to become an entrenched phenomenon worldwide, including in advanced economies with a long history of low and stable inflation. Unsurprisingly, there is now a blame game for the rise in inflation—ranging from the strong rebound in aggregate demand caused by the extraordinary policy response to the COVID-19 pandemic to global supply constraints and shock waves through international commodity markets triggered by Russia's invasion of Ukraine.

The surge in consumer price inflation has occurred worldwide, but there are considerable differences in the level of inflation and how the inflation process has changed across countries over time. We thereby aim to analyze and disentangle the confluence of domestic and external factors in explaining the evolution of inflation dynamics in Europe, where inflation reached the highest level in four decades. To this end, we use high-frequency data and employ alternative econometric methodologies, including a generalized dynamic factor model (GDFM), a standard panel model with cross-sectional correlation consideration, and the local projection (LP) method to analyze inflation dynamics in a balanced panel of 30 European countries over the period December 2002 to May 2022. We split our sample into three distinct blocks: (i) the period before the global financial crisis (GFC); (ii) the period after the GFC; and (iii) the post-pandemic period. We thus have the pre-GFC period from December 2002 to August 2008, the post-GFC period from September 2008 to December 2019, and the post-pandemic period from January 2020 to May 2022. This approach allows us to shed a particular light on post-pandemic developments and assess whether there are any structural changes in the contribution of global and country-specific factors.

Our GDFM analysis shows that global factors continue to play an essential role in shaping inflation dynamics throughout Europe, but domestic factors, including monetary and fiscal policy responses to the crisis, have become more prominent after the pandemic to the extent that they explain a larger share of the variation in inflation, especially in emerging economies. Inflation is a complex phenomenon, with multitudes of domestic and external factors directly and indirectly influencing pricing behavior. Our empirical findings confirm the role of both global and domestic developments in shaping inflation dynamics. First, we find that the observed explanatory power of global factors is significant and has remained roughly constant throughout the sample period. The share of the variance explained by global factors is about 40 percent for headline inflation and 20 percent for core inflation. Second, country-specific factors have gained greater prominence in explaining the variance of inflation dynamics during the pandemic. The share of variance explained by domestic factors increased by 10 percentage points post-pandemic. We also find heterogeneous effects of global and domestic factors in advanced and emerging market economies. While common inflation dynamics remained dominant in explaining inflation variance in advanced economies before the pandemic, the role of global and domestic factors increased in these countries after the pandemic. In the case of emerging market economies, however, the role of global factors has continued to grow even after the pandemic. However, domestic factors have gained even more significance in determining inflation dynamics across all countries post-pandemic.

We deepen the empirical analysis by estimating alternative models of inflation dynamics in a panel setting and obtaining corroborative evidence. These results show that inflation persistence is a highly significant factor across all specifications and for different measures of inflation. While the domestic output gap has a statistically significant effect on both headline and core inflation, the global output gap has only a statistically significant effect on core inflation. We also find that other global factors (international energy and non-energy commodity prices and global supply chain pressures) and the exchange rate, reflecting both global and domestic developments and policy choices, exhibit significant effects on headline and core measures of consumer price inflation in Europe. These results, robust to a battery of sensitivity checks, also indicate notable differences between advanced and emerging market economies, with global factors explaining a larger share of variation in inflation in emerging market economies. In the post-pandemic period, however, we find evidence that domestic factors have become far more critical in driving inflation dynamics across all countries.

The analysis of inflation dynamics presented in this paper has important implications for the optimal conduct of monetary policy in Europe—and beyond. A plethora of developments, outside the control of policymakers, has undoubtedly contributed to the surge in inflation worldwide. However, putting the onus on global factors alone would be misleading. While much of the recent increase in inflation is a direct result of pandemic-related disruptions and Russia's invasion of Ukraine that has pushed international commodity prices higher, our analysis shows that the relative importance of global factors has not necessarily increased after the pandemic. Instead, we find that domestic developments have become influential in determining inflation dynamics with greater persistence across the board. In other words, the evolution of aggregate demand at home—and abroad—matters more than ever for the appropriate monetary policy stance to bring inflation under control. To this end, central banks should continue recalibrating monetary conditions to achieve the primary objective of price stability.

The remainder of this study is organized as follows. Section 2 provides a brief overview of the relevant literature. Section 3 introduces the data used in the analysis and presents the stylized facts. Section 4 describes our econometric framework. Section 5 presents the empirical results and a variety of sensitivity checks aimed to confirm the baseline results and provide a more granular analysis. Section 6 concludes with policy implications.

## 2. An Overview of the Literature

Voluminous literature exists on the fundamental determinants of inflation across countries and over time. The equilibrium rate of inflation is a function of factors determining a degree of inflation aversion, including policy preferences (Rogoff 1985), macroeconomic developments including the level of income, trade openness, and fiscal deficits (Végh 1989; Romer 1993; Campillo and Miron 1997; Lane 1997; Galí and Gertler 1999; Catao and Terrones 2005; Clark and McCracken 2006; Badinger 2009), flexibility of labor market institutions (Cukierman and Lippi 1999), type of exchange rate regimes (Levy-Yeyati and Sturzenegger 2001; Husain, Mody, and Rogoff 2005), and political and institutional factors (Cukierman 1992; Aisen and Veiga 2006). While Moore, Lewis-Bynoe, and Morgan (2012) identify domestic demand pressures, commodity price shocks, and political factors as the key determinants of inflationary episodes, other studies, building on Kydland and Prescott (1977) and Barro and Gordon (1993), find a robust relationship between institutional factors such as central bank independence and inflation (Cukierman, Webb, and Neyapti 1992; Alesina and Summers 1993; Lougani and Sheets 1997; Cottarelli, Griffiths, and Moghadam 1998; Posen 1998; Arnone, Laurens, and Segalotto 2006; Brumm 2006; Walsh 2008).

Another strand of the literature connects the macroeconomic policy trilemma to inflation, reasoning that when a country maintains a pegged exchange rate regime, it loses its monetary independence and, thus, effective control of inflation dynamics. While Hausmann et al. (1999) and Frankel, Schmukler, and Serven (2004) argue that exchange rate flexibility does not necessarily provide monetary autonomy, Shambaugh (2004) finds evidence suggesting that "countries with fixed exchange rates follow the interest rate of the base country more closely than countries with flexible exchange rates" (p. 303). In other studies, Gruben and McLeod (2002), Gupta (2008), and Badinger (2009) examine the relationship between capital account openness and inflation and find that unrestricted capital mobility lowers inflation by disciplining central banks. More recently, Cevik and Zhu (2020) show that a country's ability to conduct its own monetary policy for domestic purposes independent of external monetary influences leads to lower inflation.

The standard way of modeling inflation is built on the Phillips curve, often used to examine the effectiveness of the monetary transmission mechanism. The Phillips curve forms an empirical relationship between unemployment and wage growth—or the slack in economic activity and inflation. The most widely used model of the Phillips curve, however, is the so-called hybrid New Keynesian Phillips curve, which is derived from a model characterized by monopolistic competition and short-run price rigidity, and it is hybrid in the sense that it contains past inflation (Galí and Gertler 1999; Galí, Gertler, and López-Salido 2005). In addition to the standard model, many studies have included other determinants of inflation. For example, using a sample of emerging market economies, Kamber and Wong (2020) argue that foreign shocks, i.e., commodity price shocks, have a more substantial impact on the transitory component of inflation than trend inflation. In addition, Kamber, Mohanty, and Morley (2020) find that world oil prices and the foreign output gap have a more significant impact on emerging economies than on advanced economies over the period 1996–2018.

With rising financial openness, global value chain participation, and trade openness, inflation has developed more synchronized worldwide. The greater prominence of global factors has led to efforts to augment the standard Phillips curve with relevant global variables to improve the explanatory power. As in Auer, Borio, and Filardo (2017), the "global-centric" view of the inflation process indicates that globalization is responsible for the diminishing link between domestic slack and inflation and the intensifying link between global variables and inflation. Therefore, the globalization of inflation hypothesis suggests that deeper integration into global markets would exert downward pressure on inflation because of global competition and greater global value chain (GVC) participation that raises a degree of substitution and relocate production sites to countries with lower production costs (Bems et al. 2018). While numerous studies have investigated the role of global variables on inflation, empirical findings are mixed.

On the one hand, Ihrig et al. (2010), Förster and Tillmann (2014), Mikolajun and Lodge (2016), and Bems et al. (2018) find little support for globalization having a significant effect on inflation in advanced and emerging market economies. On the other hand, Borio and Filardo (2007) and Ciccarelli and Mojon (2010) argue that with greater globalization, international factors such as commodity prices and the global state of the economy have gained more prominence in explaining domestic inflation dynamics. Forbes (2019) confirms that global factors play a considerable role in shaping inflation, as the traditional relationship between domestic slack and inflation has weakened over time.

The literature on post-pandemic inflation is developing fast, and preliminary evidence is inconclusive with mixed results. Using historical data, Bonam and Smădu (2021) find that major pandemics in the past have induced a considerable decline in trend inflation over an extended period. However, the disinflationary effects of a pandemic vary with policy responses, which are unprecedented in the case of COVID-19, with expansionary fiscal and monetary measures aimed at preventing tightening credit conditions, bankruptcies, and mass layoffs. The fast rebound of economic activities due to vaccines, lifting lockdowns, and telework could have exerted upward pressure on consumer price inflation. At the same time, supply chain disruptions contribute to rising inflation when firms can pass the increasing costs to consumers. Ha, Kose, and Ohnsorge (2023) provide early evidence for the collapse in global demand, lowering inflation during the initial stage of the COVID-19 pandemic, followed by the strong recovery in economic activity pushing consumer prices higher.

## 3. Data Overview and Stylized Facts

We construct a balanced panel data set of monthly observations covering 30 European countries over the period 2002–22.[1] The dependent variable is either the headline or core measure of consumer price inflation, which is computed as follows:

$$\pi_{c,t} = \left( \frac{CPI_{c,t}}{CPI_{c,t-12}} - 1 \right) * 100,$$

where $\pi_{c,t}$ denotes headline or core inflation in country $c$ at time $t$ based on CPI series, which are drawn from the Eurostat and national statistics institutions in the case of non-EU countries in

[1]The list of countries is presented in Appendix Table A.1.

the sample. Both headline and core inflation are based on the harmonized indices, thus comparable across countries in our sample. Following the literature, we select domestic and global variables as described below to analyze inflation dynamics before and after the pandemic. These series are obtained from various sources, including Eurostat, the International Monetary Fund (IMF), the Organisation for Economic Co-operation and Development (OECD), and the World Bank.[2] Although other variables, such as the exchange rate regime and monetary policy independence, could be important in determining inflation dynamics, the availability of monthly data limits the choice of variables. In addition, these variables are considered long-term structural factors, which would be less likely to be affected by post-pandemic developments. To obtain a more granular analysis, we include an additional variable, such as inflation forecasts, but data availability limits the number of countries and periods for the analysis.

**Domestic Variables.** In explaining inflation, the standard Phillips curve accounts only for domestic variables, including lagged inflation, inflation forecasts, and the domestic output gap.

- *Lagged Inflation:* Inflation tends to exhibit significant persistence over time, which is mainly due to price stickiness. Assuming that inflation is positively correlated with its own lags, we use lagged inflation as a measure of persistence. Lagged inflation refers to the inflation rate from the previous month, calculated on a year-on-year basis.
- *Domestic Output Gap[3]:* A measure of the slack in real economic activity is obtained by using the Hamilton (2018) filter to isolate the cyclical fluctuations and trend. Given the unavailability of the monthly GDP series, we use the seasonally adjusted industrial production index (IPI) as a proxy to calculate the domestic output gap. Our results remain unchanged when we use alternative filters, such as the Hodrick-Prescott (HP) filter.

[2]The list of data sources is presented in Appendix Table A.2.

[3]We acknowledge the absence of demand-side factors (including a measure of fiscal policy) in the regression model, mainly because incorporating fiscal policy at a monthly frequency is not possible. Nevertheless, the domestic output gap should partially capture the demand-side factors.

**Global Variables.** The globalization of inflation hypothesis suggests that as countries integrate into a higher level of global markets, downward pressure on prices is expected due to the competition that takes a more global aspect. As in Borio and Filardo (2007), Auer, Borio, and Filardo (2017), and Forbes (2019), inflation becomes more "global-centric" if global variables gradually develop into dominant factors shaping the inflation dynamics. Take, for instance, the GVC participation. Firms constantly look for ways to reduce costs, and one way to achieve that goal is to relocate production sites to countries with lower costs, which, in turn, makes domestic inflation dynamics more sensitive to global factors.

- *Global Output Gap:* Empirical evidence on the link between inflation and the slack in global economic activity is mixed.[4] Significant positive effects of global demand pressures are usually associated with higher headline inflation, whereas contrary outcomes are found in core inflation. We use the Hamilton (2018) filter to calculate the global output gap measure by resorting to the world IPI constructed by Baumeister and Hamilton (2019), which is closely associated with the general level of economic activity. Our results remain unchanged when we use alternative filters, such as the HP filter.
- *Global Energy and Non-energy Prices:* Global energy prices measure energy-related prices, including coal, natural gas, oil, and propane, while global non-energy prices include industrial inputs, food and beverages, and fertilizers. Commodity price fluctuations could have a direct impact on headline inflation and influence core inflation indirectly through input prices and inflation expectation that captures second-round impact. This measure is constructed based on a monthly year-on-year growth rate.

[4]While Borio and Filardo (2007), Forbes (2019), and Jasova, Moessner, and Takats (2020) find support for the significant role of the world output gap on inflation, Calza (2008), Ihrig et al. (2010), and Mikolajun and Lodge (2016) find no supporting evidence for the role of the global output gap in domestic inflation dynamics. One possible explanation for such a different impact of global economic slack could be the different relationship between the global output gap and headline and core inflation.

- *Global Supply Chain Pressure (GSCP):* Built by Benigno et al. (2022), the GSCP index measures supply chain disruptions according to the Baltic Dry Index (BDI), the Harpex index, air freight costs, and some components of the Purchasing Managers' Index (PMI), such as delivery time, backlogs, and purchased stocks. The principal component analysis is employed to extract a common component from these data. An increase in the standard deviation of the GSCP index implies more supply chain disruptions.
- *Nominal Effective Exchange Rate (NEER)*[5]*:* NEER is a measure of the value of a currency against a weighted average of several foreign currencies. An increase in NEER indicates an appreciation of the local currency against the weighted basket of currencies of its trading partners. While the literature tends to categorize the exchange rate as a global factor, it is not a "common" factor like other global variables included in the analysis, as domestic developments and policy choices have a significant bearing on the exchange rate. $\Delta$NEER is the monthly year-on-year change. Table 1 reports the summary statistics for all variables used in the analysis, which show considerable heterogeneity across countries and over time. For example, as measured by the headline CPI, average inflation is 2.2 percent from 2002 to 2022, with a minimum of $-4.3$ percent and a maximum of 20.1 percent. Similarly, core inflation excluding food and energy is 1.9 percent on average, with a minimum of $-4.2$ percent and a maximum of 16.4 percent during the sample period. The domestic and global output gaps are, on average, 0, respectively. However, the domestic output gap has a larger variance than the global output gap, denoting that the deviations of the domestic output gap could be significantly spread out.

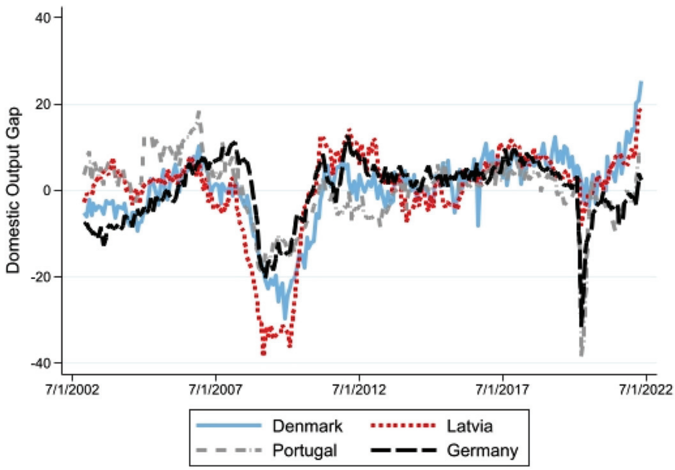
In Figure 1, we plot the series of domestic output gap for selected countries in our sample. While all series follow a similar pattern, countries such as Denmark and Latvia had a larger decline in the output gap during the GFC compared to Germany and Portugal.

[5]For robustness checks, we use the real effective exchange rate (REER) index and obtain similar results.

**Table 1. Summary Statistics**

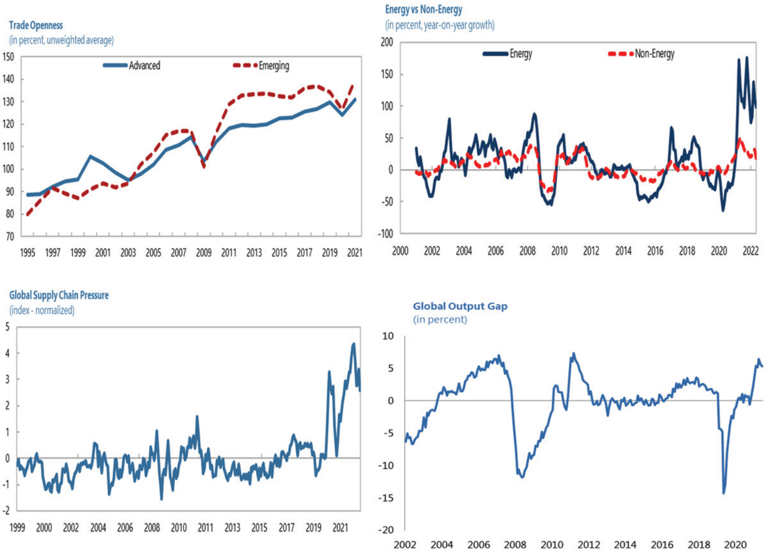
| | Mean | Std. Dev. | Variance | Minimum | Maximum |
|---|---|---|---|---|---|
| Δ Headline Inflation (%) | 2.219 | 2.397 | 5.744 | –4.347 | 20.146 |
| Δ Core Inflation (%) | 1.916 | 1.935 | 3.745 | –4.171 | 16.448 |
| Domestic Output Gap (%) | 0.000 | 4.479 | 20.058 | –60.944 | 59.880 |
| Global Output Gap (%) | 0.000 | 4.193 | 17.577 | –14.306 | 7.368 |
| Δ NEER (%) | 0.505 | 3.924 | 15.400 | –23.982 | 23.049 |
| Δ REER – ULC (%) | 0.261 | 4.638 | 21.511 | –22.911 | 29.101 |
| Δ REER – CPI (%) | 0.309 | 4.125 | 17.014 | –21.670 | 24.525 |
| Δ Energy Prices (%) | 14.406 | 41.199 | 1697.386 | –63.294 | 175.750 |
| Δ Non-energy Prices (%) | 6.701 | 16.459 | 270.884 | –34.351 | 51.508 |
| Δ Commodity Prices (%) | 8.804 | 24.451 | 597.853 | –42.122 | 71.643 |
| GSCP (Normalized) | 0.149 | 1.044 | 1.089 | –1.523 | 4.351 |

**Figure 1. Domestic Output Gap in Selected Countries**




However, the COVID-19 pandemic led to a much sharper decline in the domestic output gap for the latter group, while the former group of countries has been producing above its potential output during the post-pandemic period. One of the main differences between these groups of countries is in the way lockdown measures were enacted during the pandemic period, as Denmark and Latvia have, on average, a smaller stringency index than Germany and Portugal (Hale et al. 2021).

**Figure 2. Global Factors**




**Source:** Haver Analytics, IMF, World Bank, OECD, Baumeister and Hamilton (2019), Benigno et al. (2022), and IMF staff calculations.

The three different exchange rate measures used in the analysis show similar values across different summary statistics, but the average NEER is slightly higher due to the absence of inflation adjustment. In addition, the variance of the REER based on unit labor costs (ULC) is larger, indicating significant differences in ULC among European countries. Regarding the year-on-year variation of energy and non-energy prices, we observe more frequent fluctuations in energy prices compared to non-energy, indicating a potentially significant role played by energy prices in explaining inflation dynamics in Europe (top-right panel of Figure 2). Although global supply chain pressures appear to have a stable profile before 2019, the global pandemic and the war in Ukraine have caused larger and more volatile supply chain disruptions (bottom-left panel of Figure 2).

Overall, with rapidly increasing globalization, we expect international factors to become more prominent determinants of domestic inflation dynamics over time. For instance, at the onset of the GFC in 2008, abrupt and sharp changes in global resource utilization, commodity prices, and trade openness contributed to deflationary pressures worldwide, albeit with varying degrees across countries and in terms of headline and core inflation rates. More recently, the COVID-19 pandemic has induced a sharp decline in headline and core measures of inflation across the world due to plunging energy prices and demand. However, it quickly rebounded with the strong pace of recovery and global supply chain disruptions. Our analysis aims to unveil such relationships and shed light on how they evolved over time.

## 4. Econometric Methodology and Results

The empirical analysis presented in this study is based on a threefold econometric strategy to ensure robustness and granular assessment. First, we implement the GDFM approach to disentangle the effect of common (global) and domestic (country-specific) factors on inflation and investigate the degree of synchronization of inflation dynamics across European countries. Second, we deepen the analysis by estimating an augmented Phillips-curve model of inflation with global variables in a panel setting. Third, we use the LP method to estimate the dynamic response of alternative measures of consumer price inflation to global and domestic shocks.

### *4.1 Generalized Dynamic Factor Model*

The objective of the GDFM analysis is to decompose the variation of inflation in each country into the following components:

- *Variation Explained by Observable Global Components:* These include global factors that are observable to us (such as energy and non-energy prices) and likely to affect inflation across all countries in the sample.
- *Variation Explained by Observable Domestic Factors:* These include other observable country-specific factors that are likely to have a differential effect on inflation.
- *Variation Explained by Common Inflation Dynamics:* This is obtained by applying the GDFM to the portion of inflation that is not explained either by observable global or domestic factors. This element of the variance decomposition

captures the common co-movements of inflation across the countries by extracting $k \geq 1$ unobservable common shocks, which are weighted by some country-specific factor loadings, as explained in Forni et al. (2000; 2005).[6] That is, all countries face the same common shocks, but the way inflation reacts to these common shocks is country specific. Notice that these common shocks do not necessarily have an economic interpretation, so we refer to them as *common inflation dynamics*. The number of common shocks, $k$, is chosen using a data-driven information criterion, as explained below.

Early applications of dynamic factor models by Sargent and Sims (1977) and Stock and Watson (1989, 1991, 1993) suggest that a few latent factors can account for much of the dynamic behavior of economic aggregates.[7] The advantages of the DFM approach thereby include (i) a parsimonious representation of the data regarding unobservable common elements, which characterizes the degree of inflation co-movement and synchronization without making strong assumptions a priori (Mumtaz, Simonelli, and Surico 2011); (ii) a reduced-form solution to a standard dynamic stochastic general equilibrium (DSGE) model (Sargent 1989; Ha, Kose, and Ohnsorge 2019); and (iii) extraction of factors using non-parametric principal components, which prevents misspecification and deals with time-varying parameters and non-linearities (Miranda, Poncela, and Ruiz 2021).

We use the same baseline GDFM specification for each country in the sample in the following form:

$$\pi_{c,t} = X^{g}_{c,t}\beta_c + X^{d}_{c,t}\gamma_c + \chi_{c,t} + \varepsilon_{c,t}, \tag{1}$$

where $X^{g}_{c,t}$ and $X^{d}_{c,t}$ are the observed global and domestic components, respectively; $\chi_{c,t} = \sum_{j=1}^{k} b_{c,j}(L)u_{j,t}$ is the unobserved

[6]The dynamic factor model approach has widely been used in the literature to assess global financial and business cycles (Menden and Proaño 2017; Cerutti, Claessens, and Rose 2019; Miranda-Agrippino and Rey 2020; Mumtaz and Musso 2021) and inflation developments (Mumtaz and Surico 2008; Ciccarelli and Mojon 2010; Neely and Rapach 2011; Ha, Kose, and Ohnsorge 2019; Szafranek 2021).

[7]There are several surveys of dynamic factor models, including Breitung and Eickmeier (2006), Stock and Watson (2006, 2011, 2016), Bai and Ng (2008), Lütkepohl (2014), and Bai and Wang (2016).

*common dynamic component*, $L$ standing for the lag operator, and $k$ the number of factors. The $b_{c,j}(L)$'s are the factor loadings, which are country specific and whose dynamic structure is otherwise unspecified; and $\{u_{1,t},\ldots,u_{k,t}\}$ are the *common shocks*. Finally, $\varepsilon_{c,t}$ is the idiosyncratic component, i.e., a zero-mean stationary process, independent of $\left(X^g_{c,t}, X^d_{c,t}, \chi_{c,t}\right)$ at all leads and lags. The vector of coefficients, $(\beta_c, \gamma_c)$, represents the country-specific loadings for the observed global and domestic components. The observable global component includes the global output gap, energy and non-energy commodity prices, a measure of global supply chain pressure, and the NEER. The observable domestic component includes the domestic output gap. The unobservable common component, $\chi_{c,t}$, is allowed to have a causal dynamic structure as explained above (Forni et al. 2000). To obtain a consistent estimation of $(\beta_c, \gamma_c)$, we further assume that $Cov\left(X^g_{c,t}, \chi_{c,t}\right) = Cov\left(X^d_{c,t}, \chi_{c,t}\right) = 0$. All observables in this equation are taken to have a mean equal to zero and a standard deviation equal to one. The vector of regressors, $\left(X^g_{c,t}, X^d_{c,t}\right)$, is a normalized version of the observable global and domestic factors. The constant term is thus omitted from the model. The covariance between $X^g_{c,t}\widehat{\beta}_c$ and $X^d_{c,t}\widehat{\gamma}_c$ is assigned to each one of these components proportionally to the total variance. For instance, if $Var\left(X^g_{c,t}\beta_c\right) = 5$, and $Var\left(X^d_{c,t}\gamma_c\right) = 1$, five-sixths of the covariance is assigned to the global components, and the remaining one-sixth is assigned to the domestic component (see Gibbons, Overman, and Pelkonen 2013). As explained above, the variance of $\pi_{c,t}$ is thus decomposed as follows: (i) variance explained by the observable global component, $Var\left(X^g_{c,t}\beta_c\right)$; (ii) variance explained by the observable domestic component, $Var\left(X^d_{c,t}\gamma_c\right)$; (iii) variance explained by the common inflation dynamics, $Var(\chi_{c,t})$; and (iv) idiosyncratic variation, $Var(\varepsilon_{c,t})$.

We first obtain an estimator of $(\beta_c, \gamma_c)$, $\left(\widehat{\beta}_c, \widehat{\gamma}_c\right)$, via ordinary least square (OLS) regression of inflation on observable (global and domestic) factors. Upon the assumptions listed above, this estimator is consistent and asymptotically normal as $T \to \infty$. We then compute the percentage of the variance explained by the observable global components as $Var\left(X^g_{c,t}\widehat{\beta}_c\right) \cdot 100$ and the percentage of the variance explained by the observed domestic components as

$Var\left(X^d_{c,t}\widehat{\gamma}_c\right) \cdot 100$, where the covariance is distributed across the two components as explained above. Next, we construct

$$\pi_{c,t} - X^g_{c,t}\widehat{\beta}_c - X^d_{c,t}\widehat{\gamma}_c = \chi_{c,t} + \varepsilon_{c,t}, \tag{2}$$

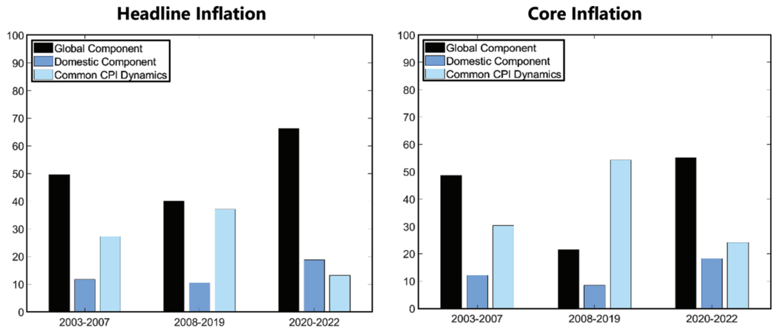
which represents the residuals from the OLS regression of each country's inflation rate onto the observed global and domestic components. To simplify notations, we have omitted from Equation (2) the estimation error that occurs from replacing $(\beta_c, \gamma_c)$ with $\left(\widehat{\beta}_c, \widehat{\gamma}_c\right)$.[8] These residuals correspond to our dependent variable, $\pi_{c,t}$, from which the effect of the observable global and domestic components has been partialled out. Next, we apply to these residuals the GDFM as in Forni et al. (2000). The estimation of the unobservable common factor, based on the matrix of inflation rates from the 30 European countries, gives us the variance explained by the common inflation dynamics. Therefore, a crucial step in estimating the GDFM is determining the number of common factors in the model. There are various statistical approaches to determining the number of factors in the GDFM. In this paper, we determine the number of factors according to the information criterion proposed by Hallin and Liska (2007). We obtain $k^* = 3$ for headline CPI and $k^* = 4$ for core CPI, as the optimal number of factors. This is also confirmed by a graphical analysis of the dynamic eigenvalues averaged over the spectral frequencies (Appendix Figure A.1).[9]

The average variance explained by each one of the components over three separate periods is presented in Figure 3. The sample is split in this manner to separately consider the effects of the common components on inflation before and after the global financial crisis and before and after the pandemic. The share of variance explained by the different components changes substantially over the period

[8]Upon the stated assumptions, the OLS estimators of $(\beta_c, \gamma_c)$ are consistent for $T \to \infty$, while the consistent estimation of $\chi_{c,t}$ requires both $n, T \to \infty$ (see Forni et al. 2000). The first-step estimation error is thus negligible when estimating the GDFM in the second step.

[9]The first six eigenvalues appear to diverge, while the others are relatively stable. Further analysis also reveals that the relative increase in the variance explained when increasing the common components from six to seven is less than 3 percent. As 5 percent is often the pre-assigned minimum to include an additional component, we conclude that the choice of six unobservable global factors is likely to be robust.

**Figure 3. Average Share of Variance Explained**




2003–22. In particular, the observable global component explains a larger share of the variance in the post-pandemic period, especially for headline inflation. Similarly, the share of variance explained by the country-specific component increases by about 10 percent for both headline and core inflation during the period 2020–22. The sharp increase in the percentage of variance explained by both the observable global and domestic factors goes along with a decrease in the variance explained by the common inflation dynamics. There are several potential explanations for this result. First, consumer price inflation in Europe was relatively stable during the pre-pandemic period, resulting in a high level of synchronization across countries, as shown by the large percentage of variance explained by the common dynamics before 2020. The COVID-19 pandemic, however, may have caused a permanent upward break in inflation dynamics, which may not be necessarily homogenous across countries and may have reduced the level of synchronization in inflation. Second, because of containment restrictions and supply disruptions during the pandemic, many economies remained below potential and consequently experienced an abrupt buildup of price pressures with the relaxation of lockdown measures.

Another interesting result that emerges from the GDFM is the heterogeneity across countries. We divide our sample into advanced economies and emerging markets. The former group includes the euro area (except for Latvia, Lithuania, Slovakia, and Slovenia), Norway, Sweden, Switzerland, and the United Kingdom, while the latter group includes most Eastern European countries. As it

**Figure 4. Average Share of Variance Explained: Advanced Europe**

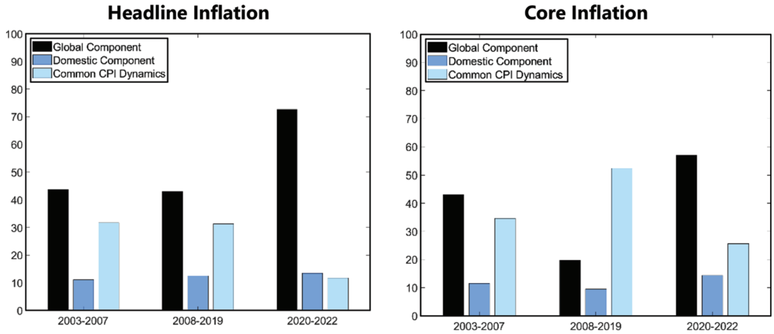
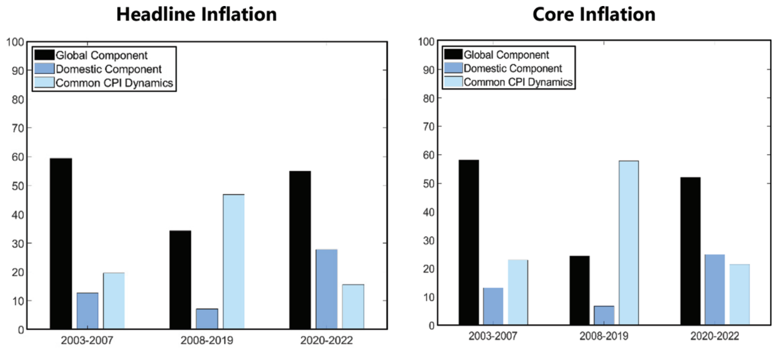



**Figure 5. Average Share of Variance Explained: Emerging Europe**




appears in Figure 4, the results for advanced economies are qualitatively different from the overall results. The relative importance of country-specific factors has increased, although not substantially, since the beginning of the COVID-19 pandemic (the variance explained by the domestic component increases by less than 1 percent for headline inflation and by less than 5 percent for core inflation). By contrast, global factors play a fundamental role, and the variance explained by co-movement in inflation in the advanced economies decreases substantially.

In the case of emerging market economies, presented in Figure 5, the importance of domestic factors has increased since the pandemic, and their total share of variance has increased from about 7 to about 25 percent for both headline and core inflation. On the contrary, the variance explained by the global components represents a smaller share of the variance in inflation, and so do the common inflation dynamics. This seems consistent with the evidence that the output gap is larger on average for emerging economies since the pandemic, and that may have spurred higher inflation compared to other advanced European economies.

### *4.2 Panel Data Analysis*

We deepen the analysis by estimating an augmented Phillips-curve model of inflation dynamics in a panel setting. We follow the literature and choose explanatory variables widely employed in the standard Phillips-curve model. For instance, Forbes (2019) and Busetti, Caivano, and Delle Monache (2021) show that lagged inflation, output gap, exchange rate, and commodity prices likely affect inflation in the standard Phillips-curve model. Given the focus of this paper on global factors and post-pandemic inflation, we augment the standard Phillips-curve model to account for the role of supply chain disruptions in post-pandemic inflation dynamics (Benigno et al. 2022; Hall, Tavlas, and Wang 2023). It should be noted, however, that the choice of the explanatory variables is partly constrained by the data at monthly frequency. We first estimate the standard Phillips-curve model and augment it with a measure of supply chain disruptions. More formally, we estimate the following specification:[10]

$$\begin{aligned}\pi_{c,t} = {} & \beta_1 + \beta_2 \pi_{c,t-1} + \beta_3 Y^D_{c,t} + \beta_4 Y^W_t + \beta_5 \triangle neer_{c,t-1} \\ & + \beta_6 \triangle energy_t + \beta_7 \triangle nonenergy_t + \eta_c + \varepsilon_{c,t},\end{aligned} \qquad (3)$$

where subscripts $c$ and $t$ denote country and time, respectively, and data are sampled at a monthly frequency. $\pi_{c,t}$ indicates monthly year-on-year inflation rate on a monthly basis as measured by the headline and core CPI following Kamber, Mohanty, and Morley (2020) and Busetti, Caivano, and Delle Monache (2021), who also

[10]The correlation diagnostics (Appendix Table A.8) indicate the absence of multicollinearity in our regressions.

consider year-on-year changes; $\pi_{c,t-1}$ is the first lag of inflation; $Y_t^D$ and $Y_t^W$ denote the domestic output gap and the global output gap, respectively; $neer_{c,t-1}$ is the nominal effective exchange rate, which is lagged to account for the delay in exchange rate pass-through to consumer prices; and $\Delta energy_t$ and $\Delta nonenergy_t$ are year-on-year growth rates of international energy and non-energy commodity prices, respectively.[11] $\eta_c$ denotes the time-invariant country-specific effect, and $\varepsilon_{c,t}$ is the error term. We use a fixed-effect estimator with the Driscoll-Kraay standard errors, which helps address cross-sectional dependence and serial correlation over time. We are not overly concerned about the Nickell bias generated by estimating a dynamic panel data model with a fixed-effect estimator, as the time-series dimension is much larger than the number of countries (see Arellano 2003, pp. 85–87 for details, and Ha, Kose, and Ohnsorge 2021). We further augment the empirical model to explore the role of global supply chain disruptions. We therefore introduce a measure of global supply chain disruptions into the model following Benigno et al. (2022) and Hall, Kose, and Ohnsorge (2023):

$$\begin{aligned}\pi_{c,t} = {}& \beta_1 + \beta_2\pi_{c,t-1} + \beta_3 Y_{c,t}^D + \beta_4 Y_t^W + \beta_5 \triangle neer_{c,t-1} \\ & + \beta_6 \triangle energy_t + \beta_7 \triangle nonenergy + \beta_8 GSCP_t + \eta_c + \varepsilon_{c,t},\end{aligned} \tag{4}$$

where $GSCP_t$ denotes global supply chain pressure, which is normalized and interpreted such that a zero implies that the index is at its average value, with negative values reflecting how many standard deviations the index is below this average value. As a result, we expect a higher value of global supply chain disruptions to exert upward pressure on headline and core measures of consumer price inflation.

The panel data analysis in Table 2 confirms the importance of inflation persistence and the domestic output gap. With all variables

[11] Time fixed effects are not included because the global output gap and energy prices, the two most significant global factors, should capture global elements changing each year common to all countries, consistent with Bems et al. (2018), Forbes (2019), and Jasova, Moessner, and Takats (2020).

**Table 2. Baseline Estimates: Full Sample**

| | Headline Inflation | | Core Inflation | |
|---|---|---|---|---|
| | **Baseline** | **+GSCP** | **Baseline** | **+GSCP** |
| Inflation$_{t-1}$ | 0.950*** | 0.950*** | 0.974*** | 0.975*** |
| | (0.015) | (0.015) | (0.012) | (0.011) |
| Domestic Output Gap | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Global Output Gap | 0.005 | 0.007 | 0.006** | 0.008*** |
| | (0.005) | (0.005) | (0.003) | (0.003) |
| $\Delta$NEER$_{t-1}$ | –0.021*** | –0.020*** | –0.014*** | –0.012*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| $\Delta$Energy Prices | 0.005*** | 0.004*** | 0.001** | 0.001** |
| | (0.001) | (0.001) | (0.001) | (0.000) |
| $\Delta$Non-energy Prices | 0.002 | 0.002 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| GSCP | | 0.0376 | | 0.0498*** |
| | | (0.0288) | | (0.0178) |
| Country FE | Yes | Yes | Yes | Yes |
| F-test: Global | 28.91*** | 26.28*** | 28.81*** | 22.23*** |
| Within $R^2$ | 0.9533 | 0.9536 | 0.9524 | 0.9530 |
| Observations | 7,020 | 7,020 | 7,020 | 7,020 |
| Countries | 30 | 30 | 30 | 30 |

**Note:** Driscoll-Kraay standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. "F-test: Global" tests the joint significance of our global variables. A constant is included in all specifications but not shown in the table. The sample period spans from December 2002 to May 2022.

in the model correctly signed, we find that inflation persistence is a critical factor across all specifications and for different measures of inflation. A relatively large coefficient of lagged inflation corroborates the generally accepted fact that inflation in Europe was persistent prior to the pandemic (Batini and Laxton 2006; Ciccarelli and Osbat 2017). The coefficients on the domestic output gap—0.004 for headline and core inflation—are positive and statistically significant at the 1 percent level. These imply that a 1 percentage point increase in the domestic output gap is associated with an increase of 0.004 percentage point in both headline and core measures of consumer price inflation, broadly consistent with previous findings in the literature.

The global output gap has a statistically significant positive effect on core inflation but not on headline inflation. A 1 percentage point increase in the global output gap is associated with an increase of 0.005–0.008 percentage point in core inflation, everything else being equal. However, the global output gap affects domestic inflation not only through the pricing decision of determinants of inflation, such as the exchange rate and global commodity prices. Hence, as discussed in the data section, previous studies usually find mixed results on the relationship between the global output gap and domestic inflation, which varies according to period, country, and measurement used in the analysis.

International energy prices exhibit a high degree of positive correlation with inflation. A 1 percentage point year-on-year growth in energy prices is associated with a 0.004 and 0.001 percentage point increase in headline and core inflation, respectively. The non-energy prices are not statistically significant, suggesting that energy prices play a more significant role in shaping domestic inflation than non-energy commodity prices. We find support for a strong relationship between energy prices and inflation. Nevertheless, the impact of energy prices varies according to different measures of inflation. International energy prices have a direct effect on headline inflation, which includes energy components. Although there is no such direct effect on core inflation, which excludes energy and food prices, we still find evidence for an indirect effect on core inflation. While the share of energy prices in consumer prices indices across the EU has been around 10 percent, Ari et al. (2022) illustrate that energy items constituted approximately half of the annual consumer price index (CPI) inflation rates as of May 2022, during the peak of the energy crisis in Europe. They further argue that this disparity may be attributed to differences in wholesale markets, regulation, and policy measures. On the other hand, non-energy commodity prices do not have a statistically significant effect on headline and core inflation in Europe, where food does not account for a large share of the average consumption basket.

The global supply chain variable also has an inflationary effect. The GSCP variable measures comprehensive global supply chain disruption in which an increase in one standard deviation is associated with a 0.05 percentage point increase in core inflation. The F-test of the joint significance of the global variables continues to show a strong joint statistical significance on headline and core inflation, underscoring their vital role in shaping domestic inflation.[12] We notice that the values of the F-test in headline inflation are considerably higher than in core inflation. One possible explanation is that commodity prices directly affect headline inflation. However, when considering the individual statistical significance of global variables, core inflation receives a quantitatively and relatively similar impact from the state of the global economy compared to headline inflation, except for commodities. This increasing role of global factors in determining core inflation might signify the persistent impact of global economic conditions on domestic inflation.

The exchange rate, capturing both global and domestic developments as well as policy choices, has a statistically significant effect on inflation. For example, a 1 percentage point year-on-year growth in the exchange rate explains about 0.01–0.02 percentage point decrease in inflation. This variable is lagged to allow for the delay in pass-through into domestic prices, operating through cheaper foreign products and services imported into the country.

We also find that the impact of global variables varies according to income level, showing notable differences between advanced and emerging countries. We estimate the model separately for advanced and emerging market economies in Europe and obtain results, presented in Table 3, that are broadly in line with our baseline findings. One crucial difference is that the global output gap is statistically significant for core inflation in both advanced and emerging market economies, but its effects are larger in emerging markets than in advanced economies (the p-values for the test that the difference in the coefficients of global output gap between advanced economies and emerging markets is equal to zero are 0.113 and 0.097, for headline and core inflation, respectively).[13] Other global

[12]To show that the F-test of joint significance of our global variables is not driven mainly by energy and non-energy prices, we run Equation (4) without the commodity variables. The values of the F-test are 8.78*** and 13.96*** for headline and core inflation, respectively. This suggests that the commodity variables are not the main drivers of the F-test of joint significance of our global variables.

[13]This and the subsequent tests are performed by running a pooled regression in which the emerging market dummy is interacted with all the independent variables in the same model as the one reported in Table 3.

**Table 3. Estimates by Country Groups**

| | Advanced | | Emerging | |
|---|---|---|---|---|
| | **Headline Inflation** | **Core Inflation** | **Headline Inflation** | **Core Inflation** |
| $\text{Inflation}_{t-1}$ | 0.903*** | 0.938*** | 0.963*** | 0.981*** |
| | (0.017) | (0.012) | (0.014) | (0.011) |
| Domestic Output Gap | 0.003*** | 0.003*** | 0.005** | 0.006*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| Global Output Gap | 0.005 | 0.005** | 0.016* | 0.013** |
| | (0.004) | (0.002) | (0.008) | (0.006) |
| $\Delta\text{NEER}_{t-1}$ | –0.016*** | –0.009*** | –0.027*** | –0.017*** |
| | (0.003) | (0.002) | (0.003) | (0.003) |
| ΔEnergy Prices | 0.005*** | 0.001*** | 0.004*** | 0.001 |
| | (0.001) | (0.000) | (0.001) | (0.001) |
| ΔNon-energy Prices | 0.001 | –0.000 | 0.003 | 0.003* |
| | (0.001) | (0.001) | (0.003) | (0.002) |
| GSCP | 0.021 | 0.031* | 0.065 | 0.076*** |
| | (0.026) | (0.016) | (0.040) | (0.026) |
| Country FE | Yes | Yes | Yes | Yes |
| F-test: Global | 22.15*** | 8.48*** | 26.45*** | 19.15*** |
| Within $R^2$ | 0.9198 | 0.8781 | 0.9697 | 0.9738 |
| Observations | 4,446 | 4,446 | 2,574 | 2,574 |
| Countries | 19 | 19 | 11 | 11 |

**Note:** Driscoll-Kraay standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. "F-test: Global" tests the joint significance of our global variables. A constant is included in all specifications but not shown in the table. The sample period spans from December 2002 to May 2022.

variables also appear to have quantitatively more prominent effects on inflation in emerging markets than in advanced economies. At the 10 percent level of significance, the coefficients of NEER and GSCP are different between advanced economies and emerging markets for headline inflation. In contrast, the effects of NEER, GSCP, non-energy prices, and domestic output gaps differ for core inflation. Overall, these results and higher values of the F-test of the emerging economies than the advanced economies align with our stylized facts that countries with higher integration into global markets will likely sustain a larger effect of global factors on inflation dynamics.

We also focus on the impact of global factors during different periods, such as the post-global financial crisis and post-pandemic periods (Table 4).[14] So far, we run our econometric specifications for the entire period. However, the contribution of global factors could vary in different periods. Accordingly, we compare post-GFC and post-pandemic periods to analyze whether the contributions of explanatory variables have changed over time. To this end, we rely on the panel structural break test (Bai and Perron 1998) to empirically test the break dates in our data (see Appendix Table A.5). It should be noted that we have two post-pandemic-period regression results to observe the contemporaneous and delayed effects of the GSCP variable separately. We find considerable differences between post-GFC and post-pandemic periods in terms of the statistical significance of global variables. These results show that global factors have contributed to shaping domestic inflation, though domestic variables still play a significant role since the GFC. Post-pandemic inflation developments appear to be primarily driven by domestic factors, surges in commodity prices, and supply chain disruption. The persistence of inflation has become even more quantitatively significant in the post-pandemic period. Europe has been characterized by an increasing persistence in inflation and declining trend inflation before the COVID-19 pandemic due to primarily cyclical domestic and global factors (Ciccarelli and Osbat 2017). While global factors were the primary driver of inflation dynamics in Europe before the pandemic, domestic factors also made significant contribution. As in Abdih, Lin, and Paret (2018), the transition process tends to be longer, especially in the case of positive inflation shocks, due to persistence in pricing behavior. Moreover, we find that the more stringent government measures for containment during the COVID-19 pandemic, the higher the inflationary pressures on prices (Appendix Table A.6). A critical question in this context is whether global factors are negligible in the post-pandemic period, but the F-test of

[14]The number of post-pandemic-period observations appears small at first sight, but we use monthly data, amounting to 870 observations. Therefore, our F-test remains stable and has fewer noises than data at a quarterly or annual frequency. For robustness, we implement a quasi-likelihood-ratio (LR) test, identical to an F-test in large samples. The quasi-LR test confirms our F-test results (Appendix Table A.9).

## Table 4. Estimates by Sub-periods

| | Headline Inflation | | | Core Inflation | | |
|---|---|---|---|---|---|---|
| | **Post-GFC** | **Post-pandemic GSCP** | **Post-pandemic GSCP$_{t-3}$** | **Post-GFC** | **Post-pandemic GSCP** | **Post-pandemic GSCP$_{t-3}$** |
| Inflation$_{t-1}$ | 0.898*** | 1.006*** | 0.999*** | 0.926*** | 0.998*** | 1.006*** |
| | (0.010) | (0.031) | (0.029) | (0.010) | (0.051) | (0.046) |
| Domestic Output Gap | 0.003 | 0.008*** | 0.009*** | 0.003** | 0.007* | 0.005 |
| | (0.002) | (0.003) | (0.003) | (0.001) | (0.004) | (0.004) |
| Global Output Gap | 0.003 | 0.032* | 0.021 | 0.007*** | 0.034** | 0.019 |
| | (0.005) | (0.019) | (0.019) | (0.002) | (0.014) | (0.011) |
| ΔNEER$_{t-1}$ | –0.026*** | –0.028* | –0.026 | –0.013*** | –0.026* | –0.030** |
| | (0.003) | (0.015) | (0.016) | (0.002) | (0.0135) | (0.014) |
| ΔEnergy Prices | 0.005*** | | | 0.000 | | |
| | (0.001) | | | (0.000) | | |
| ΔNon-energy Prices | 0.004** | | | 0.002*** | | |
| | (0.002) | | | (0.001) | | |
| ΔCommodity Prices | | 0.005 | 0.005** | | –0.002 | 0.001 |
| | | (0.004) | (0.002) | | (0.002) | (0.002) |
| GSCP | –0.033 | 0.023 | | 0.016 | 0.096** | |
| | (0.039) | (0.057) | | (0.022) | (0.041) | |
| GSCP$_{t-3}$ | | | 0.089* | | | 0.062** |
| | | | (0.047) | | | (0.028) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| F-test: Global | 44.26*** | 13.46*** | 18.36*** | 28.79*** | 7.56*** | 8.65*** |
| Within $R^2$ | 0.9248 | 0.9537 | 0.9545 | 0.8926 | 0.9078 | 0.9070 |
| Observations | 3,810 | 870 | 870 | 3,810 | 870 | 870 |
| Countries | 30 | 30 | 30 | 30 | 30 | 30 |

**Note:** Driscoll-Kraay standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. "F-test: Global" tests the joint significance of our global variables. Due to multicollinearity issues between energy and non-energy prices in the post-pandemic period, we use a single index of commodity prices. A constant is included in all specifications but not shown in the table.

joint significance still rejects the null hypothesis that global factors do not have any joint effects on inflation rates.

### *4.3 Local Projection Method*

We implement the LP method of Jordà (2005) to estimate the response of inflation to global and domestic shocks. The LP approach is found to be better suited to estimate dynamic responses and robust to non-linear model misspecification (Auerbach and Gorodnichenko 2013; Romer and Romer 2019). We estimated the following baseline specification with the LP method:

$$\begin{aligned}\pi_{c,t+h} - \pi_{c,t-1} = {} & \beta_{c,h} + \vartheta_{c,h} Y_{c,t}^{D} + \Phi_h Y_t^{W} + \sum_{m=1}^{2} \delta_{c,t,m} \Delta neer_{c,t-m} \\ & + \theta_h \Delta energy_t + \psi_h \Delta nonenergy_t + \sigma_h GSCP_t \\ & + \sum_{l=1}^{2} \gamma'_{c,t,l} X_{c,t-l} + \varepsilon_{c,t+h}, \end{aligned} \tag{5}$$

where $h$ indicates the forecast horizons. $\pi_{c,t+h} - \pi_{c,t-1}$ is the dependent variable, which is the cumulative response of inflation from $t-1$ to $t+h$. The cumulative impulse response function (IRF) values are constructed from the estimated coefficients at each time horizon $h$. Thus, the coefficients reflect the step in the cumulative IRF at a forward time $h$ and they can be interpreted as the accumulated response of inflation to an increase in one standard deviation in *GSCP*, for example. Given that the error terms could be serially correlated due to the successive leading of the dependent variable in the local projection method, we thus resort to the Driscoll-Kraay standard errors to address the serial correlation across time and cross-sectional dependence.[15] $X_{c,t}$ is a vector containing domestic and global output gap, energy and non-energy prices, inflation, and global supply chain pressure. $X_{c,t}$ and $neer_{t-2}$ are used as controls to cleanse the estimated coefficients from the dynamic effects of inflation and the effects of past changes in the domestic and global output gap, energy

[15] Olea and Plagborg-Moller (2021) argue that the lag augmentation corrects standard errors for serial correlation.

and non-energy prices, exchange rate, and global supply chain pressure. Thus, this vector and $neer_{t-2}$ are not used to construct the IRF, and lag-augmented local projection remains robust to highly persistent data and the estimation of IRs at long horizons.[16]

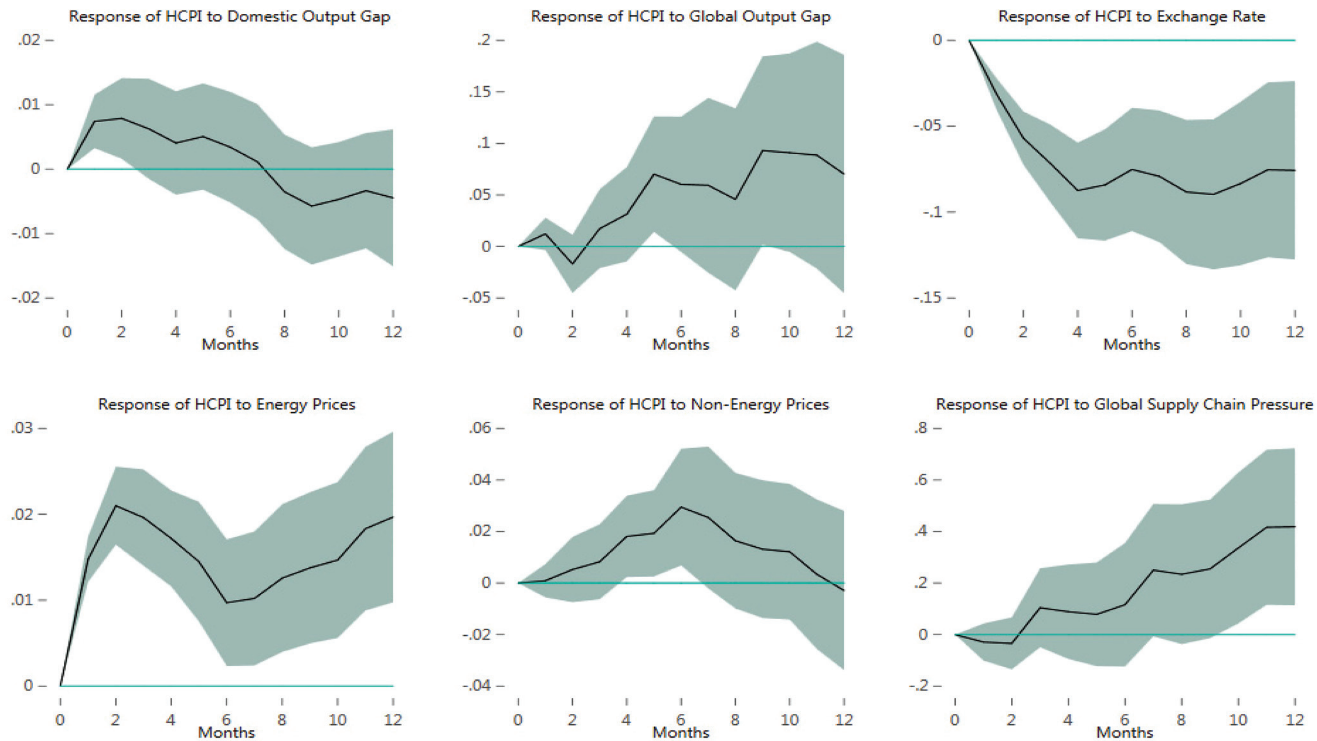
We use the LP method to examine the shocks in the post-GFC and the post-pandemic periods on the future path of inflation. Figures 6, 7, 8, and 9 report the estimated IRFs with 90 percent confidence intervals, and the discussion that follows is based on quantitative results drawn from these figures. First, we examine the post-pandemic domestic and global output gap. The domestic factor has developed into a more critical determinant in the post-pandemic period. The domestic output gap is quantitatively more significant, and the inflation responds sharply to the domestic factor in the post-pandemic period. Consistent with our fixed-effect regression estimates, the domestic output gap has grown to be a driving factor shaping domestic inflation. Moreover, they are likely to be persistent over time in the post-pandemic period.

The global output gap is quantitatively more significant than the domestic output gap in the post-pandemic period at the beginning of the future path. Inflation also responds sharply to the global output gap. Nevertheless, the domestic output gap is more persistent, and its effects last longer than the global output gap. This would imply that the impact of the domestic output gap in the post-pandemic period could be more considerable at the later stage of the future path of inflation. Accordingly, the domestic output gap being one of the driving factors in the post-pandemic period hints at monitoring domestic economic activities, consistent with Oinonen and Paloviita (2014), who argue that the domestic output gap has played a more decisive role since 2012 in steepening the Phillips curve in the euro zone. In addition, it possibly captures all the policy effects in the wake of the COVID-19 pandemic, such as fiscal and monetary policies.

Second, global factors—the global output gap, commodity prices, exchange rate, and global supply chain pressures—in the post-GFC period are likely to exert upward pressure on headline and core

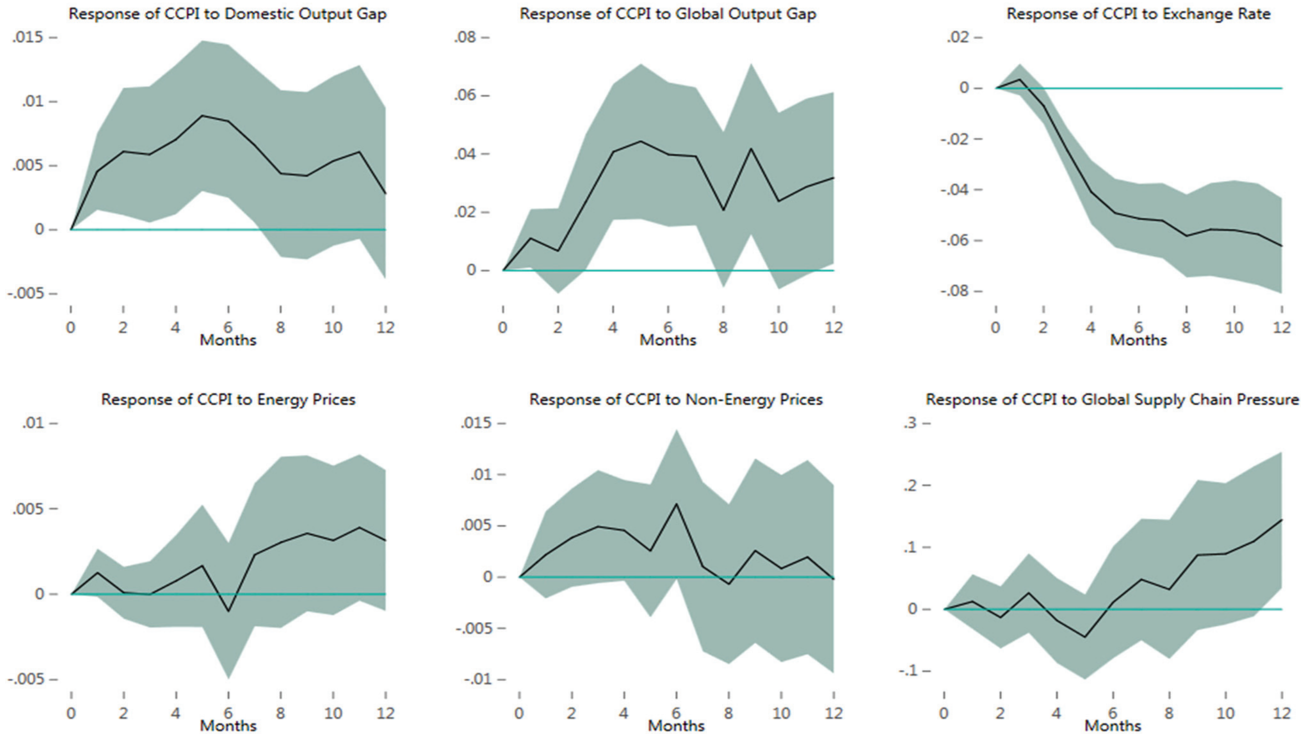
[16] Results are broadly similar when longer lags are employed in the LP method.

**Figure 6. Augmented Phillips-Curve Estimates, Post-GFC: Headline Inflation**



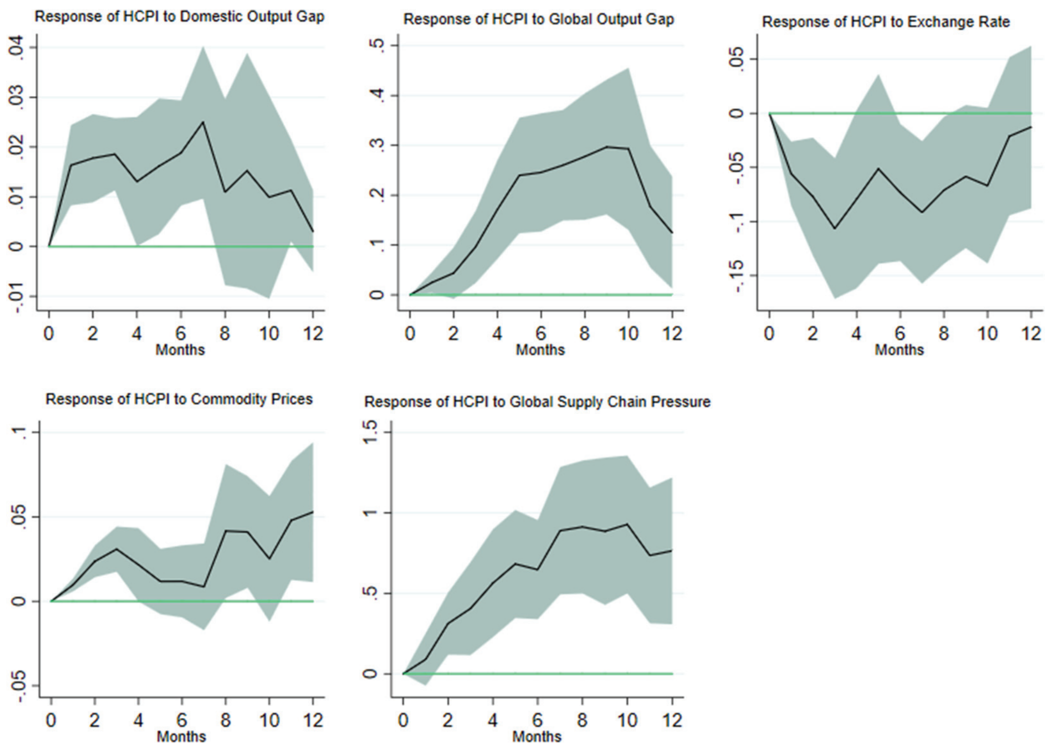

**Note:** Cumulative responses of headline inflation, with Driscoll-Kraay standard errors and 90 percent confidence interval.

**Figure 7. Augmented Phillips-Curve Estimates, Post-GFC: Core Inflation**



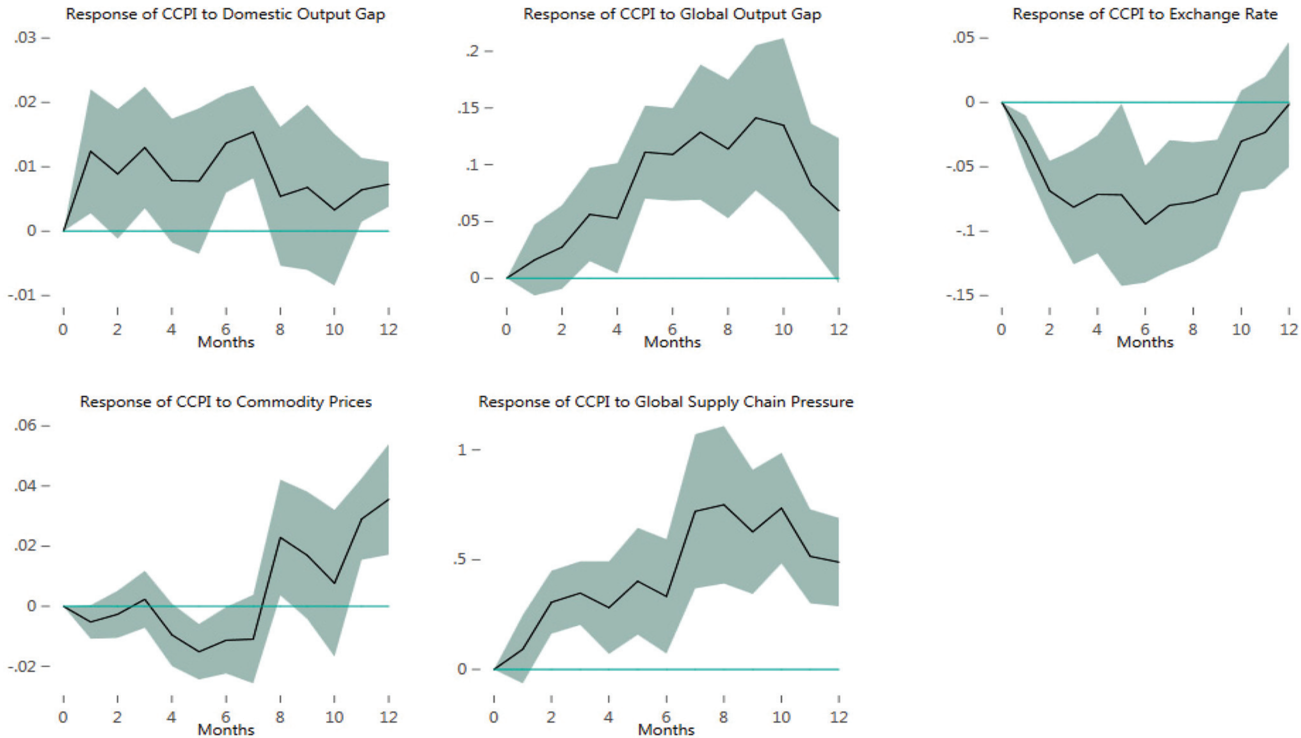

**Note:** Cumulative responses of headline inflation, with Driscoll-Kraay standard errors and 90 percent confidence interval.

**Figure 8. Augmented Phillips-Curve Estimates, Post-Pandemic: Headline Inflation**




**Note:** Cumulative responses of headline inflation, with Driscoll-Kraay standard errors and 90 percent confidence interval.

**Figure 9. Augmented Phillips-Curve Estimates, Post-Pandemic: Core Inflation**




**Note:** Cumulative responses of headline inflation, with Driscoll-Kraay standard errors and 90 percent confidence interval.

inflation, and their effects could be long-lasting. Moreover, the long-lasting effects of these global variables on core inflation draw the attention of monetary authorities to consider external factors when implementing monetary policy. In contrast, energy prices have relatively short-lived effects on inflation, and their effects quickly disappear at the end of two months in headline inflation in post-GFC headline inflation. Likewise, their effects have negligible effects on core inflation and are short-lived. On the exchange rate, its effects are relatively muted in core inflation for one to two months, also statistically insignificant, denoting a slower pass-through into prices in the post-GFC.

Considering variables other than output gap measures is crucial when comparing domestic and global factors. For instance, the response of inflation to the exchange rate in the post-pandemic period is slightly more considerable but less persistent than in the post-GFC period. Furthermore, the novelty of this paper is the integration of the impact of global supply chain pressure on inflation. We show that the global supply chain pressure exerts upward pressure on inflation with a delay of one month in the post-pandemic period. Our results align with Benigno et al. (2022), who show that recent inflationary pressures are closely associated with global supply chain pressures in the euro zone. This is because the global supply chain disruption would increase the costs of production, which could be passed on to consumers. Again, global supply chain pressure is quantitatively more considerable in the post-pandemic period than in the post-GFC period, but it is less persistent.

Overall, inflation has become more responsive to both domestic and global factors in the post-pandemic period. The more significant responsiveness of inflation to domestic and global factors indicates that a slight change in underlying domestic and global economic activities could influence the price levels quickly. When the shocks become persistent, they could affect the general trend in inflation. Given that central banks focus more on trend inflation than short-term volatility, both demand-pull and cost-push inflation from domestic and global factors during the post-pandemic period hint at the need for stronger monetary policy tightening to bring inflation under control. This is particularly critical in view of the increasing persistence in inflation dynamics we observed after the pandemic.

## 5. Robustness Checks

We use two alternative measures of the REER, inflation forecasts and a different lag structure of our variables of interest, to confirm the robustness of our baseline results. First, we rely on the REER constructed based on CPI and unit labor cost (ULC) to test whether these variables change our baseline results (Table 5). The choice of the exchange rate variable between the NEER and the REER may influence inflation dynamics differently due to the inclusion of euro zone countries in our panel. These robustness checks, however, show that there is no qualitative difference when we use the REER compared to our baseline results, including the NEER.

Second, we include inflation forecasts, which have become standard practice in the literature to control forward-looking price behavior along with past inflation (Albuquerque and Baumann 2017; Jordà and Nechio 2018; Mcleay and Tenreyro 2020). Although we cannot directly observe firms' inflation forecasts, it can be useful to rely on consensus professional forecasts. This can be especially beneficial for large firms when making economic decisions. However, small firms may not see much benefit from this type of aggregate information, as noted by Maćkowiak and Wiederholt (2009). We use a one-year-ahead inflation forecast in the model and obtain broadly similar results, which show that inflation expectations are still relevant after the pandemic (see Table 6). Notably, the effect of inflation forecast is larger in the post-pandemic period, implying a growing role of domestic factors. However, the null hypothesis that the difference between the coefficients of inflation forecast in the two periods is equal to zero cannot be rejected at standard statistical levels (for headline inflation, the difference is equal to 0.0849, and the jackknife test statistic is equal to 1.102; for core inflation, the difference is equal to 0.0702, and the jackknife test statistic is equal to 1.082; both test statistics lead to a lack of rejection of the null hypothesis at the 10 percent level assuming asymptotic normality of the resulting estimator).[17] Nonetheless, the persistence of inflation is still

[17]We performed the test of the null hypothesis that the difference between the coefficients in the two models is equal to zero using a clustered jackknife at the country level (see, e.g., Hansen 2022). Using clustered bootstrap leads to comparable results.

## Table 5. Augmented Phillips-Curve Estimates: Alternative REER Measures

| | Headline Inflation | | Core Inflation | |
|---|---|---|---|---|
| | **REER–CPI** | **REER–ULC** | **REER–CPI** | **REER–ULC** |
| $\text{Inflation}_{t-1}$ | 0.963*** | 0.951*** | 0.985*** | 0.973*** |
| | (0.015) | (0.018) | (0.011) | (0.013) |
| Domestic Output Gap | 0.004*** | 0.003*** | 0.004*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Global Output Gap | 0.006 | 0.008 | 0.008*** | 0.009*** |
| | (0.005) | (0.005) | (0.003) | (0.003) |
| $\Delta\text{REER\_CPI}_{t-1}$ | –0.018*** | | –0.012*** | |
| | (0.003) | | (0.002) | |
| $\Delta\text{NEER\_ULC}_{t-1}$ | | –0.007*** | | –0.004*** |
| | | (0.002) | | (0.001) |
| ΔEnergy Prices | 0.004*** | 0.004*** | 0.001** | 0.001** |
| | (0.001) | (0.001) | (0.000) | (0.000) |
| ΔNon-energy Prices | 0.002 | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| GSCP | 0.036 | 0.038 | 0.049*** | 0.046*** |
| | (0.028) | (0.028) | (0.017) | (0.017) |
| Country FE | Yes | Yes | Yes | Yes |
| F-test: Global | 25.34*** | 23.97*** | 17.65*** | 8.92*** |
| Within $R^2$ | 0.9534 | 0.9456 | 0.9529 | 0.9372 |
| Observations | 7,020 | 5,850 | 7,020 | 5,850 |
| Countries | 30 | 25 | 30 | 25 |

qualitatively and quantitatively substantial despite the inclusion of the inflation forecast.

Third, we employ a different lag structure for commodity prices, exchange rates, and global supply chain pressures in the post-pandemic period. For instance, exchange rate movements might take longer to feed through core inflation. Likewise, commodity prices would take longer to feed through core inflation, though they feed faster through headline inflation. Therefore, we aim to investigate various lag structures to observe the changing dynamics of these variables. First, we follow the literature on the optimal number of exchange rate pass-through on inflation. Gopinath, Itskhoki, and Rigobon (2010) argue that most of the pass-through takes place in the first two quarters and levels off soon after at the aggregate level, and we report the results in the first column in Appendix Table A.7.

## Table 6. Augmented Phillips-Curve Estimates: Inflation Forecasts

| | Headline Inflation | | Core Inflation | |
|---|---|---|---|---|
| | **Post-GFC** | **Post-pandemic** | **Post-GFC** | **Post-pandemic** |
| Inflation$_{t-1}$ | 0.882*** | 0.988*** | 0.908*** | 0.975*** |
| | (0.011) | (0.031) | (0.010) | (0.065) |
| Inflation Forecast$_{t+12}$ | 0.0941*** | 0.0179** | 0.083*** | 0.153* |
| | (0.025) | (0.065) | (0.013) | (0.079) |
| Domestic Output Gap | 0.0020 | 0.006** | 0.003** | 0.006* |
| | (0.002) | (0.003) | (0.001) | (0.003) |
| Global Output Gap | 0.0018 | 0.031* | 0.004** | 0.031** |
| | (0.005) | (0.018) | (0.002) | (0.012) |
| $\Delta$NEER$_{t-1}$ | –0.025*** | –0.025* | –0.012*** | –0.021 |
| | (0.003) | (0.014) | (0.002) | (0.013) |
| $\Delta$Energy Prices | 0.004*** | | –0.000 | |
| | (0.001) | | (0.000) | |
| $\Delta$Non-energy Prices | 0.004** | | 0.002** | |
| | (0.002) | | (0.001) | |
| $\Delta$Commodity Prices | | 0.005 | | –0.002 |
| | | (0.004) | | (0.002) |
| GSCP | –0.021 | 0.004 | 0.022 | 0.073* |
| | (0.037) | (0.057) | (0.020) | (0.037) |
| Country FE | Yes | Yes | Yes | Yes |
| F-test: Global | 37.22*** | 11.49*** | 17.85*** | 6.65*** |
| Within $R^2$ | 0.9282 | 0.9565 | 0.8986 | 0.9183 |
| Observations | 3,556 | 812 | 3,556 | 812 |
| Countries | 28 | 28 | 28 | 28 |

**Note:** Driscoll-Kraay standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Due to multicollinearity issues between energy and non-energy prices in the post-pandemic period, we use a single index of commodity prices. A constant is included in all specifications but not shown in the table.

Second, given that exchange rate pass-through takes place in the first two quarters (six months in our case), we also consider commodity prices and supply chain disruptions for six months to capture the delayed impact of it, which is reported in the second column in Appendix Table A.7. Third, to ensure that the optimal number of commodity prices and supply chain disruptions are correct in addition to exchange rate pass-through, we resort to the Bayesian information criterion (BIC) and find that four lags are the optimal number of lags in our case (third column in Appendix Table A.7).

The results show that there is indeed a lagged impact of exchange rates, commodity prices, and global supply chain pressures on core inflation with varying degrees of statistical significance. The delayed effects of the variables would continue to affect inflation in the longer term. Exchange rate appreciation tends to exert downward pressure, mostly with the first lag, while commodity prices and supply chain disruptions affect inflation with significant delays. Given that the first lag of exchange rates is always significant, we could maintain therefore our baseline specifications with the first lag of exchange rate.

## 6. Conclusion

The current inflationary wave poses substantial challenges worldwide. The origins of this surge are multifaceted, attributed to diverse sources, including pandemic-induced policy responses fueling demand, COVID-19-related supply constraints, and heightened geopolitical tensions caused by the conflict in Ukraine.

This study contributes to the ongoing debate by disentangling the confluence of contributing factors to the post-pandemic rise in inflation. Throughout this analysis, it emerges that global factors persist as pivotal drivers of inflation dynamics across Europe, yet post-pandemic domestic influences, notably monetary and fiscal responses to the crisis, have taken on a more prominent role. Our empirical findings confirm the significance of both global and domestic forces in shaping inflation dynamics. Primarily, our research unveils the sustained and substantial explanatory power of global factors, which has remained consistent over time, accounting for approximately 40 percent of headline and 20 percent of core inflation variance. Notably, the pandemic has witnessed a heightened prominence of country-specific factors, with domestic influences explaining an additional 10 percentage points of inflation variance post-COVID-19.

Further heterogeneity in inflation dynamics is evident within advanced and emerging market economies. For instance, Denmark's headline inflation variance attributed to domestic factors surged from about 15 percent to about 60 percent during the pandemic, mirroring a similar trend in Latvia from about 15 percent to over

65 percent. While before the pandemic, common inflation dynamics predominated in explaining variance among advanced economies, the post-pandemic landscape saw an augmented role for both global and domestic factors in these economies. In contrast, emerging market economies maintained the ascendancy of global factors in driving inflation, with domestic influences gaining even greater significance in the post-pandemic phase.

To strengthen the robustness of our analysis, we extend our examination of inflation dynamics with panel data models, corroborating our initial findings. Across varied specifications and inflation measures, inflation persistence emerges as a consistently significant factor. While the domestic output gap influences both headline and core inflation, the global output gap exhibits a comparatively greater impact on core inflation. Additional global factors, encompassing international energy and non-energy commodity prices, alongside global supply chain pressures and exchange rates reflecting both global and domestic elements, exert substantial effects on European inflation. These results, robust to a battery of sensitivity checks, delineate marked differences between advanced and emerging market economies, underscoring global factors' greater sway in developing countries. However, domestic influences have gained paramount importance across all countries in driving inflation dynamics in the post-pandemic period.

The implications of our inflation analysis reverberate notably in the realm of optimal monetary policy conduct, not only within Europe but also transcending its boundaries. While a mixture of exogenous factors contributes to the inflation surge, attributing blame solely to global factors would be misleading. Although pandemic-induced disruptions and geopolitical tensions indeed triggered recent inflation surges, our investigation highlights a waning significance of joint global factors post-pandemic. In other words, domestic developments have emerged as decisive drivers characterized by heightened persistence. The evolution of aggregate demand domestically and internationally now holds greater significance in recalibrating monetary policy stance to tame inflation.

However, our findings are limited by the absence of a COVID-19 fiscal stimulus measure, potentially affecting demand positively. To address this deficiency, a model with a quarterly fiscal stimulus measure should be developed. Also, exploring the continuing role of domestic factors in post-pandemic normalcy is important, given the ongoing debate on global factors' impact on inflation.

## Appendix

**Table A.1. List of Countries**

| **Advanced Europe** | **Emerging Europe** |
|---|---|
| Austria | Bulgaria |
| Belgium | Croatia |
| Cyprus | Czech Republic |
| Denmark | Estonia |
| Finland | Hungary |
| France | Latvia |
| Germany | Lithuania |
| Greece | Poland |
| Ireland | Romania |
| Italy | Slovak Republic |
| Luxembourg | Slovenia |
| Malta | |
| Netherlands | |
| Norway | |
| Portugal | |
| Spain | |
| Sweden | |
| Switzerland | |
| United Kingdom | |

**Table A.2. Data Sources**

| Variable | Source | Variable Description |
| --- | --- | --- |
| Headline Inflation | Eurostat and IMF | Year-on-year headline inflation rate (%) |
| Core Inflation | Eurostat, OECD, and CEIC | Year-on-year core inflation rate (%) |
| Domestic Output Gap | Eurostat, OECD, and IMF | Percentage deviation from the trend of log of monthly domestic industrial production index (%). The Hamilton filter (2018) is employed. |
| Global Output Gap | Baumeister and Hamilton (2019) | Percentage deviations from the trend of the log of monthly global industrial production index (%). The Hamilton filter (2018) is employed. The global industrial production index measures the weighted industrial production of the OECD and six emerging markets (Brazil, China, India, Indonesia, Russian Federation, and South Africa). |
| Nominal and Real Effective Exchange Rate | IMF | Year-on-year nominal and real effective exchange rate growth (%) |
| Energy Prices | IMF | Year-on-year energy price growth rate (%) |
| Non-energy Prices | IMF and World Bank | Year-on-year non-energy prices growth rate (%) |
| Commodity Price Index | IMF | Year-on-year commodity price growth rate (%) |
| Global Supply Chain Pressure Index | Benigno et al. (2022) | Principal component analysis is employed to extract a common component from PMI and transportation costs. This index is normalized. |
| Inflation Forecast | Consensus Economics | Survey-based one-year-ahead inflation forecast (%) |

## Table A.3. Panel Unit-Root Test

| | **Lag (1) C** | **Lag (1) C + T** | **Lag (2) C** | **Lag (2) C + T** |
|---|---|---|---|---|
| Headline $\pi_{c,t}$ | –9.635*** | –8.638*** | –8.613*** | –7.514*** |
| Core $\pi_{c,t}$ | –7.448*** | –7.587*** | –7.079*** | –6.508*** |
| $Y_{c,t}^{d}$ | –25.861*** | –25.952*** | –24.489*** | –24.001*** |
| $\Delta$NEER$_{c,t}$ | –15.294*** | –13.508*** | –13.458*** | –11.475*** |
| $\Delta$REER$_{c,t}$ CPI | –12.541*** | –10.649*** | –11.510*** | –9.559*** |
| $\Delta$REER$_{c,t}$ ULC | –10.422*** | –8.615*** | –11.047*** | –9.354*** |
| $\pi_{c,t}^{e}$ | –7.157*** | –6.079*** | –6.556*** | –5.299*** |

**Note:** Pesaran (2007) t-test for unit roots in heterogeneous panels with cross-section dependence. C and T denote constant and trend, respectively. Z[t-bar] is reported.

## Table A.4. Time-Series Unit-Root Test

| | **Drift** | **Trend** |
|---|---|---|
| $Y_t^W$ | –2.606*** | –2.615 |
| GSCP$_t$ | –2.719*** | –3.783** |
| $\Delta$Energy Prices$_t$ | –3.715*** | –3.745** |
| $\Delta$Non-energy Prices$_t$ | –3.695*** | –3.709** |
| $\Delta$Commodity Prices$_t$ | –3.397*** | –3.385* |

**Note:** The augmented Dickey-Fuller (1979, ADF) test is used. The t-statistic is reported. One lag is used based on the Akaike information criterion.

## Table A.5. Structural Break Test at Unknown Break Dates

| Bai and Perron (1998) Critical Values | | | | |
|---|---|---|---|---|
| **Headline** | **Test Statistic** | **1% Critical Value** | **5% Critical Value** | **10% Critical Value** |
| *Estimated Break Points: June 2008 and June 2019* | | | | |
| SupW($\tau$) | 28.43*** | 3.12 | 2.71 | 2.52 |
| *Estimated Break Points: June 2008 and May 2019* | | | | |
| Core SupW($\tau$) | 19.28*** | 3.12 | 2.71 | 2.52 |

**Note:** Null hypothesis of no break(s) against two breaks. This test checks for structural breaks in time series and panel data models using multiple tests. It identifies the T1, T2, . . . , and Ts breakpoints and determines if a model with accurate break dates has a smaller sum of squared residuals (SSR) than one with incorrect break dates. The panel structural break test uses an algorithm from Bai and Perron (2003) to find the break dates and select the smallest SSR. Our sample division into post-GFC and post-pandemic is close to the panel structural break test results.

## Table A.6. Impact of the COVID-19-Related Government Response to Inflation

| | **Headline Inflation** | | **Core Inflation** | |
|---|---|---|---|---|
| | **IV** | **DK** | **IV** | **DK** |
| ln Government Response$_{t-1}$ | 0.1087***<br>(0.019) | 0.1024**<br>(0.038) | 0.017<br>(0.015) | 0.007<br>(0.030) |
| Country FE | Yes | Yes | Yes | Yes |
| Control | Yes | Yes | Yes | Yes |
| Countries | 30 | 30 | 30 | 30 |
| Obs. | 822 | 822 | 822 | 822 |

**Note:** IV indicates the instrumental-variable estimator to explicitly account for the lagged inflation, whereas DK denotes the Driscoll-Kraay standard errors. Robust standard errors are included in parentheses for the IV estimator. ***p > 0.01, **p < 0.05, *p < 0.1. The COVID-19 government response stringency index is taken from https://data.humdata.org/dataset/oxford-covid-19-government-response-tracker?force_layout=desktop (see Hale et al. 2021). The estimations begin from January 2020 and onward.

## Table A.7. Augmented Phillips-Curve Estimates, Post-pandemic: Different Lags

| | 6 Lags.(NEER) | 6 Lags.(NEER, Commodity, GSCP) | 4 Lags.(NEER, Commodity, GSCP) |
|---|---|---|---|
| $\text{Inflation}_{t-1}$ | 1.007*** | 0.970*** | 0.979*** |
| | (0.049) | (0.047) | (0.045) |
| Domestic Output Gap | 0.007* | 0.006 | 0.006 |
| | (0.004) | (0.004) | (0.004) |
| Global Output Gap | 0.033** | 0.000 | 0.018 |
| | (0.013) | (0.013) | (0.011) |
| $\Delta\text{NEER}_{t-1}$ | –0.024* | –0.020* | –0.021** |
| | (0.013) | (0.011) | (0.010) |
| $\Delta\text{NEER}_{t-2}$ | –0.020 | –0.019 | –0.010 |
| | (0.015) | (0.012) | (0.015) |
| $\Delta\text{NEER}_{t-3}$ | 0.008 | 0.011 | 0.007 |
| | (0.015) | (0.020) | (0.021) |
| $\Delta\text{NEER}_{t-4}$ | 0.037* | 0.036 | 0.009 |
| | (0.022) | (0.024) | (0.018) |
| $\Delta\text{NEER}_{t-5}$ | –0.028 | –0.043* | |
| | (0.026) | (0.024) | |
| $\Delta\text{NEER}_{t-6}$ | 0.007 | 0.015 | |
| | (0.020) | (0.017) | |
| $\Delta$Commodity Prices | –0.002 | | |
| | (0.002) | | |
| $\Delta\text{Commodity Prices}_{t-1}$ | | 0.003 | 0.001 |
| | | (0.002) | (0.002) |
| $\Delta\text{Commodity Prices}_{t-2}$ | | –0.001 | –0.001 |
| | | (0.004) | (0.004) |
| $\Delta\text{Commodity Prices}_{t-3}$ | | –0.010** | –0.012** |
| | | (0.005) | (0.005) |
| $\Delta\text{Commodity Prices}_{t-4}$ | | 0.011* | 0.015*** |
| | | (0.006) | (0.003) |
| $\Delta\text{Commodity Prices}_{t-5}$ | | –0.001 | |
| | | (0.005) | |
| $\Delta\text{Commodity Prices}_{t-6}$ | | 0.003 | |
| | | (0.003) | |
| GSCP | 0.090** | | |
| | (0.038) | | |
| $\text{GSCP}_{t-1}$ | | 0.050 | 0.091 |
| | | (0.078) | (0.095) |
| $\text{GSCP}_{t-2}$ | | –0.079 | –0.107 |
| | | (0.077) | (0.092) |
| $\text{GSCP}_{t-3}$ | | 0.003 | –0.020 |
| | | (0.045) | (0.045) |
| $\text{GSCP}_{t-4}$ | | 0.050 | 0.081 |
| | | (0.077) | (0.053) |
| $\text{GSCP}_{t-5}$ | | –0.074 | |
| | | (0.059) | |
| $\text{GSCP}_{t-6}$ | | 0.125** | |
| | | (0.047) | |
| Country FE | Yes | Yes | Yes |
| F-test: Global | 11.27*** | 39.90*** | 18.29*** |
| Within $R^2$ | 0.9085 | 0.9165 | 0.9147 |
| Observations | 870 | 870 | 870 |
| Countries | 30 | 30 | 30 |

**Note:** Driscoll-Kraay standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. The post-pandemic periods are estimated from January 2020 to May 2022. A constant is included in all specifications but not shown in the table. Due to multicollinearity issues between energy and non-energy prices, we employ the commodity price index in the post-pandemic period. The dependent variable is core inflation.

**Table A.8. Collinearity Diagnostics**

| Variable | VIF | SQRT VIF | Tolerance | Condition Index |
|---|---|---|---|---|
| $Y^D_{c,t}$ | 1.60 | 1.26 | 0.6263 | 1.000 |
| $Y^W_t$ | 1.80 | 1.34 | 0.5555 | 1.3818 |
| $\pi^e_{c,t}$ | 1.09 | 1.05 | 0.9150 | 1.5605 |
| $\Delta\text{NEER}_{c,t}$ | 1.07 | 1.03 | 0.9384 | 3.4102 |
| $\Delta\text{Energy Prices}_t$ | 2.87 | 1.70 | 0.3479 | 1.7025 |
| $\Delta\text{Non-energy Prices}_t$ | 2.48 | 1.57 | 0.4033 | 2.2387 |
| $\text{GSCP}_t$ | 1.50 | 1.23 | 0.6657 | 2.6951 |
| Mean VIF | 1.77 | Condition Number | | 3.4102 |

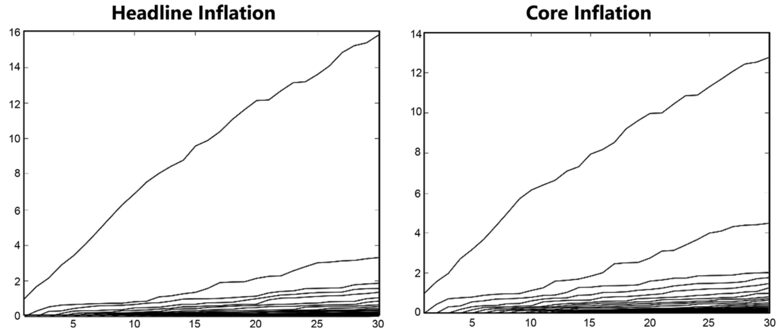
**Note:** Collinearity diagnostics measures VIF, sqrt VIF, tolerance, and condition index. The mean variance of inflation factor (VIF) is 1.77, indicating the absence of multicollinearity in our regressions. The condition number is an index of the global instability of our regression coefficients. If the condition number is larger than 10, it denotes the instability of the regression coefficients.

**Table A.9. Quasi-Likelihood-Ratio (LR) Test**

| | Without Global Factors | With Global Factors |
|---|---|---|
| Quasi-$LR$ $\chi^2$ | 130.59*** | 67.27*** |

**Note:** "With Global Factors" column estimates the following equation from January 2020 to May 2022: $\pi_{c,t} = \beta_1 + \beta_2\pi_{c,t-1} + \beta_3 Y^D_{c,t} + \beta_4 Y^W_t + \beta_5 neer_{c,t-1} + \beta_6 commodity_t + \beta_7 GSCP_t + \eta_c + \varepsilon_{c,t}$. "Without Global Factors" column estimates the same equation but excludes global factors. The quasi-LR test compares the fit of one model (with global factors) to the fit of the other (without global factors). The quasi-LR test is equivalent to an F-test in large samples. ***p < 0.001, **p < 0.05, *p < 0.1.

**Figure A.1. Dynamic Eigenvalues (averaged over frequencies)**



## Figure A.2. Share of Headline Inflation Variance

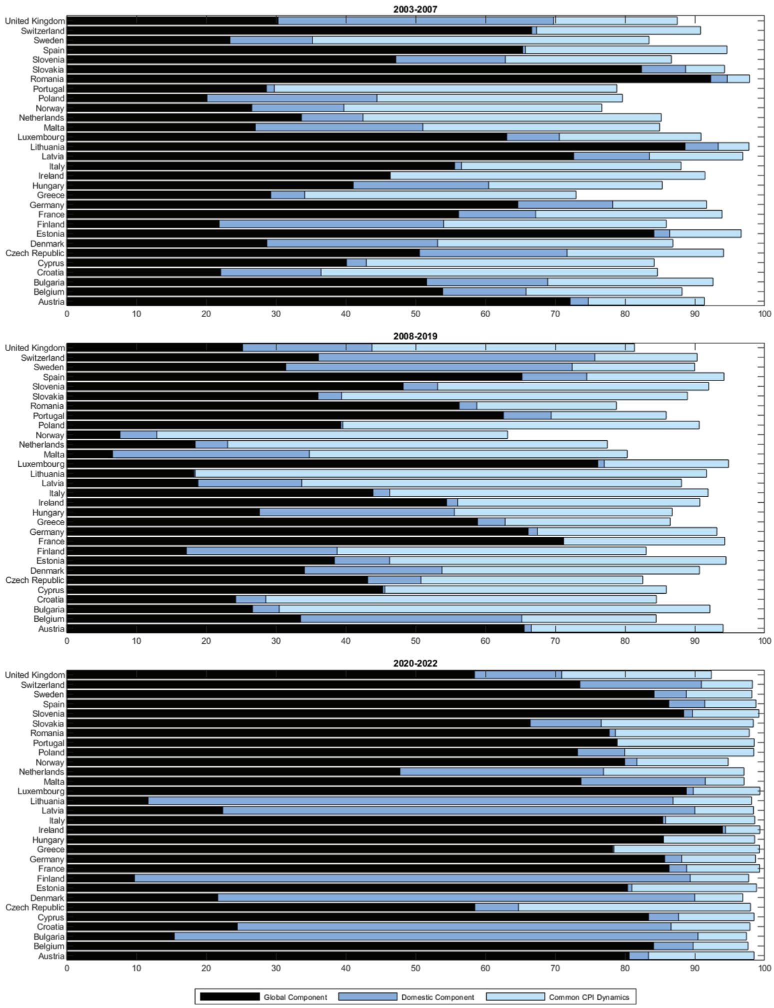
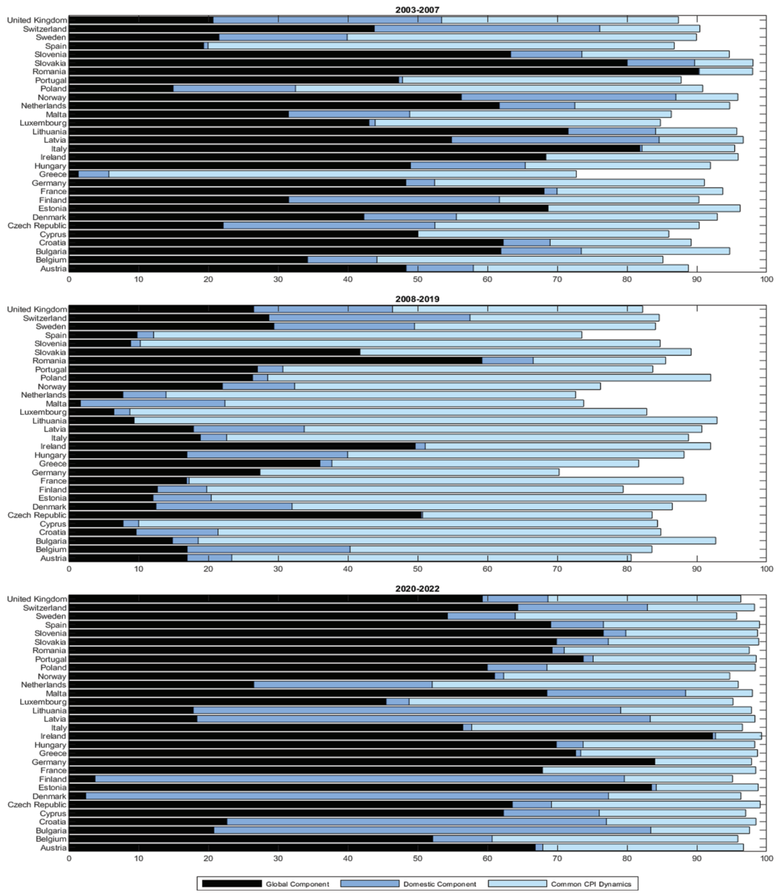


**Figure A.3. Share of Core Inflation Variance**

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# Systematic Foreign Exchange Intervention and Macroeconomic Stability: A Bayesian DSGE Approach*

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This study quantitatively assesses the role of foreign exchange interventions (FXIs) by introducing a systematic FXI policy that follows a feedback rule responding to nominal FX rates into a small open-economy DSGE model. A quantitative analysis using Vietnamese data reveals that while the systematic FXI policy amplifies the effects of productivity shocks due to the lack of FX flexibility, it contributes to macroeconomic stability overall by insulating an economy from external shocks. The real FX rate, which is modeled as a non-stationary variable on the balanced-growth path, is mainly accounted for by productivity shocks, in contrast with the exchange rate disconnect but consistent with the Balassa–Samuelson relationship.

JEL Codes: F31, F41, E58.

## 1. Introduction

The role of foreign exchange interventions (FXIs) in achieving macroeconomic stability is a recurrent and controversial policy issue. In a canonical open-economy model, on the one hand, an inflexible foreign exchange (FX) regime relying on FXIs (e.g., a currency peg) often leads to economic destabilization because it cannot benefit

*The author is grateful for the comments from two anonymous referees, Alex Mourmouras, and other colleagues at the IMF, as well as participants in the DSGE Workshop 2021 and the seminar at the Bank of Thailand, the IMF, Keio University, and the State Bank of Vietnam. This work was supported by the Japan Society for the Promotion of Science KAKENHI Grant No. 21K20157. Any remaining errors are the sole responsibility of the author. Author e-mail: mitsuru.katagiri@hosei.ac.jp.

from currency devaluation in the face of adverse shocks. In practice, on the other hand, many emerging market economies (EMEs) still extensively use FXIs to stabilize the FX rate as a nominal anchor. In particular, many EMEs adopt a "systematic managed floating" system, wherein a central bank *systematically* uses FXIs as policy tools to lean against the wind in the FX market (Frankel 2019). This systematic policy behavior of FXIs makes it challenging to examine their efficacy because a significant fraction of the effects of systematic policy is a consequence of changing the endogenous behavior or expectation formation of economic agents (i.e., rational expectations and forward-looking behavior). Hence, to investigate the role of a systematic FXI policy in achieving macroeconomic stability, it is essential to conduct quantitative analyses based on a structural model, in addition to reduced-form estimations as conducted by the previous empirical literature.

This paper contributes to the literature by introducing a systematic FXI policy into a small open-economy dynamic stochastic general equilibrium (DSGE) model and quantitatively investigating its contribution to macroeconomic stability using a Bayesian method. Specifically, the central bank is assumed to conduct FXIs that follow a systematic feedback rule, as suggested by the practices under the systematic managed floating system, in addition to conducting monetary policy that follows a feedback rule of the nominal interest rate. To quantitatively assess the efficacy of systematic FXIs, the model assumes that the FX rate can deviate from uncovered interest rate parity (UIP) due to the exogenous and time-varying risk premium for external debt and that FXIs can possibly affect the risk premium. The exogenous and time-varying deviations from UIP ("UIP shock") are commonly assumed in many open-economy DSGE models (e.g., Schmitt-Grohe and Uribe 2017; Itskhoki and Mukhin 2021a, 2021b). While this approach to modeling the effects of FXIs relies on a somewhat ad hoc assumption to make FXIs potentially effective, a Bayesian estimation in the empirical exercise may find this channel quantitatively negligible; therefore, whether FXIs are *quantitatively* effective is an empirical question in the quantitative analysis.

While a Bayesian DSGE approach is one of the standard approaches for policy analysis in many fields of macroeconomic studies recently, a technical but difficult challenge in applying this approach to the analysis for EMEs is the fact that the real FX rate seems to follow a non-stationary process in many EMEs. As the Bayesian DSGE approach must assume all variables to be stationary, a common methodology in the literature is to remove trends from data before an empirical analysis, using a filtering method such as the Hodrick-Prescott (HP) filter. However, many empirical studies on the determinants of the FX rate point to a cointegration relationship between the real FX rate and the relative productivity growth of tradable goods (i.e., the Balassa–Samuelson relationship); therefore, removing any non-stationary trends before an analysis is subject to the risk of missing important determinants of the FX rate.[1] Since an understanding of the underlying drivers of the FX rate is a prerequisite for investigating the effects of FXIs, the real FX rate in this study is modeled as a non-stationary variable characterized by the Balassa–Samuelson relationship, rather than a stationary variable—as in a standard model—and detrended on the balanced-growth path.

In the quantitative analysis, I focus on the role of FXIs in Vietnam, which is a typical country of a systematic managed floating regime, and examine the extent to which FXIs have contributed to macroeconomic stability in the country. To examine the role of FXIs in achieving macroeconomic stability, I adopt a two-step approach: First, I use Vietnamese data to estimate parameters using a Bayesian method and decompose the variance of output growth, inflation rate, and FX rates into several structural shocks. Second, by changing the parameters for the systematic FXI policy rule while keeping other estimated structural parameters unchanged, I examine how the variance decomposition results would change in the counterfactual case without FXIs. The quantitative analysis reveals that, first, in the baseline case where FXIs reasonably insulate the economy from the UIP shock, the real FX rate is mostly accounted for by productivity shocks. This result is in contrast to the exchange rate disconnect (e.g., Itskhoki and Mukhin 2021a) but consistent with the Balassa–Samuelson relationship. Second, it also shows that in the counterfactual case without FXIs, (i) the real and nominal FX rate would be much more volatile and mainly driven by

[1] For empirical studies on the Balassa–Samuelson relationship, see Canzoneri, Cumby, and Diba (1999), Lee, Milesi-Ferretti, and Ricci (2008), Chong, Jordà, and Taylor (2012), and Berka, Devereux, and Engel (2018).

the UIP shock, which is consistent with the exchange rate disconnect under a floating FX rate regime, and (ii) inflation and output growth would also be more volatile. Result (i) implies that some differences in FX rate dynamics between advanced economies and EMEs may be partly associated with an FXI policy regime. Regarding result (ii), the impulse response analysis shows that a systematic FXI policy amplifies the macroeconomic fluctuations caused by the productivity shock while dampening those caused by the UIP and monetary policy shock. Therefore, FXIs can either stabilize or destabilize the economy, depending on the type of shocks driving the business cycle. Result (ii) implies that a systematic FXI policy contributes to macroeconomic stability, at least in Vietnam, by mitigating the adverse effects of the UIP shock as well as the country's own monetary policy disturbances.

This study relates to studies on FXIs and their role in achieving macroeconomic stability.[2] Among the numerous reduced-form empirical studies on the efficacy of FXIs, Domac and Mendoza (2004), Blanchard, Adler, and de Carvalho Filho (2015), and Fratzscher et al. (2019) are particularly relevant to this study because they emphasize the role of FXIs in reducing FX rate volatility. The efficacy of FXIs is investigated using an open-economy DSGE model with some frictions to make FXIs potentially effective by, among others, Garcia, Restrepo, and Roger (2009), Devereux and Yetman (2014), Benes et al. (2015), Buffie, Ariaudo, and Zanna (2018), Adler, Lama, and Medina (2019), Erceg et al. (2020), Fanelli and Straub (2020), Jeanne and Sandri (2020), Lama and Medina (2020), and Faltermeier, Lama, and Medina (2022), but those previous studies do not conduct empirical exercises and merely perform some quantitative simulations based on calibration. In terms of the model structure for the quantitative analysis, this study follows an open-economy DSGE model with time-varying deviations from UIP (e.g., Schmitt-Grohe and Uribe 2017; Chen, Fujiwara, and Hirose 2021; Itskhoki and Mukhin 2021a, 2021b; Katagiri and Takahashi 2021), which emphasizes the importance of exogenous shocks to the UIP condition in explaining real and nominal FX

[2]See Bank for International Settlements (2005), Disyatat and Galati (2007), and Hofman et al. (2020) for an extensive survey of FXIs in EMEs, including their motivations and efficacy.

rate dynamics. Regarding the empirical methodology, this study follows Lubik and Schorfheide (2007) in adopting a Bayesian DSGE approach to identify the policy reaction functions in a small open-economy DSGE model. Finally, the present study also relates to the quantitative analysis of the Balassa–Samuelson relationship using a structural model, which was pioneered by Asea and Mendoza (1994) and Devereux (1999). Recently, Meza and Urrutia (2011) and Berka, Devereux, and Engel (2018) show that the real FX rate dynamics in Mexico and the euro area are consistent with the Balassa–Samuelson relationship, respectively.

The remainder of the paper proceeds as follows. Section 2 presents an overview of the developments in FX rates and FXIs in Vietnam. Section 3 describes the model for analyzing the effects of FXIs, while Section 4 estimates the model parameters based on Vietnamese data and provides a quantitative analysis. Concluding remarks are presented in Section 5.

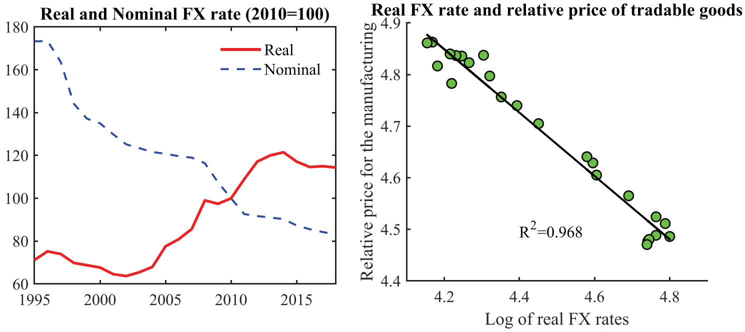
## 2. Foreign Exchange Rate and Intervention in Vietnam

This section presents an overview of the FX rate and FXI policy in Vietnam. First, it describes the developments in the real and nominal FX rates in the last several decades, and shows that those developments have been consistent with the Balassa–Samuelson relationship. It then describes the FXI policy in Vietnam and shows that FXIs are well approximated by a feedback rule that responds to the nominal FX rate; the rule is derived from a simple optimization problem for the central bank in the appendix. Finally, it shows several key business cycle moments with respect to the FX rate and compares them with those for advanced economies.

### *2.1 Developments in Foreign Exchange Rate*

Over the last several decades, Vietnam has experienced secular appreciation and depreciation trends in the real and nominal FX rates, respectively. The first panel in Figure 1 shows the real and nominal FX rates vis-à-vis the U.S. dollar, from 1995. The figure indicates that the real FX rate is on a secular trend of appreciation, and that it has appreciated by more than 60 percent in the last two

**Figure 1. Foreign Exchange Rate in Vietnam**




**Source:** Haver Analytics.
**Note:** In the left panel, the real FX rate is the nominal FX rate vis-à-vis the U.S. dollar deflated by the CPI in Vietnam and the United States. In the right panel, the relative price for the manufacturing sector is defined as the GDP deflator for the manufacturing sector divided by the GDP deflator for the whole economy.

decades. On the other hand, the nominal FX rate has moved in the opposite direction and has continuously depreciated by more than 50 percent in total for the last two decades. Thus, by definition, the difference between the trends in the real and nominal FX rates is accounted for by high and volatile inflation, which has averaged approximately 8 percent for the last two decades.

The developments in the real FX rate in Vietnam have mostly been tracked by the manufacturing sector's relative price. Theoretically, if the law of one price for tradable goods is satisfied, the real FX rate can be approximated by the tradable-goods price relative to the price index of a consumption basket.[3] Following the literature, the relative price for the manufacturing sector (= the GDP deflator for the manufacturing sector divided by the GDP deflator

[3]The law of one price for tradable goods is defined as $P_{T,t} = F_t P^*_{T,t}$, where $P_{T,t}$ and $P^*_{T,t}$ are the tradable-goods prices in the home and foreign countries, respectively, while $F_t$ is the nominal FX rate. By dividing both sides of the equation by the aggregate price levels in the home and foreign countries, $P_t$ and $P^*_t$, respectively, we obtain $P_{T,t}/P_t = (F_t P^*_t/P_t)P^*_{T,t}/P^*_t$, suggesting that the real FX rate, $F_t P^*_t/P_t$, is proportional to the relative price of tradable goods, $P_{T,t}/P_t$, if the relative price in the foreign country is stable.

for the whole economy) is used as a proxy for the relative price of tradable goods in Vietnam. The second panel in Figure 1 shows the scatter plots between the relative price for the manufacturing sector and the real FX rate in the last two decades. While the law of one price for tradable goods fits the data poorly in some countries, the figure indicates that the real FX rate vis-à-vis the U.S. dollar can be surprisingly well tracked by the relative price for the manufacturing sector in Vietnam, as predicted by the theory (R-squared is more than 0.96); this probably reflects the fact that the manufacturing sector in Vietnam is an export-oriented sector, with many foreign direct investment (FDI) firms.

Such an almost one-to-one relationship between the relative price for tradable goods and the real FX rate implies that the secular trend of appreciation in the real FX rate can perhaps be explained by the Balassa–Samuelson relationship. The Balassa–Samuelson relationship, which is one of the conventional theories that explain developments in the real FX rate, predicts a cointegration relationship between the real FX rate and the relative productivity of the tradable goods sector, given that the relative price of tradable goods should be inversely proportional to the sector's productivity relative to the whole economy. Since the share of output is cointegrated with relative productivity on the balanced-growth path in a standard growth model under some conditions, the theoretical prediction of the Balassa–Samuelson relationship can be reformulated by a cointegration relationship between the output share of tradable goods and the real FX rate. To examine this hypothesis in Vietnam, first, the output share of the manufacturing sector is chosen as a proxy for the output share of tradable goods. Then, the Engle–Granger cointegration test is applied to these two series in Vietnam to test the null hypothesis that they are not cointegrated. Even with the relatively small sample size ($n = 24$) for annual data, the null hypothesis is rejected at the 10 percent level (p-value is 0.081), suggesting that the real FX rate in Vietnam can be accounted for by the relative productivity of tradable goods, consistent with the Balassa–Samuelson relationship. In the next section, I use this cointegration relationship to characterize the balanced-growth path in our small open-economy DSGE model and more formally examine the underlying drivers of the real FX rate by a Bayesian method.

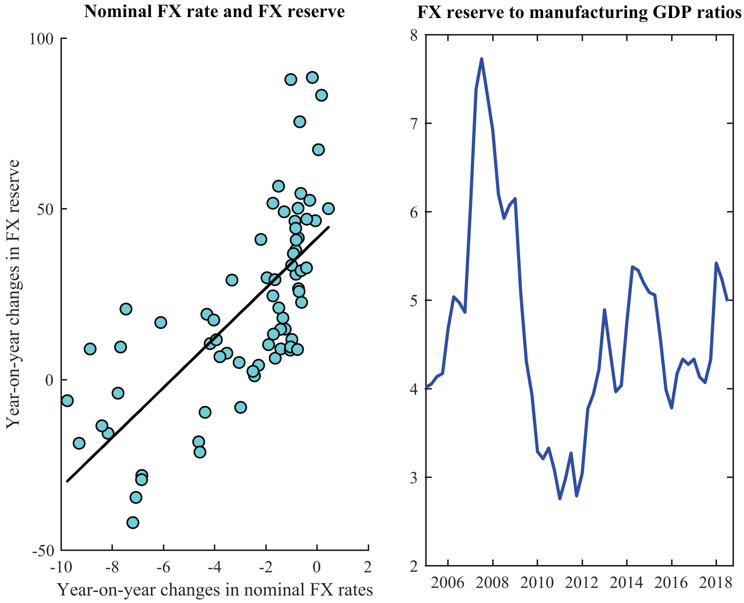
### 2.2 Policy Rule for Foreign Exchange Intervention

FXIs have been actively used in many EMEs to stabilize FX rate fluctuations. Specifically, Frankel (2019) has recently pointed out that most EMEs adopt neither a free-floating regime nor a hard-currency peg; instead, they follow a "systematic managed floating" system, which is an intermediate regime wherein a central bank systematically responds to market pressure by FXIs to avoid abrupt fluctuations in the FX market (i.e., lean against the wind) while allowing some of the market pressure to be reflected in the FX rate. Under the systematic managed floating regime, a central bank intervenes in the FX market to lean against the wind by carefully balancing the benefit from reducing the volatility of FX rates against the risk of running out of FX reserves. Since holding excessive FX reserves is also costly for them, a typical strategy of central banks is to accumulate FX reserves during normal times, up to a certain target level, and sell the FX reserves in the FX market to support their own currencies in the event of depreciation pressure.

Considering the Vietnamese FX regime and developments in the country's FX reserves, Vietnam is categorized as a typical country that adopts the systematic managed floating regime. First, in Vietnam, the central bank sets the target FX rate vis-à-vis the U.S. dollar, and attempts to smooth the volatility of the FX rate by systematically intervening in the FX market to contain it within a $+/-$ 3 percent trading band of the target rate. Furthermore, the central bank does not adopt a fixed target rate, but gradually adjusts it daily to allow some market pressure to be reflected in the FX rate, which is also consistent with the systematic managed floating system. Second, the developments in the FX reserves also imply that Vietnam follows the systematic managed floating regime. The first panel in Figure 2 shows the scatter plots between changes in the nominal FX rate and Vietnam's FX reserves on the U.S. dollar basis. The figure shows a clear and positive relationship between them, implying that the central bank in Vietnam sells their FX reserves in response to depreciation in the nominal FX rate to lean against the wind in the FX market.[4] The right panel in Figure 2 shows the FX reserves

[4]As FX reserves are measured by the U.S. dollar rather than the domestic currency in the figure, any changes due to valuation do not matter here.

**Figure 2. Foreign Exchange Interventions in Vietnam**




**Source:** Haver Analytics, IMF.
**Note:** The left panel uses the data from 2001:Q1 to 2018:Q3, while the right panel uses the data from 2005:Q1 to 2018:Q3.

relative to the manufacturing GDP in Vietnam. The figure indicates that the ratio does not have a trend but has fluctuated around a certain level, implying that the central bank stabilizes the FX reserves around a specific level by accumulating them in normal times for sale in the face of depreciation pressure.

Given these motivations for the systematic managed floating regime, this study assumes that the central bank follows a feedback rule that responds to the FX rate and the lagged reserve-to-GDP ratios, as in Frankel (2019):

$$\Delta Res_t = \beta_0 + \beta_1 \Delta FX_t + \beta_2 \frac{Res_{t-j}}{GDP_{t-j}} + \varepsilon_t, \tag{1}$$

where $\Delta Res_t$ is the percentage change in the amount of FX reserves while $\Delta FX_t$ is the percentage change in the FX rate. Here, $\varepsilon_t$ is the discretionary deviation from the policy rule (i.e., an FX policy shock), which is estimated as an error term in estimating the FX-policy rule. In this FXI policy rule, it is expected that $\beta_1 > 0$ and $\beta_2 < 0$, implying that the central bank accumulates FX reserves when (i) the nominal FX rate appreciates and (ii) their reserve-to-GDP ratio is low, and vice versa. That is, under the systematic managed floating regime, the central bank is expected to conduct FXIs to lean against the wind in the FX market while taking care of the level of FX reserves. This FXI policy rule is a reduced-form policy rule for the central bank; however, in the appendix, it is shown that the rule can be derived from the optimization problem of the central bank to minimize the loss function based on (i) the volatility of the FX rate, (ii) the deviations from the optimal level of the FX reserves, and (iii) the volatility of the FX reserves.

To examine the empirical fit of the FXI policy rule, the parameter values, $\beta_1$ and $\beta_2$, are estimated using Vietnamese quarterly data from 2004:Q4 to 2018:Q3. In the estimation, $\Delta FX_{t-1}$ is used as an instrumental variable for $\Delta FX_t$ to avoid a potential endogeneity problem that stems from the effect of the FXI policy shock on the FX rate, following the literature on the estimation of a monetary policy rule.[5] Additionally, the lag for the reserve-to-GDP ratio is set at $j = 2$ to fit the Vietnamese data. The estimation result shows that both $\beta_1$ and $\beta_2$ are statistically significant in Vietnam, and that the quarter-on-quarter growth in FX reserves will (i) decline by 8.6 percent in response to an FX depreciation of 1 percentage point, and (ii) increase by 0.1 percent in response to a percentage-point decline in reserve-to-GDP ratios, both of which imply that Vietnam follows the systematic managed floating regime.[6] While the FXI policy rule is more formally estimated in Section 4 using a Bayesian method,

[5]Given that the selling of FX reserves by the central bank positively affects FX rates, any discretionary FXI policy shocks, $\varepsilon_t$, in (1) are negatively correlated with $\Delta FX_t$, and lead to a negative bias in the OLS estimator of $\beta_1$. In the estimation of a monetary policy rule, Clarida, Galí, and Gertler (2000) estimate the feedback rule of the nominal interest rate that responds to inflation using historical inflation rates as an instrumental variable to avoid the endogeneity problem that stems from the effects of the monetary policy shock on inflation.

[6]Frankel (2019) estimates a similar FXI policy rule for Turkey and obtains a statistically significant result for $\beta_1 > 0$ and $\beta_2 < 0$, and concludes that Turkey follows the systematic managed floating regime.

the estimation result here is used as a prior means for the Bayesian estimation to help identify the parameters of the FXI policy rule.

Given that the central bank in Vietnam systematically conducts FXIs by following a feedback rule (1), the next question is, to what extent does the systematic FXI policy contribute to macroeconomic stability? In the empirical literature, Fratzscher et al. (2019) show that many central banks attempt to smooth the volatility of FX rates through FXIs, and that they succeed in doing so in many cases. Furthermore, Domac and Mendoza (2004) and Blanchard, Adler, and de Carvalho Filho (2015) show that countries associated with frequent FXIs have experienced lower volatility or smaller responses of FX rates in the event of capital flow shocks. These empirical studies, which use reduced-form estimation, provide strong evidence for the efficacy of FXIs. However, these studies alone may not suffice to explain the role of a systematic FXI policy because a significant proportion of the effects of any systematic policy is a consequence of changing the endogenous behavior or expectation formation of economic agents (i.e., rational expectations and forward-looking behavior). Therefore, quantitative studies based on a structural model are necessary to investigate further the effects of systematic FXI policy and its contribution to macroeconomic stability. Such effects of a systematic FXI policy are analogous to a systematic monetary policy that follows a feedback rule. For instance, Clarida, Galí, and Gertler (2000) argue that the monetary policy rule of the nominal interest rate that systematically responds to inflation more strongly is key to understanding the decline in inflation in the Volcker and Greenspan era, by comparing simulation exercises under different monetary policy regimes in a DSGE model. In a similar vein, in Section 4, the efficacy of systematic FXIs is quantified by comparing simulation exercises with and without the systematic FXI policy in a small open-economy DSGE model.

### *2.3 Business Cycle Moments for FX Rate*

Table 1 summarizes key business cycle moments for real and nominal FX rates in Vietnam from 2005:Q1 to 2018:Q3. In the table, $\Delta F_t$, $\Delta Q_t$, and $\Delta Y_t$ denote growth in nominal FX rates, real FX rates, and real GDP, respectively. For comparison, the table also shows

**Table 1. Business Cycle Moments for the FX Rate**

| | Vietnam | Japan | Euro Area |
|---|---|---|---|
| $\rho(\Delta Q_t)$ | 0.52 | 0.27 | 0.38 |
| $\sigma(\Delta Q_t)/\sigma(\Delta F_t)$ | 1.65 | 1.01 | 1.07 |
| $\sigma(\Delta F_t)/\sigma(\Delta Y_t)$ | 1.51 | 3.82 | 4.55 |
| $\rho(\Delta F_t, \Delta Q_t)$ | 0.36 | 0.99 | 1.00 |

**Note:** The table summarizes key business cycle moments with respect to real and nominal FX rates vis-à-vis the U.S. dollar in Vietnam, Japan, and the euro area. In the table, $\Delta F_t$, $\Delta Q_t$, and $\Delta Y_t$ denote growth in nominal FX rates, real FX rates, and real GDP, respectively.

the business cycle moments for the euro area's and Japan's FX rate vis-à-vis the U.S. dollar during the same periods.

The table shows that the business cycle moments for the euro area and Japan are basically in line with the literature of the "exchange rate disconnect" (i.e., Itskhoki and Mukhin 2021a). Namely, real and nominal FX rates (i) follow a near-random walk process, (ii) have the same level of volatility, (iii) are about threefold more volatile than GDP, and (iv) are almost perfectly correlated with each other.

In contrast to these features observed in advanced economies under a floating FX rate system, the table highlights the following four key features in Vietnam under the systematic managed floating system. First, real FX rates are much more persistent than a random walk. The autocorrelation of the first difference of the real FX rate in Vietnam is around 0.5, meaning that the real FX rate is nonstationary and significantly more persistent than a random walk. Second, real FX rates are more volatile than nominal FX rates. The standard deviation of real FX rates is larger than that of nominal FX rates by about 60 percent. Third, changes in real and nominal FX rates are more volatile than GDP growth but not as much as in advanced economies. The standard deviation of nominal FX rate growth is larger than that of GDP growth only by around 50 percent. Fourth, the correlation between real and nominal FX rates is positive but weak. The correlation coefficient between them is only 0.36.

The last three features imply that under the systematic managed floating regime, systematic FXIs to lean against the wind in the FX market possibly help stabilize the nominal FX rate. Under a fixed FX rate regime, the nominal FX rate has zero volatility and no correlation with any variables because it remains constant by construction. Hence, the lower standard deviation of the real and nominal FX rate, as well as the weaker correlation between them, observed in Vietnam implies that FX rate dynamics under the systematic managed floating regime are characterized in between the two extremes, namely a floating FX rate regime and a fixed FX rate regime.

## 3. Small Open-Economy DSGE Model

This section describes a small open-economy DSGE model for a quantitative analysis of FXIs. While the model follows a standard small open-economy DSGE model (e.g., Schmitt-Grohe and Uribe 2017), there are two main features that distinguish it from conventional models. First, the real FX rate is modeled as a non-stationary variable, rather than a stationary variable, to be consistent with Vietnamese data. As shown in the previous section, the real FX rate is well tracked by the relative price of the manufacturing sector and cointegrated with its output share. Thus, the real FX rate is modeled as a non-stationary variable, consistent with the Balassa–Samuelson relationship, and detrended using the cointegration relationship on the balanced-growth path. Second, FXIs are modeled as a policy rule, as in the previous section, and are assumed to have possible effects on the FX rate. In the next section, the parameters associated with the policy effect are estimated using a Bayesian method on Vietnamese data.

Except for the two features above, the model mostly follows a standard small open-economy DSGE framework. The economy comprises households, consumption-goods firms, and intermediate-goods firms. There are two types of consumption goods, tradable and non-tradable, while the law of one price for tradable goods between the country and the outside world is assumed. In the spirit of small open-economy models, the real interest rate in the world is assumed to be exogenous, while the FX rate is determined by the uncovered interest rate parity (UIP), with risk premiums to induce short-term deviations from it. In what follows, each type of agent's behavior is described in turn.

### *3.1 Households*

A representative household allocates its income to the consumption basket, $C_t$, and savings. The consumption basket consists of tradable and non-tradable consumption goods,

$$C_t = \left[ \iota^{\frac{1}{\eta}} C_{T,t}^{\frac{\eta-1}{\eta}} + (1-\iota)^{\frac{1}{\eta}} C_{N,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{2}$$

where $C_{T,t}$ and $C_{N,t}$ are the consumption of the tradable and non-tradable goods, respectively. $\iota$ and $\eta$ are the parameters for the share of the tradable goods in the consumption basket and that for the elasticity between the tradable and non-tradable goods, respectively. The price level of the consumption basket (i.e., the consumer price index, CPI) is given by

$$P_t C_t = P_{T,t} C_{T,t} + P_{N,t} C_{N,t}, \tag{3}$$

where $P_{T,t}$ and $P_{N,t}$ are the prices of the tradable and non-tradable consumption goods, respectively. Then, the demand functions for the tradable and non-tradable goods are derived from the household's optimal allocation between the tradable and non-tradable goods,

$$C_{T,t} = \iota \left( \frac{P_{T,t}}{P_t} \right)^{-\eta} C_t \quad \text{and} \quad C_{N,t} = (1-\iota) \left( \frac{P_{N,t}}{P_t} \right)^{-\eta} C_t. \tag{4}$$

Given these demand functions for tradable and non-tradable goods, the monopolistic firms in each sector solve their optimization problems.

The household supplies a labor force to obtain the wage income, $W_t L_t$, where $W_t$ denotes the nominal wage and $L_t$ denotes the hours worked. In addition, since all firms in the economy are owned by the household, it obtains the dividend, $D_t$, from the firms as another source of income. The household then allocates the income to the consumption basket, $C_t$, and savings. The household can borrow and save in the form of nominal one-period domestic bonds, $B_t$, and one-period external debt, $b_t^*$. The household's budget constraint in period $t$ is formulated as

$$P_tC_t + \frac{B_t}{R_t} + P_t\frac{b_t^*}{Q_t(r_t^* + \zeta_t)} = B_{t-1} + P_t\frac{b_{t-1}^*}{Q_t} + \sum_{j=T,N} W_{j,t}L_{j,t} + D_t + T_t, \tag{5}$$

where $Q_t$ is the real FX rate, $R_t$ is the nominal domestic interest rate, $r_t^*$ is the real foreign interest rate, $\zeta_t$ is a time-varying risk premium for external debt, and $T_t$ is a lump-sum transfer from the government. Following convention, an increase in $Q_t$ means an appreciation of the domestic currency. In the spirit of a small open-economy model, the foreign real interest rate is assumed to be exogenous, and to follow the process,

$$\log r_t^* = (1 - \rho_{rr})\bar{r^*} + \rho_{rr}\log r_{t-1}^* + \varepsilon_{rr,t},$$

where $\varepsilon_{rr,t}$ is an iid shock with standard deviation, $\sigma_{rr}$, while $\bar{r^*}$ is a steady-state value for $r_t^*$. The time-varying risk premium for external debt, $\zeta_t$, captures all deviations from the interest parity due to various factors, including the effects of capital control.[7] $\zeta_t$ will be specified in more detail later.

The household chooses their consumption, $C_{T,t}$ and $C_{N,t}$, labor supply, $L_{T,t}$ and $L_{N,t}$, and short-term domestic bonds and external debt, $B_t$ and $b_t^*$, to maximize their lifetime utility,

$$E_0\sum_{t=0}^{\infty}\beta^t U\left(C_t - hC_{t-1}, L_{T,t}, L_{N,t}\right),$$

subject to Constraints (2) and (5). $\beta \in (0,1)$ is the constant discount factor, while $h$ is the parameter for external habit formation. A functional form for the utility function, $U(\cdot)$, will be specified shortly.

[7] Jeanne and Korinek (2010) analyze the impact of a debt tax similar to the specification of $\zeta_t$ in (5) and interpret this additional cost for foreign borrowing as capital controls.

### *3.2 Consumption-Good Firms*

The tradable and non-tradable consumption-good firms produce the final goods, $Y_{T,t}$ and $Y_{N,t}$, by aggregating the intermediate goods, $Y_{T,t}(i)$ and $Y_{N,t}(i)$, based on the following constant elasticity of substitution (CES) production function in a competitive market:

$$Y_{j,t} = \left( \int_0^1 Y_{j,t}(i)^{\frac{\nu-1}{\nu}} di \right)^{\frac{\nu}{\nu-1}}, \ j = T, N,$$

where $\nu > 1$ is the elasticity of substitution. Let $P_{T,t}(i)$ and $P_{N,t}(i)$ be the prices of the tradable and non-tradable intermediate goods. The price index for the tradable and non-tradable intermediate goods, $P_{T,t}$ and $P_{N,t}$, is then defined as

$$P_{j,t} = \left( \int_0^1 P_{j,t}(i)^{\nu-1} di \right)^{-\frac{1}{\nu-1}}, \ j = T, N,$$

while the demand for each intermediate good is derived from profit maximization by the consumption-good firms,

$$Y_{j,t}(i) = \left( \frac{P_{j,t}(i)}{P_{j,t}} \right)^{-\nu} Y_{j,t}, \ j = T, N. \tag{6}$$

### *3.3 Intermediate-Good Firms*

A continuum of intermediate-good firms indexed by $i$ produces differentiated intermediate tradable and non-tradable goods using labor, $L_{T,t}(i)$ and $L_{N,t}(i)$, based on the following technology:

$$Y_{j,t}(i) = Z_t A_{j,t} L_{j,t}(i)^{\alpha}, \ j = T, N, \tag{7}$$

where $Z_t$ is a stationary component of aggregate productivity, which is common to all firms across the two sectors and follows the process,

$$\log Z_t = \rho_z \log Z_{t-1} + \varepsilon_{z,t},$$

where $\varepsilon_{z,t}$ is an iid shock with standard deviation, $\sigma_z$. Additionally, $A_{j,t}$ is a non-stationary and sector-specific component of productivity in period $t$. Let $a_{j,t} \equiv A_{j,t}/A_{j,t-1}$, and assume that $a_{j,t}$ follows the process,

$$\log a_{j,t} = (1 - \rho_{aj}) \log \bar{a_j} + \rho_{aj} \log a_{j,t-1} + \varepsilon_{aj,t}, \ j = T, N,$$

where $\varepsilon_{aj,t}$ is an iid shock with standard deviation, $\sigma_{aj}$, while $\bar{a_j}$ is a steady-state value for the sector-specific productivity growth. Previous empirical studies find that those non-stationary productivity shocks, in addition to stationary productivity shocks, play an important role in accounting for business cycles in EMEs (e.g., Aguiar and Gopinath 2007).

Under monopolistic competition, the intermediate-good firm, $i$, in each sector, $j$ ($j = T, N$), maximizes its discounted profits by setting the price of its differentiated product subject to the household's demand (4) and the consumption-good firms' demand (6). Furthermore, following the New Keynesian literature, the intermediate-good firm faces a quadratic cost for deviating from the target inflation rate, $\bar{\pi}$, as well as the previous period's inflation rate, $\pi_{t-1}$. The optimization problem for the intermediate-good firm in period $t$ is formulated as

$$\max \sum_{k=1}^{\infty} \frac{\Lambda_{t+k}}{\Lambda_t P_{t+k}} \Bigg[ P_{j,t+k}(i) Y_{j,t+k}(i) - W_{t+k} L_{j,t+k}(i) - \frac{\gamma_j}{2} \left( \frac{P_{j,t+k}(i)}{P_{j,t+k-1}(i)} - \pi^{\xi}_{t+k-1} \pi^{*1-\xi} \right)^2 P_{t+k} Y_{t+k} \Bigg]$$

subject to (4), (6), and (7). Here, $\gamma_j$ is the parameter for sector-specific price stickiness, while $\xi$ is that for inflation indexation common across the two sectors. $\Lambda_{t+k}/\Lambda_t$ is a stochastic discount factor for the household from periods $t$ to $t+k$, where $\Lambda_t \equiv \partial U(\cdot)/\partial C_t$. As in a conventional New Keynesian model, the New Keynesian Phillips curve with inflation indexation for the tradable and non-tradable sectors is derived from the intermediate-good firm's optimization.

### *3.4 Central Bank*

Unlike a conventional DSGE model, the central bank has two policy tools for stabilizing the economy: the short-term nominal interest rate, $R_t$, and the FXI using the FX reserves, $Res_t$. For both policy tools, this study does not examine the optimal policy; instead, it assumes a simple feedback rule to investigate these policies' effects empirically. The following section estimates the parameter values for the policy rules using a Bayesian method and performs some counterfactual simulations under different parameter values to examine the efficacy of FXIs.

Regarding the interest rate policy, the central bank sets the short-term nominal interest rate following the Taylor-type policy rule with interest rate smoothing. In addition to the response to inflation and output growth, as in a conventional monetary policy rule, the nominal interest rate possibly responds to changes in the nominal FX rate,

$$R_t = (R_{t-1})^{\rho_R} \left[ R^* \left( \frac{\pi_t}{\bar{\pi}} \right)^{\phi_\pi} \left( \frac{Y_t}{Y_{t-1}} \right)^{\phi_y} \left( \frac{Q_t/P_t}{Q_{t-1}/P_{t-1}} \right)^{\phi_q} \right]^{1-\rho_R} \times \exp(v_{m,t}). \tag{8}$$

The central bank can deviate from the rule by adding the "monetary policy shock," $v_{m,t}$, which follows the process,

$$v_{m,t} = \rho_m v_{m,t-1} + \varepsilon_{m,t},$$

where $\varepsilon_{m,t}$ is an iid shock with standard deviation, $\sigma_m$. This monetary policy shock captures all discretionary deviations from the monetary policy rule.

Regarding the FXI policy, the central bank buys and sells their FX reserves, $Res_t$, following a simple feedback rule based on the nominal FX rate and the amount of the FX reserves, as described in Subsection 2.2:

$$\Delta Res_t = \Delta \bar{Res}_t \left( \frac{Q_t/P_t}{Q_{t-1}/P_{t-1}} \right)^{\theta_q} \left( \frac{Res_{t-1}/Y_{T,t-1}}{\bar{Res}_t/\bar{Y}_T} \right)^{\theta_{res}} \exp(v_{f,t}), \tag{9}$$

where the variables with bars are the steady-state values on the balanced-growth path. As discussed in Subsection 2.2, the central bank is expected to lean against the wind (i.e., $\theta_q > 0$) and accumulate the FX reserves when the amount is insufficient (i.e., $\theta_{res} < 0$). When these parameters are estimated by a Bayesian method, the estimated values in Subsection 2.2 are used for their prior means.

Finally, the central bank can deviate from the FXI rule by adding the "FXI policy shock," $v_{f,t}$, which follows the process,

$$v_{f,t} = \rho_f v_{f,t-1} + \varepsilon_{f,t},$$

where $\varepsilon_{f,t}$ is an iid shock with standard deviation, $\sigma_f$. The FXI policy shock captures all discretionary and unsystematic deviations from the FXI rule.

The central bank's balance sheet comprises FX reserves on its asset side and one-period nominal bonds on its liability side. Thus, the central bank's balance sheet identity is specified as

$$P_t \frac{Res_t}{Q_t(r_t^* + \zeta_t)} = \frac{B_t}{R_t}.$$

Finally, the amount of lump-sum transfer from the government is specified as follows:

$$T_t = \frac{P_t}{Q_t}\left(Res_{t-1} - \frac{Res_t}{r_t^* + \zeta_t}\right) - \left(B_{t-1} - \frac{B_t}{R_t}\right). \tag{10}$$

This transfer rule suggests that the central bank transfers all the profits and losses associated with the management of their FX reserves and open-market operations.

### *3.5 Market Clearing*

To close the model, the market clearing conditions for the tradable- and non-tradable-goods markets need to be satisfied. First, since the non-tradable goods should be consumed only in the domestic market, their market clearing condition is

$$Y_{N,t} = C_{N,t}.$$

Second, the market clearing condition for the tradable goods is derived by aggregating the household's budget constraint with (i) the central bank's balance sheet; (ii) the government's transfer rule (10); and (iii) the law of one price for the tradable goods in the domestic and foreign markets. The law of one price for the tradable goods between the country and the outside world is specified as

$$\frac{P_{T,t}}{P_t} = \frac{1}{Q_t}, \tag{11}$$

which suggests that the relative price of the tradable goods is equal to the reciprocal of the real FX rate.[8] As is well known, the law of one price for the tradable goods specified in (11) is empirically controversial for some countries. In Vietnam, however, as described by Figure 1 in Subsection 2.1, the manufacturing sector's deflator relative to the GDP deflator, which is a proxy for the relative price of the tradable goods—i.e., the left-hand side of Equation (11)—has almost perfectly tracked the real FX rate for the last two decades, which implies that the assumption in Equation (11) is reasonable in the empirical analysis, at least for the last several decades in Vietnam. Under Assumptions (i), (ii), and (iii), the market clearing condition for the tradable goods is formulated as

$$Y_{T,t} - C_{T,t} = \frac{Res_t + b_t^*}{r_t^* + \zeta_t} - (Res_{t-1} + b_{t-1}^*).$$

Note that the market clearing condition for the tradable goods is equivalent to the balance-of-payment identity in the model. That is, since the excess supply for the tradable goods in the domestic market, $Y_{T,t} - C_{T,t}$, is consumed in foreign countries, the left-hand side of this equation can be interpreted as the trade surplus. The right-hand side is the income balance and the resultant increase in net foreign assets, which comprise those held by the household, $b_t^*$, and the FX reserves held by the central bank, $Res_t$.

### *3.6 UIP Condition and Effects of FXIs*

To derive the equilibrium conditions, first, the utility function is parameterized as follows:

$$U\left(\tilde{C}_t - h\tilde{C}_{t-1}, L_{T,t}, L_{N,t}\right) = \frac{\left(\tilde{C}_t - h\tilde{C}_{t-1} - \chi \sum_{j=T,N} \frac{L_{j,t}^{1+\omega}}{1+\omega}\right)^{1-\sigma}}{1-\sigma}, \tag{12}$$

[8] Here, as in the conventional small open-economy models in Chapter 8 of Schmitt-Grohe and Uribe (2017), it is implicitly assumed that the relative prices of the tradable and non-tradable goods in foreign countries are stable.

where $\tilde{C}_t \equiv C_t/(A^{\iota}_{T,t}A^{1-\iota}_{N,t})$. That is, following the literature (e.g., An and Schorfheide 2007), the consumption basket in the utility function is deflated by productivity in each sector to ensure that the economy evolves along the balanced-growth path. As is well known, without this assumption, the above form of the utility function (i.e., the Greenwood–Hercowitz–Huffman, or GHH, utility function) is not consistent with the balanced-growth path. The first-order conditions for the household's optimization yield the equilibrium conditions, including the labor-supply function for each sector, $W_{j,t}/P_t = \chi L^{\omega}_{j,t},\ j = T, N$, and the Euler equation for consumption, $U_C(t) = \beta R_t \mathbb{E}_t[U_C(t+1)/(\pi_{t+1} a^{\iota}_{T,t+1} a^{1-\iota}_{N,t+1})]$, where $U_C$ is a marginal utility of consumption. In addition, by defining the stochastic discount factor, $\Lambda_{t+1} \equiv \beta U_C(t+1)/(U_C(t) a^{\iota}_{T,t+1} a^{1-\iota}_{N,t+1})$, the first-order condition for the external debt, $b^*_t$, yields the UIP condition,

$$\mathbb{E}_t\left[\Lambda_{t+1}\frac{R_t}{\pi_{t+1}}\right] = (r^*_t + \zeta_t)\mathbb{E}_t\left[\Lambda_{t+1}\frac{Q_t}{Q_{t+1}}\right], \tag{13}$$

indicating that the return from domestic bonds should be equal to that from external debt. This UIP condition implies that changes in the risk premium for external debt, $\zeta_t$, potentially influence the real exchange rate by inducing time-varying deviations from UIP. As emphasized by Itskhoki and Mukhin (2021a), the exogenous deviations from UIP are interpreted as a consequence of financial frictions in the FX market, including the segmented financial market proposed by Gabaix and Maggiori (2015).

With the UIP condition (13) in mind, next, the risk premium for external debt, $\zeta_t$, is assumed to consist of the following three components:

$$\zeta_t = \zeta\left[\exp(-b^*_t - \bar{b^*}) - 1\right] + v_{q,t} + X_t. \tag{14}$$

The first component, $\zeta\left[\exp(-b^*_t - \bar{b^*}) - 1\right]$, indicates that the risk premium is a decreasing function with respect to $b^*_t$. That is, the risk premium for external debt increases as the net foreign debt held by the household increases, thus pushing back the amount of the household's foreign assets to their steady-state value. As is well known in the small open-economy model literature, without this risk premium, a steady state for foreign assets would not exist (Schmitt-Grohe and

Uribe 2003). Nevertheless, this first component is not quantitatively important for the FX rate dynamics because the parameter $\zeta$ is calibrated to an arbitrarily small number just for the existence of a steady state.

The second component of the risk premium in (14), $v_{q,t}$, is an exogenous fluctuation, which follows the process,

$$v_{q,t} = \rho_q v_{q,t-1} + \varepsilon_{q,t},$$

where $\varepsilon_{q,t}$ is an iid shock with standard deviation, $\sigma_q$. As in the previous studies using an open-economy DSGE model with time-varying deviations from UIP, this exogenous component helps the model account for the real and nominal FX rate dynamics in the quantitative analysis. Following Itskhoki and Mukhin (2021a), the stochastic shock, $\varepsilon_{q,t}$, is called the "UIP shock" hereafter.

The third and last component of the risk premium in (14), $X_t$, represents the effects of FXIs on the risk premium. $X_t$ is assumed to follow the process,

$$X_t = \rho_X X_{t-1} + \psi FXI_t, \tag{15}$$

where $FXI_t$ is the size of FXIs in period $t$. This formulation implies that FXIs are assumed to directly influence the risk premium on external debt and consequently have effects on the FX rate and the real economy through the UIP condition (13) in the model.[9] The parameters $\psi$ and $\rho_X$ represent the magnitude of the FXI policy effects and their persistence, respectively. Based on the segmented financial market model by Itskhoki and Mukhin (2021a), where noise traders entail deviations from UIP by affecting financial intermediaries' financial position, FXIs in the formulation (15) can be interpreted as a source of portfolio rebalance for financial intermediaries, thus entailing deviations from UIP. While this reduced-form approach makes FXIs potentially effective by assumption, a Bayesian estimation in the empirical exercise may find this channel quantitatively negligible (i.e., $\psi \approx 0$); therefore, whether FXIs are *quantitatively* effective is an empirical question in the quantitative

[9]Erceg et al. (2020) also assume that the FX rate deviates from UIP and that FXIs influence the deviations as this paper does, while their main focus is on non-linearity through the balance sheet channel.

analysis. Note that when $\psi = 0$ in (15), any transfers between $b_t^*$ and $Res_t$ associated with a standard form of FXIs—namely, the selling and buying of foreign currencies in the FX market by the central bank—have no effects on the FX rate as in a conventional DSGE model.

On the size of FXIs in period $t$, $FXI_t$, the literature emphasizes the importance of distinguishing FXIs from other changes in the FX reserves driven by, for instance, the FX reserve accumulation in normal time. Hence, given the FXI policy rule (9), the size of FXIs in this model is defined as

$$\begin{aligned} FXI_t &\equiv \log\left(\frac{\Delta Res_t}{\Delta \bar{Res}_t}\right) - \theta_{res}\log\left(\frac{Res_{t-1}/Y_{T,t-1}}{\bar{Res}_t/\bar{Y}_T}\right) \\ &= \theta_q \log\left(\frac{Q_t/P_t}{Q_{t-1}/P_{t-1}}\right) + v_{f,t}, \end{aligned}$$

implying that $FXI_t$ equals the changes in the FX reserves excluding the mean-reverting FX reserve accumulation in normal time. Then, given the FXI policy rule (9), $FXI_t$ consists of systematic and non-systematic FXIs, the first and second component of the second line of the equation.

### *3.7 Balanced-Growth Path*

Since the model assumes the sector-specific non-stationary component of productivity, $A_{T,t}$ and $A_{N,t}$, the existence of a balanced-growth path is not trivial. Specifically, the following proposition specifies the conditions for having a balanced-growth path in the model:

PROPOSITION 1. *A balanced-growth path exists if and only if either of the following two conditions is satisfied: (i) The functional form for the consumption basket in (2) is Cobb-Douglas (i.e., $\eta = 1$), or (ii) the non-stationary components of productivity in the tradable and non-tradable sectors, $A_{T,t}$ and $A_{N,t}$, respectively, are cointegrated.*

*Proof.* Let the rate of cumulative non-stationary growth (i.e., the non-stationary growth rate from time 0 to time $t$) of $C_t$, $C_{j,t}$, and $P_{j,t}/P_t$ be $\exp(g_{c,t})$, $\exp(g_{c,j,t})$, and $\exp(g_{p,j,t})$, respectively, where $j = T, N$. The demand function in (4) implies that $g_{c,j,t} = -\eta g_{p,j,t} + g_{c,t}$ for all $j$ and $t$. Meanwhile, the budget constraint in (3) implies that $g_{c,t} = g_{p,j,t} + g_{c,j,t}$ for all $j$ and $t$. Hence, if a balanced-growth path exists, we should have

$$(1-\eta)g_{p,j,t} = 0 \quad \text{for all } j, t.$$

This implies that either (i) $\eta = 1$, or (ii) $g_{p,j,t} = 0$ for all $j$ and $t$ should be satisfied. In the case in (ii), we have $g_{c,t} = g_{c,T,t} = g_{c,N,t}$, indicating that $A_{T,t}$ and $A_{N,t}$ are cointegrated, because $g_{c,j,t}$ is equal to $\log(a_{j,t})$. □

While this proposition merely suggests that either Condition (i) or Condition (ii) needs to be satisfied for a balanced-growth path to exist, the following corollary provides a useful clue to which condition is more likely to be satisfied for a particular country.

COROLLARY 1. *On the balanced-growth path, if Condition (i) in Proposition 1 is satisfied, the real FX rate is non-stationary and cointegrated with the relative productivity of the tradable sector,* $A_{T,t}/A_t$, *of order 1, as argued by the Balassa–Samuelson relationship. On the other hand, if Condition (ii) in Proposition 1 is satisfied, the real FX rate is stationary on the balanced-growth path.*

*Proof.* Let the non-stationary growth rate of the real FX rate be $g_{q,t}$. Then, we have $g_{q,t} = -g_{p,T,t}$, by the definition of the real FX rate. In the case in (i), given that $g_{c,t} = \iota g_{c,T,t} + (1-\iota)g_{c,N,t}$, we have

$$g_{q,t} = g_{c,T,t} - g_{c,t} = (1-\iota)(g_{c,T,t} - g_{c,N,t}),$$

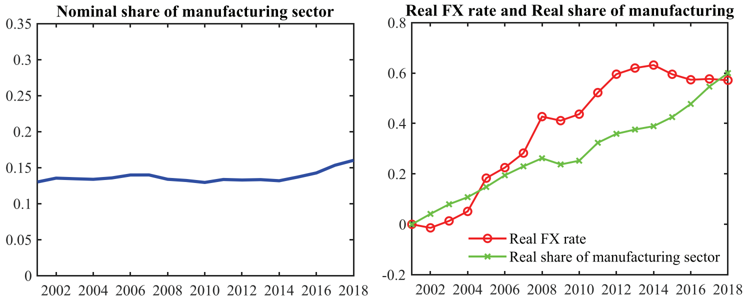
which implies that the real FX rate is cointegrated with the relative productivity, $A_{T,t}/A_t$, of order 1. On the other hand, in the case in (ii), given that $p_{T,t} = 0$, we have $g_q = 0$, which means that the non-stationary growth of the real FX rate is zero, and the real FX rate is stationary. □

Intuitively, if the productivity across the sectors is cointegrated, as stated in Condition (ii), the relative productivity, $A_{T,t}/A_{N,t}$, is stationary, by definition, thus leading the real FX rate to be a stationary variable as well. On the other hand, if the productivity across the sectors is not cointegrated, either of the sectors (tradable or non-tradable) produces the goods increasingly more efficiently than the other. Therefore, the output share and the relative price for the growing sector continue to increase and decrease, respectively, and a balanced-growth path exists only if those two forces are entirely offset each other under the Cobb-Douglas consumption basket. In this case, since the real FX rate is proportional to the relative price across the sectors under the law of one price for tradable goods, it is also cointegrated with the relative productivity growth for the tradable goods sector, which is exactly what is suggested by the Balassa–Samuelson relationship in the literature. As discussed in Subsection 2.1, a salient feature of the Vietnamese data is that the real FX rate exhibits a non-stationary upward trend that is cointegrated with the share of tradable goods in output, consistent with the Balassa–Samuelson relationship. Hence, in the empirical analysis hereafter, the CES function for the consumption basket (2) is assumed to be Cobb-Douglas (i.e., Condition (i) is satisfied and $\eta = 1$) to reconcile the stylized fact in Vietnam with the existence of a balanced-growth path.

While the Cobb-Douglas consumption basket looks somewhat restrictive at first glance, it is not a bad assumption, at least for the Vietnamese economy for the last several decades. A well-known property of the Cobb-Douglas consumption basket is a constant nominal share across sectors. As the left panel of Figure 3 shows, the nominal share of the manufacturing sector in output has remained almost constant since 2000, which implies that the Cobb-Douglas consumption basket is not a bad assumption for Vietnam. In addition, as the proof of Proposition 1 indicates, the Cobb-Douglas consumption basket implies $g_{q,t} = g_{c,T,t} - g_{c,t}$ in the long run. Since the right-hand side is the growth rate of tradable goods' share in real output, this property means that the long-run growth rate of real FX rate should be equal to that of tradable goods' share in real output. The right panel of Figure 3 shows that this property is satisfied in Vietnam, which also implies that the Cobb-Douglas consumption basket is not a bad assumption for Vietnam.[10]

[10]The right panel of Figure 3 is obtained by combining the constant nominal share in the left panel and the law of one price in the right panel of Figure 1. That

**Figure 3. Nominal and Real Share of Manufacturing**




**Source:** Haver Analytics.
**Note:** The left panel shows the nominal share of manufacturing sector in output since 2000 in Vietnam. The right panel shows the developments in log of the real FX rate (the red line with circles) and log of the share of manufacturing in real output (the green line with x-marks). In the right panel, both variables are normalized to zero in 2000.

While the balanced-growth path under Condition (i) (i.e., Cobb-Douglas consumption basket) is consistent with Vietnamese data for the last two decades, the relationship between the sectoral growth rate and the non-stationary real FX rate is an arguable issue in general. First, the non-stationarity of the real FX rate is arguable. In particular, it is statistically difficult to determine whether the real FX rate is stationary or non-stationary if time-series data are available only for several decades. While some empirical studies that use very long time-series data find the real FX rate to be non-stationary, quantitative studies that focus on advanced economies offer some evidence that the real FX rate is a very persistent but stationary variable.[11] Second, whether the sectoral-growth pattern should be consistent with the balanced-growth path is arguable in the first

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is, when a nominal share across sectors is constant, a decrease in the manufacturing sector's relative price and an increase in its share in the real output should be offset with each other.

[11]For empirical studies using long time-series data, see Engel and Kim (1999) and Engel (2000). For the analysis on advanced economies, Rabanal, Rubio-Ramirez, and Tuesta (2011) and Rabanal and Rubio-Ramirez (2015) argue that the real FX rate is very persistent but stationary.

place.[12] While this study assumes the existence of a balanced-growth path, the relationship between the longer-term sectoral-growth pattern and the real FX rate across countries is a challenging but interesting topic for future research.

## 4. Quantitative Analysis

This section quantitatively assesses the effects of FXIs using the small open-economy DSGE model described in the previous section. Specifically, the effects of FXIs in Vietnam are examined through a two-step approach: First, I estimate the structural parameters based on Vietnamese data and decompose the variances of the macroeconomic variables (e.g., the real and nominal FX rates, inflation, and output growth) into the structural shocks. Second, I quantify the efficacy of FXIs through the variance decomposition in a counterfactual exercise. In this exercise, the hypothetical economy without FXIs is constructed by changing the parameters of the FXI policy, while keeping the other structural parameters unchanged.

### *4.1 Baseline Analysis*

#### *4.1.1 Estimation*

First, some parameters are calibrated to their conventional values in the literature.[13] For the preference parameters, the discount factor, $\beta$, the constant relative risk aversion (CRRA) coefficient, $\sigma$, and the inverse of Frisch elasticity, $\omega$, are calibrated to $0.99^{1/4}$, 2.0, and 1/2, respectively. The elasticity of the risk premium, $\zeta$, is assigned an arbitrarily small number, 0.001, to secure the steady state as in Schmitt-Grohe and Uribe (2003). For the production parameters, the labor share, $\alpha$, and the mark-up parameter, $\nu$, are set to 0.64 and 6.0, respectively, both of which are conventional values. The target inflation rate, $\bar{\pi}$, is set to $1.04^{1/4}$, based on the targeted value

[12] Herrendorf, Rogerson, and Valentinyi (2014) argue that sectoral-growth patterns across countries are not consistent with balanced growth in the long run and suggest some theories to account for them. Meza and Urrutia (2011) examine the real FX rate under the "unbalanced" growth path to analyze the real FX rate in Mexico.

[13] See, for instance, Smets and Wouters (2007) and Galí (2015).

for inflation in Vietnam. Finally, the steady-state level of external debt, $\bar{b}^*$, is chosen such that the ratio of the external debt to the manufacturing GDP equals 247 percent, which has been the average level in Vietnam for the last decade.

Second, the rest of the structural parameters, including the volatility of shocks, are estimated using a Bayesian method on Vietnamese data. Specifically, I estimate 31 parameters ($\gamma_H$, $\gamma_F$, $\xi$, $h$, $\psi$, $\iota$, $\bar{Res}$, $\bar{a}_N$, $\bar{a}_T$, $\bar{r}^*$, $\rho_R$, $\phi_\pi$, $\phi_y$, $\phi_q$, $\theta_{res}$, $\theta_q$, $\rho_{a,N}$, $\rho_{a,T}$, $\rho_z$, $\rho_m$, $\rho_q$, $\rho_f$, $\rho_{rr}$, $\rho_s$, $\sigma_{aN}$, $\sigma_{aT}$, $\sigma_z$, $\sigma_m$, $\sigma_q$, $\sigma_f$, $\sigma_{rr}$) using the quarterly data from 2005:Q1 to 2018:Q3 for the following seven variables in Vietnam: (i) GDP growth, (ii) GDP growth for the manufacturing sector, (iii) the inflation rate, (iv) the short-term nominal interest rate (the discount rate), (v) the ratio of FX reserves to manufacturing GDP, (vi) the FX rate vis-á-vis the U.S. dollar, and (vii) the real interest rate in the United States (the federal funds rate deflated by the U.S. CPI).[14] The prior distributions for the parameters of the FXI policy rule are based on the estimated values in Subsection 2.2, while those for the other parameters are based on their conventional values.

Table 2 summarizes the prior distributions and the estimation results. While most prior distributions are based on conventional values or set to be consistent with the Vietnamese data, several parameters with little information use distributions with relatively large standard deviation.[15] Some comments are in order: First, the estimated values of the parameters for the cost of price changes in both sectors and indexation, $\gamma_T$, $\gamma_N$, and $\xi$—in particular, $\gamma_T$—are very small, implying that the Phillips curve in Vietnam is steep and that the inflation inertia is small. The steep Phillips curve probably reflects the fact that the inflation rate in Vietnam has been

[14]While the annual data are available from 1995 in Vietnam, as shown in Section 2, the quarterly data are available only from 2005.

[15]The prior mean of steady-state values for growth rate, FX reserves, and interest rates are set to the historical average. For the policy parameters, the FXI policy parameters are based on the estimation results in Section 2, while the response of interest rates to inflation follows the original Taylor rule. The prior means of price adjustment costs are set to 60, which implies that the price change probability is around two-thirds in the Calvo model. The parameter of consumption habit is based on the estimation results in Havranek, Rusnak, and Sokolova (2017). For other parameters, I use a distribution with relatively large standard deviation, such as Beta[0.5, 0.15], given that there is little prior information.

**Table 2. Estimated Parameter Values**

| Parameter | Posterior Mean | 90% CI | Prior Dist. | Prior Mean | Prior St. Dev. |
|---|---|---|---|---|---|
| $\gamma_H$ | 13.34 | [6.68 19.68] | Gamma | 60 | 30 |
| $\gamma_F$ | 0.36 | [0.11 0.59] | Gamma | 60 | 30 |
| $\xi$ | 0.25 | [0.11 0.38] | Beta | 0.5 | 0.15 |
| $h$ | 0.55 | [0.5 0.61] | Beta | 0.4 | 0.05 |
| $\psi$ | 37.49 | [25.07 50.07] | Gamma | 5.0 | 5.0 |
| $\iota$ | 0.14 | [0.11 0.18] | Beta | 0.5 | 0.15 |
| $R\bar{e}s$ | 0.03 | [0.02 0.03] | Gamma | 0.04 | 0.01 |
| $\bar{a}_N$ | 1.016 | [1.014 1.019] | Gamma | 1.016 | 0.002 |
| $\bar{a}_T$ | 1.021 | [1.018 1.025] | Gamma | 1.024 | 0.004 |
| $\bar{r}^*$ | 0.998 | [0.997 1] | Gamma | 0.998 | 0.002 |
| $\rho_R$ | 0.91 | [0.87 0.94] | Beta | 0.5 | 0.15 |
| $\phi_\pi$ | 1.93 | [1.12 2.72] | Gamma | 1.5 | 0.5 |
| $\phi_y$ | 0.70 | [0.2 1.18] | Gamma | 1.0 | 0.5 |
| $\phi_q$ | 0.58 | [0.19 0.94] | Gamma | 1.0 | 0.5 |
| $\theta_{res}$ | –0.11 | [–0.14 –0.07] | Norm | –0.1 | 0.03 |
| $\theta_q$ | 9.33 | [7.72 10.89] | Gamma | 8.6 | 1.00 |
| $\rho_{a,N}$ | 0.46 | [0.28 0.63] | Beta | 0.5 | 0.15 |
| $\rho_{a,T}$ | 0.30 | [0.14 0.47] | Beta | 0.5 | 0.15 |
| $\rho_z$ | 0.85 | [0.76 0.95] | Beta | 0.5 | 0.15 |
| $\rho_m$ | 0.67 | [0.55 0.8] | Beta | 0.5 | 0.15 |
| $\rho_q$ | 0.66 | [0.52 0.79] | Beta | 0.5 | 0.15 |
| $\rho_f$ | 0.36 | [0.19 0.51] | Beta | 0.5 | 0.15 |
| $\rho_{rr}$ | 0.38 | [0.22 0.54] | Beta | 0.5 | 0.15 |
| $\rho_X$ | 0.31 | [0.13 0.49] | Beta | 0.5 | 0.15 |
| $\sigma_{aN}$ | 0.009 | [0.007 0.011] | Invg | 0.01 | Inf |
| $\sigma_{aT}$ | 0.014 | [0.011 0.016] | Invg | 0.01 | Inf |
| $\sigma_z$ | 0.006 | [0.004 0.008] | Invg | 0.01 | Inf |
| $\sigma_m$ | 0.002 | [0.002 0.003] | Invg | 0.01 | Inf |
| $\sigma_q$ | 0.021 | [0.014 0.029] | Invg | 0.01 | Inf |
| $\sigma_f$ | 0.104 | [0.08 0.128] | Invg | 0.01 | Inf |
| $\sigma_{rr}$ | 0.006 | [0.005 0.007] | Invg | 0.01 | Inf |

high and volatile, while the real GDP growth has been relatively stable. Second, the posterior mean of the effects of FXIs on the risk premium, $\psi$, is positive and statistically significant, although the prior distribution is set to strongly favor zero.[16] The positive and

[16] While the prior mean for $\psi$ is set to 5.0, note that this prior distribution strongly favors zero because the mode of the gamma distribution with the same values for the mean and standard deviation is zero, while the density function is decreasing.

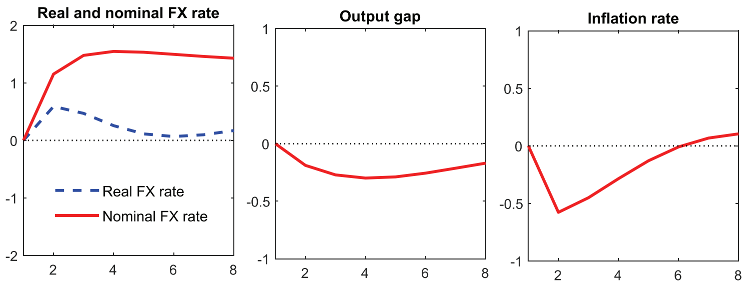
statistically significant estimated value of $\psi$ implies that FXIs in Vietnam have significantly affected the FX rate. Furthermore, the persistence parameter, $\rho_X$, is around 0.3, implying that the effects of FXIs are moderately persistent. Third, the estimated monetary policy rule suggests that the central bank raises the nominal interest rate in response to depreciation in the nominal FX rate ($\phi_q < 0$) in addition to inflation and output growth. This result suggests that the central bank in Vietnam leans against the wind in the FX market not only by FXIs but also by the nominal interest rate, as done by some small open-economy countries (Lubik and Schorfheide 2007). Fourth, the parameters for the FXI policy, $\theta_{res}$ and $\theta_q$, are estimated in a way that is consistent with the practice under the systematic managed floating system, due partly to the use of the estimation results in Section 2 as their prior means. Fifth and finally, while not shown in the table, the estimated mean of the time-varying risk premium, $\zeta_t$, is 0.0243, which implies that the annual risk premium for foreign borrowing in Vietnam is around 9.7 percent. While it seems too high at first glance, note that $\zeta_t$ in Equation (5) possibly includes the effects of capital control. Hence, this estimation result implies that Vietnam is characterized by relatively strict capital control, as is consistent with the Fernández et al. (2016) database on capital control measures.

#### *4.1.2 Impulse Response to FXIs*

To quantify the effects of FXIs, this subsection examines the impulse response to the FXI shock, $\varepsilon_f$, in the FXI policy rule (9). As a positive (negative) FXI shock means a decrease (an increase) in the supply of the U.S. dollar by the central bank, it is expected to make it difficult (easy) for private investors to borrow in the external debt market. To capture this transmission mechanism of FXIs inside the model, a positive (negative) FXI shock is assumed to raise (reduce) the risk premium for external debt, $\zeta_t$, by influencing $X_t$ in (14). Then, the change in the risk premium influences the FX rate through the UIP condition (13).

Figure 4 shows the impulse response of the nominal and real FX rate, the output gap, and the inflation rate to a negative FXI shock (i.e., selling of the U.S. dollar) of 1 percentage point of GDP. The figure indicates that FXIs have intuitive and sizable policy effects in

**Figure 4. Impulse Response to the FXI**




**Note:** The figure shows the impulse response to the FXI shock, $\varepsilon_f$, to quantify the effects of the FXI of 1 percentage point of GDP.

Vietnam. Regarding the effects on the real and nominal FX rate (the left panel in Figure 4), the figure indicates that (i) the real FX rate appreciates by an approximate 0.3 percentage point on impact and returns to the previous level within a few quarters, and (ii) the nominal FX rate appreciates by an approximate 1.2 percentage points on impact and keeps the appreciated level in the long run. The moderate and short-lived effects on the real FX rate and the significant and persistent effects on the nominal FX rate are consistent with the past empirical literature. Furthermore, as a result of the FX rate appreciation, FXIs have sizable effects on output and inflation as well (the middle and right panel in Figure 4). Specifically, the output gap declines by around 0.25 percentage point at the peak, while the inflation rate declines by 0.5 percentage point on impact and gradually returns to the previous level. Hence, selling the U.S. dollar through FXIs helps dampen the inflationary pressure by supporting the domestic currency value, while it induces moderate but adverse effects on real economic activity.

### *4.1.3 Variance Decomposition*

Table 3 presents the results of the variance decomposition for the real and nominal FX rates, the inflation rate, output growth, and the FX reserves. Using Kalman smoothing, the fluctuations of these five variables are decomposed into the contributions of four groups of structural shocks: (i) the productivity shock (the non-stationary

**Table 3. Variance Decomposition**

| | **Productivity** | **External** | **FXI** | **Monetary** |
|---|---|---|---|---|
| Real FX Rate | 69.7 | 2.6 | 8.8 | 18.9 |
| Nominal FX Rate | 2.2 | 23.4 | 72.1 | 2.3 |
| Inflation Rate | 62.3 | 3.8 | 13.5 | 20.4 |
| Output Growth | 78.7 | 2.8 | 10.9 | 7.7 |
| FX Reserve | 12.4 | 47.1 | 8.3 | 32.2 |

**Note:** The table shows the results of the variance decomposition for the real and nominal FX rate, inflation rate, output growth, and FX reserves. The fluctuations of these five variables are decomposed into the contributions of four groups of structural shocks: (i) the productivity shocks (the non-stationary productivity shock for the tradable and non-tradable sectors, $\varepsilon_{aT}$ and $\varepsilon_{aN}$, and the stationary productivity shock, $\varepsilon_z$), (ii) the external shocks (the UIP shock, $\varepsilon_q$, and the U.S. monetary policy, $\varepsilon_{rr}$), (iii) the FXI shock ($\varepsilon_f$), and (iv) the monetary policy shock ($\varepsilon_m$).

productivity shock for the tradable and non-tradable sectors, $\varepsilon_{aT}$ and $\varepsilon_{aN}$, and the stationary productivity shock, $\varepsilon_z$), (ii) the external shock (the UIP shock, $\varepsilon_q$, and the U.S. monetary policy shock, $\varepsilon_{rr}$), (iii) the FXI shock ($\varepsilon_f$), and (iv) the monetary policy shock ($\varepsilon_m$).

The table shows the following three notable features. First, around 70 percent of the fluctuations in the real FX rate can be explained by the productivity shocks. This result implies that the real FX rate is determined in a way that is consistent with the Balassa–Samuelson relationship in the model. Accordingly, the policy shocks that include the FXI and monetary policy shock account for only less than 30 percent of the real FX rate fluctuations, while the external shock that includes the deviations from the UIP condition (i.e., the UIP shock) and the U.S. monetary policy shock is almost negligible in explaining the real FX rate in Vietnam. Second, in contrast, the productivity shock can explain only a negligible amount of fluctuations in the nominal FX rate. Instead, the FXI policy shock is a dominant driver for it. This result is intuitive, given that the nominal FX rate in Vietnam has been relatively stable and moving in the completely opposite direction to the real FX rate due to the active FXIs under the systematic managed floating system, as described in Section 2. Third, the inflation rate and output growth are driven mainly by the productivity shock, and the external shock plays an almost negligible role in explaining their fluctuations, as is similar to the real FX rate. Fourth and finally, the FXI shock accounts for only less than 10 percent of FX reserve fluctuations. Thus, more than 90 percent of changes in the FX reserves in Vietnam are accounted for by systematic responses to the nominal FX rate, pointing to the importance of the analysis of the systematic FXIs that respond to the nominal FX rate fluctuations. Regarding the root drivers of the systematic responses of the FX reserves, the external shock and the monetary shock have larger shares than the productivity shock, implying that the systematic FXIs absorb and mitigate the propagation of those shocks. In the following subsection, we will explore the effects of the systematic FXI policy by a counterfactual analysis.

### *4.2 Counterfactual Analysis for the Efficacy of FXIs*

The estimation result in the previous subsection indicates that Vietnam's central bank has actively used FXIs as a tool for leaning against the wind in the FX market, and that the FXI policy shock has significant effects on the real and nominal FX rate. Given these significant effects of FXIs, an essential question for policymakers is, to what extent does the FXI policy contribute to macroeconomic stability in Vietnam? To answer this question, a counterfactual policy exercise is conducted in this subsection for the case without FXIs. Specifically, a hypothetical economy without FXIs is constructed by assuming that (i) the FX reserves do not respond to the nominal FX rate (i.e., $\theta_q = 0$) and (ii) the FXI shock is always zero (i.e., the variance of $\varepsilon_{f,t}$ is set to zero). Assumption (i) aims to stop systematic FXIs from leaning against the nominal FX rate fluctuations, while Assumption (ii) aims to stop non-systematic and discretionary FXIs through the FXI policy shock. Since the central bank is assumed to stop conducting both the systematic and the non-systematic FXIs in this scenario, this counterfactual policy framework can be interpreted as a floating FX regime without any FXIs. Since all the structural parameters, except these two, remain unchanged in the counterfactual simulation, we can examine the extent to which FXIs contribute to macroeconomic stability by comparing the counterfactual simulation results to the baseline results.

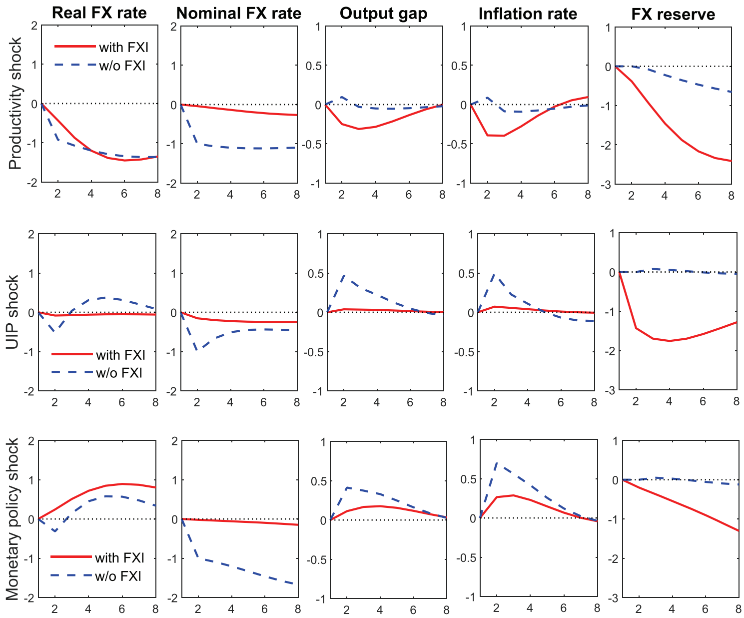
In what follows, first, the impulse responses to the productivity, UIP, and monetary policy shocks under the counterfactual FX policy regime are computed and compared with the baseline results to understand how the systematic FXI policy dampens or amplifies those responses. Then, by examining the variance decomposition in the counterfactual exercise, we investigate how much and why FXIs contribute to macroeconomic stability in Vietnam. Finally, we briefly consider the case of a flexible inflation-targeting regime to examine whether an interest rate policy can replace FXIs by more aggressively responding to the FX rate.

#### *4.2.1 Impulse Responses under the Counterfactual FX Policy*

Figure 5 presents the impulse response functions under the baseline and the counterfactual FX policies. The figure shows the responses of the real and nominal FX rates, output gap, inflation rate, and FX reserves to the productivity shock for the tradable goods ($\varepsilon_{aT}$), the UIP shock ($\varepsilon_q$), and the monetary policy shock ($\varepsilon_m$). In the figure, the red, bold lines represent the responses in the baseline case (i.e., with FXIs), while the dashed, blue lines represent the ones under the counterfactual FX policy (i.e., without FXIs). The signs and sizes of these shocks are adjusted and standardized, such that the nominal FX rate without FXIs depreciates by 1 percentage point on impact. Since the impulse response function is an endogenous reaction to exogenous shocks, the differences between the red, bold lines and blue, dashed lines are interpreted as the effects of the systematic FXIs formulated in Equation (9).

There are several notable features in the figure: First, while the systematic FXIs have minor effects on the real FX rate (the first column), they effectively mitigate the depreciation pressure on the nominal FX rate (the second column). More specifically, when the central bank conducts systematic FXIs that respond to the nominal FX rate based on the FXI policy rule (9), the size of the response of the nominal FX rate vis-à-vis the U.S. dollar to the productivity, UIP, and monetary policy shocks becomes less than 10 percent of those for the case without the systematic FXI policy. These mitigating effects of systematic FXIs emanate from the endogenous response

**Figure 5. Impulse Responses with and without FXIs**




**Note:** The figure presents the impulse response functions under the baseline and the counterfactual FX policies. In the figure, the red, bold lines represent the responses in the baseline case (i.e., with FXIs), while the dashed, blue lines represent those under the counterfactual FX policy (i.e., without any FXIs). The responses in the figure include those of the real and nominal FX rates, output gap, inflation rate, and FX reserves to the negative productivity shock for tradable goods ($\varepsilon_{aT}$), the depreciation UIP shock ($\varepsilon_q$), and the easing monetary policy shock ($\varepsilon_m$). The size of the shocks is standardized, such that the absolute size of the response of the nominal FX rate is equal to 1 percentage point on impact.

of the FX reserves. That is, with the systematic FXIs, the central bank sells and decumulates the FX reserves in response to the depreciation pressure in the FX market, as shown in the last column in Figure 5, suggesting that the systematic FXI policy uses the FX reserves as an effective shock absorber to stabilize the nominal FX rate as a nominal anchor.[17]

[17]In response to the productivity shock, the figure shows that the FX reserves decline even in the case without FXIs. In the event of an unexpected negative shock of tradable goods productivity, the neutral level of the FX reserves on the

Second, considering the response of the output gap or inflation rate to the productivity shock (the first row), the volatility is larger for the case with than for the case without FXIs. This result implies that the systematic FXI policy amplifies their responses, thus possibly destabilizing the economy. With a negative productivity shock in the tradable goods sector, the real and nominal FX rates depreciate due to the changes in the relative price between the tradable and non-tradable goods (i.e., the Balassa–Samuelson effect). With FXIs, however, such depreciation pressure in the FX market would be mitigated and become smaller. The smaller depreciation of the nominal FX rate reduces inflationary pressure in the domestic economy, thus decreasing the inflation rate and output gap further, and amplifying their responses. This transmission mechanism to amplify the responses to the negative productivity shock is the same as in previous studies on the currency peg, such as Galí and Monacelli (2005) and Chapter 9 in Schmitt-Grohe and Uribe (2017). In these studies, given a negative shock to tradable goods endowment or the terms of trade, a country adopting a currency peg faces a more severe economic downturn because it cannot benefit from the mitigating effects through currency devaluation. That is, as several empirical studies, including Forbes and Klein (2015), advocate, FX flexibility, rather than FXIs, can work as a shock absorber to dampen economic fluctuations when the productivity shock drives them.

Third, considering the responses of the output gap and inflation rate to the UIP and monetary policy shocks (the second and third row), the sizes of the responses are smaller in the case with FXIs. Therefore, in contrast to the case of the productivity shock, the systematic FXI policy dampens these responses rather than amplifies them. While the UIP shock induces the FX rate depreciation and thus positively affects both the output and the inflation rate by making the tradable goods more competitive, the systematic FXIs mitigate the depreciation pressure and dampen the responses of the output and the inflation rate. Similarly, while the easing monetary policy shock raises the inflation rate and the output gap, as in a canonical DSGE model, the systematic FXIs dampen these policy effects by counteracting the depreciation pressure in the FX market.

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balanced-growth path becomes lower than before the shock, thus leading the FX reserves to decline and converge to the new steady-state level gradually.

Hence, in contrast to the case of the productivity shock, this result implies that the systematic FXIs can possibly contribute to macroeconomic stability by suppressing the nominal FX rate fluctuations caused by the UIP or the monetary policy shocks.

The above quantitative results imply that FXIs contribute to macroeconomic stability if the external shocks and the monetary policy shock are the more dominant drivers in the economy than the productivity shocks, and vice versa. This policy implication is consistent with a traditional Mundell-Fleming prescription of optimal exchange rate regimes: If real (nominal) shocks are dominant, then a flexible (inflexible) exchange regime is optimal. While this prescription is generally obtained in the model with imperfect goods markets as emphasized in Lahiri, Singh, and Végh (2008), the above quantitative results suggest that their prescription is also valid in a small-open economy DSGE model with a systematic FXI policy.

#### *4.2.2 Variance Decomposition under the Counterfactual FX Policy*

Given that the systematic FXIs can either dampen or amplify impulse responses, depending on the type of the exogenous shocks, whether the systematic FXI policy contributes to macroeconomic stability is an empirical question. To answer this empirical question, Table 4 shows the standard deviation (SD) of the real and nominal FX rates, output growth, inflation rate, and FX reserves in the model. In the table, the SD in the baseline (i.e., the case with FXIs, the first column) is normalized to 1. Considering the case without FXIs (the second column), the table indicates that FXIs substantially dampen the fluctuations of the nominal FX rate in Vietnam. Specifically, without FXIs, the SD of the nominal FX rate would be more than triple, which is consistent with the impulse response analysis in the previous subsection. Second and more importantly, the table indicates that the SD for the output growth and inflation rate would increase by 131 percent and 52 percent, respectively, in the counterfactual simulation without FXIs. Thus, while FXIs can either stabilize or destabilize the economy, as shown by the impulse response analysis, Table 4 implies that FXIs contribute to macroeconomic stability in Vietnam.

**Table 4. Standard Deviation of Macroeconomic Variables**

| | With FXI (Baseline) | Without FXI | Flexible IT |
|---|---|---|---|
| Real FX Rate | 1.00 | 1.87 | 1.54 |
| Nominal FX Rate | 1.00 | 3.65 | 2.76 |
| Output Growth | 1.00 | 2.31 | 1.81 |
| Inflation Rate | 1.00 | 1.52 | 1.02 |
| FX Reserve | 1.00 | 0.24 | 0.21 |

**Note:** The table shows the standard deviation (SD) of the real and nominal FX rates, output growth, inflation rate, and FX reserves in the model. The table shows the counterfactual SD relative to the baseline (the case with FXIs) by normalizing its SD to 1.

In the model, the FXIs contribute to macroeconomic stability solely through the systematic FXIs that respond to the nominal FX rate. The non-systematic FXIs, on the other hand, are modeled as an iid exogenous policy shock to the FXI policy rule in Equation (9); thus, they do not contribute to macroeconomic stability by construction. As discussed in Section 2, how the systematic FXIs stabilize the economy is analogous to how systematic monetary policy contributes to macroeconomic stability. That is, similarly to how a systematic monetary policy that strongly responds to the inflation rate contributes to stabilizing inflation by calming down inflation expectations (Clarida, Galí, and Gertler 2000), the systematic FXI policy contributes to macroeconomic stability by influencing the household's conditional expectations about future developments in the nominal FX rate. Such a policy implication about the systematic FXI policy is basically consistent with the previous literature on the efficacy of rule-based FXIs under a scarcity of FX reserves (Basu et al. 2018).

To further investigate how FXIs contribute to macroeconomic stability, Table 5 shows the results of the variance decomposition for the counterfactual case without FXIs. The structural shocks are grouped as in Table 3; however, the contribution of the FXI policy shock is equal to zero by construction because the FXI policy shock (i.e., non-systematic FXIs) is set to zero in the counterfactual simulation. The table indicates that in comparison with the baseline case in Table 3, the share of the external and the monetary policy

**Table 5. Variance Decomposition without FXIs**

| | Productivity | External | FXI | Monetary |
|---|---|---|---|---|
| Real FX Rate | 22.0 | 67.2 | 0.0 | 10.8 |
| Nominal FX Rate | 9.4 | 74.2 | 0.0 | 16.3 |
| Inflation Rate | 10.3 | 52.3 | 0.0 | 37.5 |
| Output Growth | 13.8 | 73.7 | 0.0 | 12.6 |
| FX Reserve | 61.7 | 30.5 | 0.0 | 7.8 |

**Note:** The table shows the results of the variance decomposition for the real and nominal FX rate, inflation rate, output growth, and FX reserves without FXIs. The fluctuations of these five variables are decomposed into the contributions of four groups of structural shocks: (i) the productivity shocks (the non-stationary productivity shock for the tradable and non-tradable sectors, $\varepsilon_{aT}$ and $\varepsilon_{aN}$, and the stationary productivity shock, $\varepsilon_z$), (ii) the external shocks (the UIP shock, $\varepsilon_q$, and the U.S. monetary policy, $\varepsilon_{rr}$), (iii) the FXI shock ($\varepsilon_f$), and (iv) the monetary policy shock ($\varepsilon_m$). The contribution of the FXI policy shock is, however, equal to zero, by construction, because the FXI policy shock is set to zero in the counterfactual simulation.

shocks rises, while the share of the productivity shocks declines. This result is consistent with the impulse response analysis, wherein FXIs amplify the response to the productivity shock while they dampen the responses to the UIP and monetary policy shocks. Particularly, the rise in the share of the external shock is remarkable. For the case with FXIs in Table 3, the share of the external shock is only around 20 percent for the nominal FX rate and less than 5 percent for the real FX rate, inflation rate, and output growth, respectively; however, in the case without FXIs, the shares rise to 50 to 70 percent for those variables. Thus, FXIs in Vietnam contribute to macroeconomic stability by dampening the effects of the external shocks, as well as the effects of their own monetary policy shock.

While the counterfactual simulation without FXIs suggests that a systematic FXI plays an important role in stabilizing output and inflation, the next question relevant to policymakers is whether an interest rate policy appropriately responding to the FX rate can replace FXIs. This question is important for many EMEs because some countries, including Vietnam, discuss a shift from the monetary policy regime relying on FXIs to the one with flexible FX rates and inflation targeting (IT). To answer this question, we examine the SD of the macroeconomic variables for the "flexible IT regime," where the central bank (i) does not conduct any systematic and non-systematic FXIs (i.e., $\theta_q = 0$ and the variance of $\varepsilon_{f,t}$ is zero), (ii) does not add any monetary policy shocks (i.e., the variance of $\varepsilon_{m,t}$ is zero), and (iii) adjusts the interest rate more aggressively in response to the FX rate (i.e., the value of $\phi_q$ is tripled). Those assumptions replicate the flexible IT regime in the sense that the central bank's interest rate policy is flexible enough to respond to the FX rate but strictly follows the monetary policy rule (i.e., no ad hoc monetary policy shocks). The third column of Table 4 indicates that the flexible IT regime can reduce the SD of the inflation rate to the same level as in the baseline with FXIs, but it can do little to reduce the SD of the real and nominal FX rate and the output growth from the counterfactual case without FXIs. Hence, this exercise suggests that the central bank can stabilize the inflation rate even without FXIs, by following a monetary policy rule aggressively responding to the FX rate, but the interest rate policy cannot substitute for FXIs in terms of the whole macroeconomic stability including real economic activity.

Given the result that the monetary policy shock, in addition to the external shock, would substantially destabilize the economy without systematic FXIs, the next question relevant to policymakers is, what if the monetary policy shock does not exist? Since the monetary policy shock is a discretionary deviation from the monetary policy rule based on the 4 percent inflation target, this question is equivalent to asking, what if Vietnam's central bank adopts a more stringent inflation-targeting regime? This question is important for many EMEs because some, including Vietnam, discuss a shift from the monetary policy regime relying on FXIs to the one with flexible FX rates and more stringent IT. To answer this question, we examine the SD of the macroeconomic variables in the case without the monetary policy shock (i.e., the variance of $\varepsilon_{m,t}$ is set to zero), in addition to the FXIs. The third column of Table 4 indicates that the SD of the inflation rate is higher than in the baseline but substantially smaller than in the case without FXIs, and that the SD of the real and nominal FX rate and the output growth is almost at the same level as in the case with the monetary policy shock. Therefore, the central bank can stabilize the inflation rate to some extent, even without FXIs, by following a stricter IT regime as a nominal anchor for monetary policy, but a stricter IT regime is hard to substitute for FXIs in terms of macroeconomic stability as a whole.

In summary, the counterfactual simulation exercises have the following two policy implications. First, while FXIs can either stabilize or destabilize the economy, they contribute to macroeconomic stability in Vietnam by mitigating the effects of the external and monetary shock. Second, an interest rate policy aggressively responding to the FX rate can possibly stabilize the inflation rate without FXIs, but it generally hard to achieve macroeconomic stability as a replacement for FXIs. Note, however, that these policy implications come with the caveat that the role of FXIs highly depends on which shocks are dominant for business cycles. For instance, for a country where the nominal FX rate is mainly driven by domestic productivity shocks rather than external shocks, including the nonfundamental deviations from UIP, more FX flexibility rather than FXIs is desirable for macroeconomic stability. Thus, FXIs should have a relatively important role in small EMEs with underdeveloped FX markets because such countries tend to be more susceptible to external shocks and deviations from UIP. In other words, with more developed and deeper FX markets, a flexible interest rate policy appropriately responding to the FX rate can perhaps replace FXIs as a policy tool to achieve macroeconomic stability, which is in line with policy recommendations in International Monetary Fund (2020).

#### *4.2.3 Business Cycle Moment*

This subsection discusses the business cycle moments in the baseline and the counterfactual simulation by comparing with data (Table 6). As discussed in Section 2, key features for the Vietnamese economy in comparison with advanced economies such as the euro area and Japan include (i) real FX rates are much more persistent than a random walk, (ii) real FX rates are more volatile than nominal FX rates, (iii) changes in real and nominal FX rate are more volatile than GDP growth but not as much as in advanced economies, and (iv) correlation between real and nominal FX rates is positive but weak. First, Table 6 indicates that the baseline case with FXIs fairly well replicates those key features of business cycle moments observed in data. While this good model fit is not that surprising because the

**Table 6. Business Cycle Moments: Data vs. Model**

| | Data | Model | |
|---|---|---|---|
| | | With FXI | Without FXI |
| $\rho(\Delta Q_t)$ | 0.52 | 0.68 | 0.03 |
| $\sigma(\Delta Q_t)/\sigma(\Delta F_t)$ | 1.65 | 1.62 | 0.83 |
| $\sigma(\Delta F_t)/\sigma(\Delta Y_t)$ | 1.51 | 1.28 | 2.01 |
| $\rho(\Delta F_t, \Delta Q_t)$ | 0.36 | 0.36 | 0.76 |

**Note:** The table summarizes key business cycle moments with respect to real and nominal FX rates vis-à-vis the U.S. dollar in the Vietnamese data and the model. In the table, $\Delta F_t$, $\Delta Q_t$, and $\Delta Y_t$ denote growth in nominal FX rates, real FX rates, and real GDP, respectively.

model parameters are estimated using Vietnamese data, it implies that the simple small open-economy model in this paper captures a key mechanism of FX rate dynamics in Vietnam.

Second, Table 6 shows that the business cycle moments are remarkably different in the counterfactual case without FXIs. Compared with the baseline case with FXIs, the business cycle moments in the counterfactual case without FXIs are characterized by the properties that (i) real FX rates are much less persistent and close to a random walk, (ii) real FX rates are as volatile as nominal FX rates, (iii) changes in real and nominal FX rate are twofold more volatile than GDP growth, and (iv) correlation between real and nominal FX rates is positive and close to one. In other words, the business cycle moments in the counterfactual case without FXIs become much closer to those in advanced economies under a floating FX regime in Table 1. Hence, while the business cycle properties in advanced economies and EMEs are different in many ways (e.g., Aguiar and Gopinath 2007), this result suggests that the differences with respect to FX rate dynamics may be partly associated with those in their FXI policy.

#### *4.2.4 Robustness Check: Is the Result Specific to Vietnam?*

One of the main takeaways from the quantitative analysis is that a systematic FXI policy amplifies the macroeconomic fluctuations caused by the productivity shock while dampening those caused by the UIP and monetary policy shock. While this implication is consistent with a traditional Mundell-Fleming prescription of optimal exchange rate regimes, a key question for policymakers is whether it is not specific to Vietnam but applicable to other countries. To answer this question, this subsection focuses on the following two Vietnam-specific features in the quantitative exercise—namely, (i) the tight Balassa–Samuelson (BS) relationship and (ii) the small price adjustment cost in a tradable goods sector—and then examines how the above takeaway changes when these two features are relaxed.

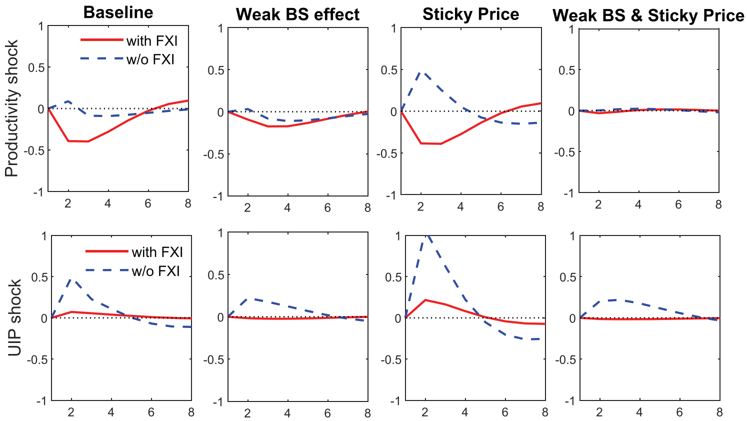
First, the tight BS relationship is relaxed. As Section 2 shows, real FX rates have been almost perfectly tracked by the relative price of manufacturing goods in Vietnam, which implies that the Vietnamese economy is characterized by a tight BS relationship. Since such a law of one price for tradable goods is empirically controversial for some countries, it is worthwhile to examine how the result differs for the economy with a less obvious BS effect. To describe a weak BS relationship in the model, the tradable goods sector is assumed to have some market power in a global market, and the equilibrium of the export market is modeled as

$$Y_{T,t} - C_{T,t} = \left( \frac{P_{T,t}/P_t}{1/Q_t} \right)^{-\nu_X} \bar{C}_W, \tag{16}$$

where the left-hand side is net export while the right-hand side is a demand for tradable goods in an export market. Note that the law of one price for tradable goods in the baseline specification (11) is a special case that the demand elasticity goes to infinite, $\nu_x \to \infty$. The demand in the global market, $\bar{C}_W$, is calibrated so that the law of one price is satisfied at the steady state. Hereafter, in the model with a weak BS effect, $\nu_X$ is set to 100.

Figure 6 shows the response of inflation to the productivity and UIP shock. In the model with a weak BS effect (the second column), the responses to the productivity and UIP shock become smaller than the baseline (the first column). This is because in the model with a weak BS effect, the tradable goods firms do not need to set their prices to be entirely consistent with the real FX rate but flexibly do so by accepting some fluctuations of export demand,

**Figure 6. Response of Inflation to Productivity and UIP Shock**




**Note:** The figure presents the response of inflation to the negative productivity shock for tradable goods ($\varepsilon_{aT}$) in three different environments. In the "weak BS effect" model, the law of one price for tradable goods does not hold because the tradable goods sector is assumed to have some market power in a global market, as described in (16). In the "sticky price" model, the price adjustment cost in the tradable sector, $\gamma_T$, is assumed to take the same value as that in the non-tradable goods sector, $\gamma_N$. Both of them are assumed in the "weak BS and sticky price" model.

thus making the responses to the shocks smaller. Hence, while the main takeaway does not qualitatively change, a systematic FXI is more effective (both negatively and positively) for the country with a tight BS effect because those countries are more susceptible to FX fluctuations.

The second robustness check examines the case where the price adjustment cost in the tradable goods sector is higher. Specifically, while the estimation value of the price adjustment cost in the tradable goods sector, $\gamma_T$, is close to zero in Vietnam, the "sticky price" model in Figure 6 assumes that it is as large as that in the non-tradable goods sector, $\gamma_N$. The third column in the figure shows that the response of inflation becomes larger in the "sticky price" model, while the fourth column shows that the higher price adjustment cost in the tradable goods sector does not significantly change the responses when the BS effect is weak. In other words, the price adjustment cost in the tradable goods sector significantly changes the quantitative result only in the model with a tight BS relationship. With a tight BS relationship, tradable goods firms are forced to set prices entirely consistent with the real FX rate; therefore, the higher price adjustment cost requires more significant changes in the output gap, thus leading to larger economic fluctuations, including those in the non-tradable goods sector. In reality, however, the tight BS relationship and the higher price adjustment cost in a tradable goods sector may hardly coexist because firms possibly differentiate their products to avoid costly adjustments due to high price adjustment costs. While such endogenous dynamics between price adjustment costs and product differentiation is an interesting topic, it is beyond the scope of this paper.

## 5. Concluding Remarks and Policy Implications

This study quantitatively assesses the role of foreign exchange interventions by introducing a systematic FXI policy that follows a feedback rule responding to the nominal FX rate in a small open-economy DSGE model. Consistent with a traditional Mundell-Fleming prescription of optimal exchange rate regimes, a systematic FXI policy amplifies the macroeconomic fluctuations caused by the productivity shock while dampening those caused by the UIP and monetary policy shock. A quantitative analysis of Vietnamese data using a Bayesian method reveals that FXIs significantly contribute to macroeconomic stability and that with reasonable FXIs that insulate an economy from the external shock, the real FX rate is mainly accounted for by productivity shocks, pointing to the importance of the Balassa–Samuelson relationship in Vietnam.

Those quantitative results have some policy implications regarding macroeconomic stability in a post-pandemic world as of October 2022. First, in the face of the FX rate depreciation due to the rapid monetary tightening by the Federal Reserve (the Fed), the EMEs' authorities could consider temporally using FXIs as one of the tools for economic stability. In particular, if they believe that part of the Fed's monetary tightening is temporary or the FX depreciation is somewhat caused by non-fundamental and speculative factors associated with the Fed's monetary policy captured by the UIP shock, the quantitative results suggest that FXIs are an appropriate policy tool for economic stability. Second, when signs of domestic inflation due, for example, to higher commodity prices are observed, EMEs' authorities should not hesitate to increase the interest rate following the monetary policy rule. Any delays in monetary tightening would result in high inflation, thus leading to further FX rate depreciation. While the FX rate depreciation caused by the monetary policy shock would eventually force the EMEs' authority to conduct FXIs, as observed in Vietnam, FXIs can only partially mitigate such adverse effects. All in all, EMEs' authorities should appropriately use FXIs in combination with other policy tools for economic stability by carefully identifying the causes of FX rate depreciation.

## Appendix. FXI Policy and Central Bank's Optimization

In the estimation, the following feedback rule responding to the nominal FX rate and the historical reserve-to-GDP ratio is used for the FXI policy:

$$\Delta Res_t = \beta_0 + \beta_1 \Delta FX_t + \beta_2 \frac{Res_{t-1}}{GDP_{t-1}} + \varepsilon_t. \tag{A.1}$$

This appendix aims to derive this feedback policy rule from a central bank's optimization problem.

First, given that the central bank attempts to (i) smooth out the volatility of the nominal FX rate, (ii) keep the FX reserves close to the optimal level, and (iii) avoid large changes in the FX reserves, the loss function for the central bank is formulated as follows:

$$\frac{1}{2}\left(\Delta FX_t\right)^2 + \frac{\lambda_1}{2}\left(Res_t - \bar{Res}\right)^2 + \frac{\lambda_2}{2}\left(\Delta Res_t\right)^2.$$

In the loss function, the first term represents the loss incurred by the volatility of FX rates, $(\Delta FX_t)^2$, while the second term represents the loss incurred by the deviations of FX reserves, $Res_t$, from their optimal level, $\bar{Res}$. The last term implies that the central bank would gradually change the amount of their FX reserves. $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$ are the parameters for the weight of each term in the loss function.

Second, changes in FX rates are assumed to follow a simple process:

$$\Delta FX_t = x_t - \chi \Delta Res_t, \tag{A.2}$$

where $x_t$ is an exogenous component for FX rate growth, and the second part implies that the central bank can support their own currency's value by selling their FX reserves in the FX market (i.e., $\chi \geq 0$). In other words, if FXIs are not effective at all, then $\chi = 0$ and the FX rate is exogenously determined only by $x_t$.

Finally, the optimization problem for the central bank is formulated as a minimization problem of the loss function (5) subject to (A.2). The first-order condition with respect to $\Delta Res_t$ yields the following policy rule for FXIs:

$$\Delta Res_t = \frac{\chi}{\lambda_1 + \lambda_2} \Delta FX_t - \frac{\lambda_1}{\lambda_1 + \lambda_2} \left( Res_{t-1} - \bar{Res}, \right), \tag{A.3}$$

which is exactly the same as the feedback rule used in the main text. Some comments are in order. First, the policy rule suggests that the central bank's FX reserves positively respond to FX rates. Particularly, the central bank sells their FX reserves ($\Delta Res_t < 0$) in the event of depreciation pressure ($\Delta FX_t < 0$) to lean against the wind. Second, the second term suggests that when the FX reserves are less than optimal, the central bank attempts to raise the reserves to converge them to their optimal level, and vice versa. The convergence speed depends on the relative sizes of the weights in the loss function, $\lambda_1$ and $\lambda_2$. Third, if the central bank follows this policy rule for FXIs, it is challenging to identify and estimate the effects of FXI from data. That is, even if Equation (A.2) specifies the *negative* correlation between FXIs and the FX rates (i.e., selling the FX reserves positively affects FX rates), the observed relationship between them in empirical data should be *positive*, as described in Equation (A.3), due to the endogenous policy response by the central bank. Thus, while we usually observe a clear and positive relationship between them in many EMEs, it should not be interpreted to mean that selling FX reserves causes depreciation of the nominal FX rate. Rather, it should be interpreted to mean that the central bank systematically sells their FX reserves in response to the depreciation of the nominal FX rates. Paradoxically, Equation (A.3) implies that the more negative the relationship between FXIs and the FX rates in Equation (A.2) is, the more positive the relationship between them is observed in data. The economic intuition is that when the central bank knows that FXIs are more effective in supporting their own currency in the face of depreciation pressure, it reacts to the depreciation pressure more aggressively, thus leading to the more positive correlation between FXIs and FX rates.

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# Spillover Effects of Sovereign Bond Purchases in the Euro Area*

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This paper investigates cross-border spillover effects from the Eurosystem's Public Sector Purchase Program (PSPP) on euro area government bond returns. We distinguish between the direct effects of domestic bond purchases by national central banks and the indirect effects from bond purchases by national central banks in other euro area countries over the period March 2015–December 2018. The results reveal substantial spillover effects across the euro area, providing evidence for arbitrage within euro area sovereign bond markets. These spillover effects are particularly large for longer-term bonds and for bonds issued by non-core countries. The larger impact of spillovers in these cases can be explained by investors rebalancing towards higher-yielding government bonds.

JEL Codes: E52, E58, G12.

## 1. Introduction

Over the past decade, major central banks have conducted large-scale asset purchase programs.[1] One of these programs is the

*We thank Martin Admiraal for data assistance and Christina Bräuning for involvement and literature review during an early stage of this project. For useful feedback, we thank Maurice Bun, Mattia Girotti, Roel Grandia, Jurian Hoondert, Aerdt Houben, Jan Kakes, Sarah Mouabbi, Benoît Nguyen, Christiaan Pattipeilohy, René Rollingswier, four anonymous referees, and the participants of the MOC ECB teleconference and the research seminars at the Bank of England, Banque de France, Latvijas Banka, Central Bank of Malta, and De Nederlandsche Bank. The views expressed do not necessarily reflect the official views of de Nederlandsche Bank, the ECB, or the Eurosystem. Corresponding author: a.samarina@dnb.nl.

[1]See Dell'Ariccia, Rabanal, and Sandri (2018) for an overview of unconventional monetary policies in the euro area, Japan, and the United Kingdom, and Kuttner (2018) for the United States.

Eurosystem's Public Sector Purchase Program (PSPP), which was launched in 2015 to ease financing conditions across the euro area (EA, hereafter) by lowering government bond yields.[2] This paper investigates the impact of PSPP purchases on individual bond returns for the 10 largest EA countries. In addition, we distinguish between the direct effect of purchases of a specific bond by a country's national central bank and spillover effects from bond purchases by other national central banks in the Eurosystem. We further disentangle these purchases by a breakdown into different maturity segments and country groups. This empirical approach accounts for the unique characteristics of the EA bond markets and examines market arbitrage within the EA. While the unique settings of the EA should be taken into account, our work improves the understanding of spillover effects between government bond market segments (e.g., between bonds of different maturities or between bonds issued in different jurisdictions). In addition, it provides knowledge on the transmission mechanism of large-scale asset purchases and offers insights for the calibration of future purchase programs.

The literature on the effectiveness of the PSPP in the EA has expanded in recent years. Several studies focus on announcement effects, which capture the pricing-in of future central bank purchases, while others investigate the effects of actual purchases. Most studies find that bond purchases significantly reduced yields and raised bond returns in the EA (see Section 2). Our paper builds on De Santis and Holm-Hadulla (2020), who analyze the effects of actual purchase operations on sovereign bond prices using daily PSPP purchase data from March 2015 up to June 2016. These authors find that purchases of a specific bond as well as purchases of domestic

[2]Note that the PSPP is different from the European Central Bank's (ECB's) Pandemic Emergency Purchase Program (PEPP) launched in March 2020 and discontinued at the end of March 2022. While the goal of purchases under the PSPP was to ease general monetary conditions in the EA, the PEPP was introduced as a temporary asset purchase program for private- and public-sector securities, with a purpose to "address illiquidity and heightened volatility in core segments of EA financial markets that threatened to impair the smooth transmission of monetary policy" (Schnabel 2020) and to counter serious risks to the monetary policy transmission mechanism and the economic outlook for the EA posed by the COVID-19 crisis. Evaluating the effects of the PEPP is a promising avenue for future research.

bonds with comparable characteristics (i.e., close substitutes) significantly increase bond prices. De Santis and Holm-Hadulla (2020) do not examine spillovers from purchases by central banks in other EA countries, however.

We contribute to the existing literature in three directions. First, we investigate how the price effects of actual purchases are transmitted across heterogeneous EA bond markets. The EA sovereign bond markets comprise bonds issued by 19 national governments. These government bonds are not perfect substitutes since national bond markets vary in creditworthiness, liquidity, and size, as well as attract different types of investors. In addition, governments have different issuance needs and preferences, while macroeconomic conditions differ considerably between countries. As a result, sovereign bond yields contain credit and liquidity spreads which the European sovereign debt crisis clearly revealed (see e.g., Costantini, Fragetta, and Melina 2014; Bekkour et al. 2015; Paniagua, Sapena, and Tamarit 2017).

Second, we examine the effects of bond purchases using different categories of purchase volumes. We do so by regressing the return of a specific bond on the relative volume purchased of (i) the bond itself, (ii) other bonds issued by the same government (domestic close and distant substitutes), and (iii) bond purchases by other EA countries (non-domestic spillovers). Purchase volumes and bond returns are taken on a monthly frequency. Similar to the previous empirical literature, our identification strategy relies on an instrumental-variable (IV) approach to address a potential simultaneity bias in the estimated relationship between bond returns and central bank purchases, by using exogenous instruments for the own purchases variable. Spillovers from other countries are distinguished based on an individual country's credit risk group and a bond's maturity segment. As an extension, we investigate whether the effects of purchases differ across country groups and maturity segments.

Third, our study contributes in terms of the scope. In contrast to country-specific studies, (e.g., Arrata and Nguyen 2017; Schlepper et al. 2020), our analysis comprises bond purchases in 10 EA countries. Moreover, we cover the entire first phase of net PSPP purchases from March 2015 until the end of 2018, while the related studies are limited to a narrower time interval.

Our findings show that both domestic and non-domestic PSPP purchases significantly increased bond returns, i.e. decreased yields, in the EA. In terms of magnitude, however, the monthly effect of non-domestic purchases on bond returns is substantially larger than the effect of own purchases. This suggests that spillovers from other countries in the EA—i.e., the general purchase pace of the ECB—are a dominant component of the PSPP's effectiveness. It also provides evidence for the importance of arbitrage within the EA government bond markets, despite the segmentation mentioned above. The impact of spillovers is found to be particularly large for both longer-term government bonds and for bonds issued by non-core jurisdictions (Ireland, Italy, Portugal, and Spain). The larger impact of spillovers in these cases can be explained by investors rebalancing towards higher-yielding government bonds.

The rest of the paper is structured as follows. Section 2 reviews the related theoretical literature and previous empirical evidence. Section 3 provides details on the structure and implementation of the PSPP. Sections 4 and 5 describe the methodology and data construction, respectively. Section 6 presents the main empirical results, robustness checks, and extensions. Section 7 concludes with a summary and policy implications.

## 2. Literature Review

### *2.1 Channels and Spillovers from Asset Purchases to Bond Yields and Prices*

The literature describes several channels through which central bank asset purchases may reduce bond yields. The two prominent ones are the *signaling channel* and the *portfolio rebalancing channel*.[3]

Through the *signaling channel*, central bank communication on asset purchases shapes investors' expectations about future monetary policy and short-term interest rates, which are transmitted to long-term interest rates and asset prices (Joyce et al. 2011; Bauer and Rudebusch 2014; Bhattarai, Eggertsson, and Gafarov 2015;

[3]Quantitative easing may also affect asset prices through other channels, involving liquidity and credit risk (see e.g., Krishnamurthy and Vissing-Jorgensen 2011; Christensen and Gillan 2022).

King 2020). While the *signaling* channel emphasizes the importance of communication and market expectations, tracing primarily the impact of central bank announcements, actual transactions conducted under asset purchase programs can influence bond yields through the *portfolio rebalancing* channel.

The *portfolio rebalancing* channel implies that a purchase-induced price change in one asset spills over to prices of other assets that investors perceive as close substitutes (Vayanos and Vila 2021; Greenwood and Vayanos 2014). Thus, by purchasing government bonds, the central bank changes supply and demand conditions in various market segments beyond the targeted instrument of a specific asset purchase program.

The *portfolio rebalancing* channel is distinct from the direct effects of central bank purchases which influence the price of the asset being bought directly. Krishnamurthy and Vissing-Jorgensen (2013) consider for the transmission of the direct effect the "capital constraints" and the "scarcity" channels. The capital constraints channel is effective when an asset is traded in a narrow and segmented market. When the central bank purchases are large relative to the outstanding amount, a scarcity premium arises which reduces interest rates.

The *portfolio rebalancing* channel asserts that through the indirect effects, transactions in the bond market influence a broader spectrum of asset prices by changing relative yields. These indirect effects can be triggered by other domestic purchases (i.e., domestic purchases of bonds other than the specific bond that is bought under the PSPP) as well as by spillovers from purchases of bonds issued by other countries.

Ferdinandusse, Freir, and Ristiniemi (2020) show with a search theoretical model that the strength of the portfolio rebalancing channel depends on a share of bonds held by preferred habitat investors. These investors have a preference for holding assets of a specific market segment and are only willing to move out of that segment when they receive a risk premium. In a similar vein, Vayanos and Vila (2021) and Greenwood and Vayanos (2014) develop a term structure model where investors have preferences for specific maturities, while risk-averse arbitrageurs integrate markets by trading across different maturities. However, when the group of preferred habitat investors is large, they create a shortage that drives up bond prices and returns and thereby reduces bond yields in specific markets. Meanwhile, arbitrageurs spread the shortage—created by central bank purchases in a particular bond—across maturities and bonds with similar characteristics.

Apart from domestic purchases, spillovers from purchases by central banks in other jurisdictions play a role. Two theoretical studies are relevant in this regard. The first one, by Alpanda and Kabaca (2020), evaluates the international spillovers of large-scale asset purchases (LSAPs) using a two-country (the United States and the rest of the world) dynamic stochastic general equilibrium (DSGE) model. In their model, portfolio balance effects arise from imperfect substitutability between short- and long-term bonds, as well as between domestic and foreign bonds in bond portfolios of each country. Alpanda and Kabaca (2020) show that LSAPs in the United States reduce domestic and foreign long-term bond yields and stimulate economic activity both in the United States and in the rest of the world. The key for this result is the decline in the term premiums abroad through the portfolio rebalancing channel, as relative demand for the rest of the world's long-term bonds increases following LSAPs in the United States.

In a similar framework, Kabaca et al. (2023) examine an optimal allocation of government bond purchases within a monetary union, using a two-region (core and periphery) DSGE model where regions are asymmetric with respect to their economic size and portfolio characteristics. The authors show that a union-wide quantitative easing (QE) affects government asset prices in three ways: first, it directly lowers the term premium of domestic long-term yields; second, lower term premiums spill over through portfolio rebalancing of cross-border assets within the monetary union; third, lower outstanding government long-term debt held by private agents lowers term premiums on these assets. Kabaca et al. (2023) find that a union-wide QE reduces term premiums somewhat more in the core than in the periphery. This is explained by a relatively lower elasticity of substitution between long- and short-term bonds and higher home bias in bond holdings in the periphery compared to the core.

Based on the two studies discussed above, the impact of spillovers may depend on a number of factors, such as the size of asset purchases relative to the pool of substitutable assets, the degree of substitutability of domestic bonds with foreign ones, the risk premium on domestic and foreign bonds, as well as maturity of different assets.

### 2.2 *Effects of Central Bank Purchases on Government Bond Yields and Prices—Evidence*

Previous studies show that unconventional monetary policy measures through government bond purchases have a significant and lasting impact on bond yields and other asset prices.[4] The magnitude of the estimated effect varies across purchase programs, countries, applied methodologies, and sample periods.[5] While there is broad evidence showing a significant and lasting effect of central bank purchases on bond yields and prices, different magnitudes are reported across countries due to different characteristics of the purchase programs across countries, different markets being targeted, and different sizes of purchase programs.

Several studies find that announcements of quantitative and qualitative monetary easing measures by the Bank of Japan significantly lowered yields by 10–14 basis points (bps) on average for a 10-year Japanese government bond (see, e.g., Lam 2011; Hausman and Wieland 2014; Arai 2017). Similarly, De los Rios and Shamloo (2017) and De Rezende (2017) conclude that the effects of QE were relatively small in the case of the Sveriges Riksbank's program. They find that 10-year government bond yields in Sweden dropped on average by around 13–17 bps after five Riksbank's announcements involving bond purchases in 2015, with an estimated cumulative total decline of around 46 bps.

The estimates for the effect of QE programs in the United Kingdom on medium- to long-term government bond yields range between −45 and −100 bps (e.g., Joyce et al. 2011; Christensen and Rudebusch 2012; Joyce and Tong 2012; McLaren, Banerjee, and Latto 2014). Several studies for the United States report that

[4]The effects of LSAPs on other market segments, e.g., corporate bonds or bank loans, is beyond the scope of our paper. See, e.g., Albertazzi, Becker, and Boucinha (2021) for transmission effects of the PSPP to other market segments.

[5]See Hohberger, Priftis, and Vogel (2019) and Bhattarai and Neely (2022) for an elaborate overview of the literature on international unconventional monetary policy.

the effect of the Federal Reserve's QE programs on 10-year Treasury bond yields ranges between −30 and −123 bps (Gagnon et al. 2011; Krishnamurthy and Vissing-Jorgenson 2011; Chen, Curdia, and Ferrero 2012; D'Amico et al. 2012; D'Amico and King 2013; Kandrac and Schlusche 2013; Bauer and Neely 2014), although results vary across the studies (Kuttner 2018).

Previous studies for the EA come to mixed conclusions about the QE impact (see Table A.1 in the appendix for an overview). They estimate the PSPP announcement effects on bond yields to range between −45 and −95 bps for an average 10-year government bond (e.g., Andrade et al. 2016; Eser et al. 2019; De Santis 2020; Altavilla, Carboni, and Motto 2021). Meanwhile, the actual PSPP purchases are reported to have led to a significant further reduction in bond yields, ranging between 13 and 63 bps per 10 percent of outstanding amount purchased (Arrata and Nguyen 2017; Koijen et al. 2021). Using the EA daily data for bond prices and purchase volumes, De Santis and Holm-Hadulla (2020) find that central bank purchases of a security amounting to 1 percent of its outstanding amount raised its return by 5.5–7.5 bps on the day of purchase, while Schlepper et al. (2020), based on transaction-level data for German bonds, find that a daily €100 mln purchase volume increased the average bond return by 8.9 bps. The evidence is inconclusive on how asset purchases transmit to bond yields (returns) and which channels contribute the most to the monetary policy transmission.

The empirical literature on spillovers of central bank asset purchases across government bond markets—i.e., the empirical analyses beyond the domestic bond markets—is scant.[6] To the best of our knowledge, two studies—Bauer and Neely (2014) and Neely (2015)—find evidence for such spillovers from the United States to other countries. More specifically, they show that the Federal Reserve's (Fed's) QE announcements significantly reduced international bond yields. For the euro area, Fratzscher, Lo Duca, and Straub (2016) document that unconventional ECB programs (LTROs, SMP, and OMT) resulted in significant international spillovers on bond yields and portfolio flows.

[6] Alpanda and Kabaca (2020) and Kolasa and Wesołowski (2020) provide some theoretical insights on cross-border spillovers.

Our paper contributes to the debate by considering spillovers of the PSPP in the EA. Specifically, we examine how PSPP influences bond returns and to what extent the rebalancing of investors' portfolios spreads the impact to other bond market segments. Such spillover effects may reflect, for instance, search for yield by investors (Becker and Ivashina 2013), externally imposed risk limits or the need to match durations (Domanski, Shin, and Sushko 2015; Koijen et al. 2017). To account for various factors driving spillover effects, we examine purchases on the basis of countries' credit risk group and bonds' maturity segment.

## 3. The Eurosystem's Public Sector Purchase Program (PSPP)

In the period between March 2015 and December 2018, the Eurosystem expanded its balance sheet by €2575 bln through several QE programs. These purchases comprised more than a quarter of the entire outstanding sovereign debt in the EA and were in same order of magnitude as the QE programs implemented by the Fed, the Bank of England, and the Bank of Japan.

The Eurosystem's QE program—the extended asset purchase program (APP)—includes several subprograms, of which the public sector purchase program (PSPP) was the largest (82 percent of total net APP purchased volume). Under the PSPP, bonds issued by EA central and local governments, agencies, and European institutions were bought in the secondary market. The largest share of purchases involved bonds issued by national governments and agencies, accounting for around 90 percent of total PSPP purchases, compared to 10 percent for bonds issued by European (supranational) institutions.

During our sample period (March 2015–December 2018), the ECB communicated a fixed calendar date on which the APP would end, with the additional qualification that the program could run until the ECB's Governing Council sees a sustained adjustment in the path of inflation consistent with its inflation aim of "below, but close to, 2 percent." Over time, there had been several extensions of the program and adjustments of the net APP purchase pace. In addition, the ECB lowered its main policy rate—the rate on the deposit facility—twice. Table 1 provides an overview of the most

**Table 1. An Overview of the ECB's Decisions with Respect to the APP during 2015–18**

| Announcement Date | Announced Decision | Time Horizon | Announced Volume |
|---|---|---|---|
| January 22, 2015 | Start of PSPP; net APP purchases pace set to €60 bln per month | Until September 2016 + SAPI | €1080 bln |
| November 9, 2015 | Increase of the issue share limit to 33% for bonds issued by national authority | Until September 2016 + SAPI | N/A |
| December 3, 2015 | Extension of APP<br>Reinvestment of maturing bonds | Until March 2017 + SAPI | €1440 bln |
| March 10, 2016 | Increase of net APP purchases pace to €80 bln per month<br>Start of CSPP and TLTRO-II from April 2016<br>Increase of the issue share limit of supranationals to 50% | Until March 2017 + SAPI | €1720 bln |
| December 8, 2016 | Reduction in net APP purchases pace to €60 bln per month<br>Broadening of the criteria for eligible bonds (removal of DFR restriction and inclusion of one- to two-year bonds) | Until December 2017 + SAPI | €2260 bln |
| October 26, 2017 | Reduction in net APP purchases pace to €30 bln per month | Until September 2018 + SAPI | €2530 bln |
| September 13, 2018 | Reduction in net APP purchases pace to €15 bln per month<br>Announced end of net APP purchases by December 2018 | End of December 2018 | €2575 bln |
| December 13, 2018 | End of net purchases under APP | End of December 2018 | €2575 bln |
| | *Interest Rate Decisions* | | |
| December 3, 2015<br>March 10, 2016 | Reduce the deposit facility rate (DFR) to –0.3%<br>Reduce the deposit facility rate (DFR) to –0.4% | Forward Guidance on DFR and APP | |

**Note:** SAPI—sustained adjustment in the path of inflation consistent with the ECB's inflation aim.

relevant ECB decisions with respect to the APP during the sample period.

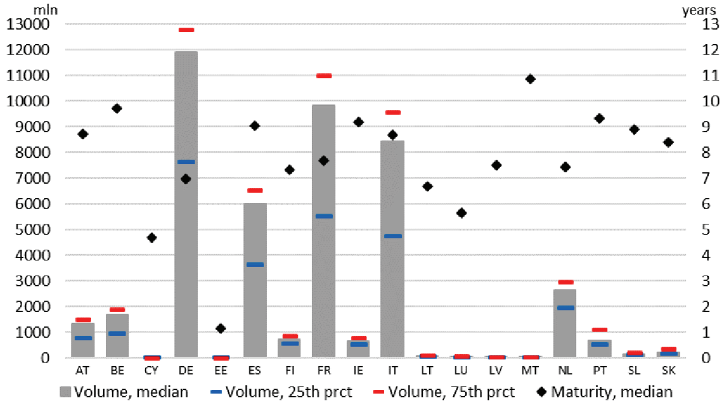
The Eurosystem's purchases were conducted by national central banks (90 percent) and the ECB (10 percent of purchases). The ECB communicated ex ante an aggregate volume target (for the net APP) and published each month purchase volumes disaggregated by jurisdiction and subprogram, to inform market participants about the distribution of conducted purchases. Furthermore, the ECB communicated its intention to use the national central banks' capital key to distribute the planned purchases over different jurisdictions. The capital key is each national bank's stake in the ECB and reflects population and GDP size (equally weighed) of each country in the EA. National central banks bought bonds issued by their domestic governments and supranational institutions, while the ECB conducted purchases in all markets.

The actual purchases per country were in practice not fully aligned with the distribution by the capital key. Typically, this occurred when there were insufficient (liquid) bonds satisfying the eligibility criteria to match the intended volume based on the capital key.[7] Moreover, on a bond level the selection of bonds to be purchased may also be constrained by eligibility rules. Following the intention of market-neutral implementation, national central banks also took into account liquidity conditions of specific market segments or bonds (see Figure 1 for an overview of purchases under the PSPP by country).[8] On a bond level, the eligibility limitations,

[7]For example, Greek government bonds could not be bought, because the credit rating of Greece was too low. In addition, the market liquidity was a limiting factor for smaller countries. Also, the issuer limit (preventing the Eurosystem bond holdings from exceeding 33 percent of the outstanding market debt of a specific country) could have been at the moment a limiting factor for the purchase volume. Finally, also for some smaller countries a limited number of bonds have been bought.

[8]See Cœuré (2015) and Hammermann et al. (2019) for a discussion of the PSPP implementation considerations, such as the interplay between the pursuit of market neutrality, implementation limitations, and market conditions. First, the concept of market neutrality can be perceived in several ways. An important question is to what extent the Eurosystem takes into account market liquidity—which would imply that following the outstanding debt profile is not necessarily market neutral. Market liquidity may differ from one market segment to another. Furthermore, the PSPP was bound by several limitations (issue share limit, issuer limit, and the minimum yield at the deposit facility rate in the first period of the

**Figure 1. Overview of Monthly (net) PSPP Purchase Volume and Maturity per Country**




**Source:** ECB.
**Note:** The left y-axis measures purchase volumes in € mln; the right y-axis measures maturity in years. The median, 25th percentile, and 75th percentile are calculated on the basis of monthly (net) PSPP purchase volumes during March 2015–December 2018. The median maturity of purchased bonds is calculated for the same time period. AT = Austria, BE = Belgium, CY = Cyprus, DE = Germany, EE = Estonia, ES = Spain, FI = Finland, FR = France, IE = Ireland, IT = Italy, LT = Lithuania, LU = Luxembourg, LV = Latvia, MT = Malta, NL = Netherlands, PT = Portugal, SL = Slovenia, and SK = Slovakia.

the market-neutrality principles, as well as country-specific considerations provide the sources of variation in terms of which bonds exactly are being bought, facilitating our empirical analyses.

Purchases in our sample took place almost on the entire spectrum of outstanding government bonds with remaining maturities ranging from 2 years (at a later stage 1 year) up to 30 years and 364 days. Until January 2017, purchases did not take place if bonds traded below the deposit facility rate (DFR). As a result, in several jurisdictions the minimum maturity of purchasable bonds was in practice much higher than two years. In December 2016 the ECB

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program until 2017). These factors constrained the degree of freedom the Eurosystem had in its implementation, which was reinforced by uncertainty about future volume of purchases and new bond issuance by national governments.

lifted the DFR restriction and allowed government bond purchases below the DFR, to the extent necessary.

The Eurosystem's PSPP differs in several ways from QE programs conducted by the U.S. Federal Reserve and the Bank of England. Firstly, and most evidently, the EA bond market consists of multiple national governments, implying a combination of common factors (e.g., single monetary policy) as well as national factors (e.g., budgetary considerations). Second, the Fed and the Bank of England had more explicit maturity objectives and/or communication. While the ECB did not have an explicit duration objective, the Fed operated its maturity extension program and, similarly to the Bank of England, steered and communicated clearly on the allocation of purchase volumes across maturity segments.[9] Third, the extent to which individual bonds were bought also differs. Relatively high issue share limits allowed the Fed and the Bank of England to be more flexible in bond selection. Moreover, the reserves auction system by which the Fed conducted its asset purchases motivates price selection, in comparison to the Eurosystem's purchases, which were to the largest extent conducted on a bilateral basis.

## 4. Methodology

### *4.1 Theoretical Motivation*

The objective of the paper is to quantify the direct effects of own purchases in a security and to distinguish (indirect) portfolio rebalancing effects from domestic and non-domestic purchases. In essence this can be compared to the estimation of cross-price elasticities for differentiated goods (Berry 1994), with goods being viewed as individual bonds. Ideally one obtains the full cross-price elasticities matrix of all government bonds in the EA. However, due to the existence of thousands of government bonds, estimating such matrix is infeasible.

[9]For more information, see Bank of England (2022); FAQs: Treasury Purchases—Federal Reserve Bank of New York (https://www.newyorkfed.org/markets/treasury-reinvestments-purchases-faq), Federal Reserve Board—Open Market Operations. See https://www.federalreserve.gov/monetarypolicy/openmarket.htm#:∼:text=Open%20market%20operations%20(OMOs)%2D%2D,Open%20Market%20Committee%20(FOMC).

In order to identify the different channels through which PSPP purchases may affect bond returns, we impose more structure on the demand function to reduce the number of estimated parameters. This is similar to the approaches proposed in Portes and Rey (2005) and Koijen and Yogo (2019) for reducing the dimensionality in demand systems. Specifically, to capture the direct effect, the purchases in the single bond $b$ are considered. In order to capture the portfolio rebalancing effect from other domestic purchases, we aggregate the purchases in all domestic government bonds except bond $b$. Similarly, to capture the price elasticity of non-domestic purchases, we aggregate the central bank purchases in non-domestic government bonds, that is, bonds issued by other jurisdictions than country $j$.

Based on previous empirical evidence and theoretical papers, we expect that domestic and non-domestic purchases would increase bond returns (while lowering yields). In the absence of a clear guidance from the literature on the magnitude of different effects from purchases, we remain agnostic about the expected size of price elasticities to different types of purchases.

## *4.2 Baseline Model*

We use the panel data set for 10 EA countries with information on individual bonds issued by these countries, at monthly frequency over the period March 2015–December 2018 (see Section 5.1 for data description). Our methodological approach is comparable to De Santis and Holm-Hadulla (2020) and follows the related literature in using panel data regression techniques to analyze the effects of central bank purchases. The baseline model is specified as

$$\begin{aligned} r_{bjt} = {} & \beta * own\_purch_{bjt} + \gamma * oth\_dom\_purch_{bjt} \\ & + \theta * nondom\_purch_{bjt} + u_t + \mu_b + \varepsilon_{bjt}, \end{aligned} \tag{1}$$

where $r_{bjt}$ denotes the monthly return of a specific bond $b$ (issued by jurisdiction $j$) in month $t$, defined as the log change in its price level from end-of-month $(t-1)$ to end-of-month $t$, in percentage.

We use bond returns as our dependent variable in line with previous studies (e.g., D'Amico and King 2013; Kandrac and Schlusche 2013; De Santis and Holm-Hadulla 2020). $own\_purch_{bjt}$ denotes own relative purchases of bond $b$ in month $t$. This variable captures the direct effect of central bank purchases on bond returns through the capital constraints and/or scarcity channels (Krishnamurthy and Vissing-Jorgenson 2013). $oth\_dom\_purch_{bjt}$ is net relative purchases of domestic substitutes (close and distant) for bond $b$ in month $t$. $nondom\_purch_{bjt}$ denotes non-domestic purchases, i.e., monthly net relative purchases by EA central banks other than the central bank in country $j$. To the best of our knowledge, our paper is the first in the literature to explicitly control for and examine the impact of non-domestic purchases on bond returns in the EA. Construction of different purchases variables is described in Section 5.2. $\beta, \gamma$, and $\theta$ are vectors of parameters on the respective purchases variables.

$u_t$ denotes time fixed effects, capturing monthly time-specific common factors such as central bank announcements, market expectations, changing economic indicators, global and regional (European) financial conditions, and geopolitical events, among others.[10] $\mu_b$ denotes unobserved time-invariant bond-specific fixed effects, which capture the characteristics of the bond such as its original maturity, coupon rate, and type (inflation linked or not), among others. $\varepsilon_{bjt}$ is an idiosyncratic error term with mean 0 and variance $\sigma^2_{\varepsilon,bjt}$.[11] Standard errors are clustered at the bond level to account for heteroskedasticity and autocorrelation in the error term.[12]

This set-up allows distinguishing the direct effect of central bank purchases on the return of a particular bond being purchased (captured by $\beta$), as well as the indirect effects of other domestic and non-domestic purchases (captured by $\gamma$ and $\theta$, respectively) that might affect a bond *b's* return through the portfolio rebalancing channel. The use of relative purchase variables (in percent of outstanding amounts) is justified by the assumption that the scarcity induced by a given amount of central bank purchases depends inversely

[10]We include time fixed effects to ensure that variation between bonds is captured by the regression and not by the (communicated) overall purchase pace of the PSPP. In case there was no variation across bonds, the regression would not show any effect of the purchases.

[11]The cross-sectional dimensions $b$ (bond) and $j$ (country) in our panel data set are nested, i.e., multiple bonds are issued by one country. Therefore, bond-specific effects automatically control for country-specific effects.

[12]The post-estimation tests show that there is no remaining (second-order) serial correlation in the residuals.

on the total size of the respective market segment (De Santis and Holm-Hadulla 2020).

### 4.3 Instrumental-Variables Approach

Empirical studies on the effects of central bank asset purchases face a potential identification problem: the ordinary least squares (OLS) method may produce inconsistent estimates if the allocation of overall purchase volumes to individual bonds by a purchasing central bank depends on the observed bond returns in the market on a given purchase day (Arrata et al. 2020; De Santis and Holm-Hadulla 2020). In this case, bond returns and purchases would be jointly determined, resulting in a potential simultaneity bias in the estimated relationship between them. As such, the effect of PSPP might be underestimated if this endogeneity problem is not properly addressed.

Existing studies for the EA and the United States solve this problem by employing an instrumental-variable (IV) approach. For example, De Santis and Holm-Hadulla (2020) apply the IV estimation based on a natural experiment, using "blackout periods" embedded in the PSPP legal set-up, to identify exogenous variation in daily central bank purchase volumes. Arrata et al. (2020) follow a similar approach, additionally using the PSPP eligibility rules to create instruments for purchases. Arrata and Nguyen (2017) build an instrument from a set of variables indicating specialness and liquidity/scarcity of each bond in the French bond market. Koijen et al. (2021) construct each country's predicted government bond purchases by using its capital key in the EA. For the U.S. data D'Amico and King (2013) instrument the LSAP amounts with purchased securities' characteristics prior to the announcement of the program, such as remaining maturity, percentage of issue held by the Fed, and on-the-run dummy.[13]

[13]Other papers propose alternative strategies to deal with identification problems for the price impact of central bank purchases. These approaches arguably provide a clear source of variation. For instance, Krishnamurthy, Nagel, and Vissing-Jorgensen (2018) use differences in corporate credit default risk from securities denominated in U.S. dollars to identify the redenomination component of sovereign euro-denominated bond yields. Di Maggio, Kermani, and Palmer (2020) use rules on the eligibility of mortgages for central bank purchases to

Compared to these studies, we address the identification problem in the following way. First, we use monthly (instead of daily or intraday) bond purchases and monthly bond returns. This setting partly alleviates the simultaneity bias that is inherent in daily data, since price differences are less likely to persist on a monthly basis; if they did, dealers would only be able to buy these bonds to a certain extent, as they would need to fulfill a relatively large volume objective. Note that monthly total purchases are predetermined at the start of the month, so the purchase volume during a month is not sensitive to developments during this month. For example, on March 10, 2016 the ECB announced that it would increase monthly net APP purchases as of April 2016 from €60 bln to €80 bln per month. This implies that the risk of monthly purchases being correlated with a common factor during the month is small, thereby decreasing the risk of a simultaneity bias.

Next, we propose two instrumental variables to deal with the endogeneity of own purchases. For this purpose, we use the three eligibility criteria based on the legal and technical rules imposed by the Eurosystem on the PSPP purchases. First, eligible securities must have a residual maturity of between 2 and 30 years. The lower threshold of two years was relaxed to one year from January 2017 onwards. Second, the yield on eligible securities must be higher than the DFR. This rule was set before the start of the PSPP and relaxed from January 2017 onwards, implying that the Eurosystem could also buy bonds with yields below the DFR. Third, the Eurosystem (i.e., the ECB and national central banks) cannot hold more than 33 percent of a bond issued by a national authority. We construct a dummy variable $Eligible_{bjt}$ that takes the value one when a specific bond $b$ issued by country $j$ is considered eligible to be purchased based on the eligibility criteria 1 and 2, and zero otherwise. The second instrumental variable $Deviation_{bjt}$ is constructed using criterion 3 as a difference between the 33 percent threshold and the relative cumulative purchases of a specific bond $b$. Thus, this variable measures the distance from the volume of the specific

study the impact of LSAPs by the Fed on the refinancing activity. Rodnyansky and Darmouni (2017) use the relative prevalence of mortgage-backed securities on the banks' books before the launch of QE in the United States to identify the exposure of banks to LSAPs.

bond already purchased by the central bank and the allowed purchase limit of 33 percent. These variables are suitable instruments in our context, as they provide exogenous variation in the amount of bonds bought under the PSPP and are themselves not affected by the market constellation of bond returns.

The first-stage regression in the two-stage least-squares (2SLS) set-up writes as follows:

$$\begin{aligned} own\_purch_{bjt} &= \delta_1 * Eligible_{bjt-1} + \delta_2 * Deviation_{bjt-1} + \varphi_t \\ &\quad + \vartheta_b + \omega_{bjt}, \end{aligned} \tag{2}$$

where $own\_purch_{bjt}$ denotes the own purchases variable; $\varphi_t$ and $\vartheta_b$ are month and bond fixed effects, respectively; and $\omega_{bjt}$ is an error term. We use one-month lags of the instruments, as own purchases of bond $b$ in current month $t$ are likely to be determined by this bond's eligibility and the distance of cumulative purchase in this bond so far from the 33 percent allowed limit, as of the end of the previous month. Based on the estimated coefficients $\widehat{\delta_1}$ and $\widehat{\delta_2}$, the fitted values of the own purchases variable are computed. Subsequently the second-stage regression, specified in Equation (1), replaces the own purchase variable with its fitted values from Equation (2) to obtain the estimates of the slope coefficients $\beta, \gamma$, and $\theta$.[14]

## 5. Data

### 5.1 Data Description

Our sample period covers the first phase of net asset purchases conducted under the PSPP and runs from March 9, 2015 (the day PSPP was launched) until December 31, 2018. We use monthly data on PSPP purchases of individual government bonds as summed-up daily purchases over each corresponding month. Each PSPP transaction has the assigned trade and settlement dates, the book value, the nominal amount, and the International Securities Identification Number (ISIN) identifier. We merge the monthly purchase data with end-of-the-month data from Bloomberg on prices and yields of individual government bonds across all EA countries and with

[14] All the reported 2SLS IV regressions in our paper are estimated using the `xtivreg` packages in Stata.

data on individual bond characteristics from the Centralized Securities Database (CSDB). The latter include quarterly data on issuer country, issuer sector, outstanding amount, issuance date, maturity date, and coupon type.

We exclude purchases of government agencies and supranational institutions from our sample. Thus, we keep only bonds issued by the government (central and regional) in each country. In addition, we drop the data for nine EA countries that had no or few purchases within the PSPP and/or whose markets are relatively illiquid (Cyprus, Estonia, Greece, Latvia, Lithuania, Luxembourg, Malta, Slovakia, and Slovenia). This results in a sample comprising 10 EA countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain).[15] These countries account for over 98 percent of the PSPP net sovereign debt purchases during the sample period. The final sample consists of about 33,000 observations for around 1,000 individual government bonds. The panel is unbalanced, as not all bonds were purchased every month during the sample period. Table 2 provides an overview of the bond coverage in our sample, reporting per jurisdiction the number of bonds and the median nominal outstanding amount of these bonds, based on the data for the first (March 2015) and the last (December 2018) month in our sample.

## *5.2 Construction of Purchases Variables*

In order to examine the effects of domestic and non-domestic purchases on bond returns, we use monthly relative net purchases, measured as the nominal amount (in € mln) of central bank net purchases of a specific bond (group of bonds), in percent of the total nominal outstanding amount issued (in € mln) of the corresponding bond (group of bonds). We distinguish "domestic purchases" (all purchases by country $j$'s central bank of bonds issued by the country $j$'s national authority) and "non-domestic purchases" (all purchases by the rest of the Eurosystem, i.e., all other EA central banks without country $j$'s central bank).

[15]In a sample selection we consider the universe of government bonds issued by national governments in the EA. The selection of bonds is based on excluding bonds issued by the smallest countries in the EA as well as Greece due to liquidity concerns and eligibility rules. See also the discussion in Section 3.

**Table 2. Number of Bonds and (median) Outstanding Amount in Our Sample, per Country**

| Jurisdiction | March 2015 | | December 2018 | |
|---|---|---|---|---|
| | Number of Bonds | Nominal Amount Outstanding in €mln (Median) | Number of Bonds | Nominal Amount Outstanding in €mln (Median) |
| Austria (AT) | 63 | 100.0 | 81 | 100.0 |
| Belgium (BE) | 142 | 71.0 | 172 | 50.0 |
| Germany (DE) | 130 | 7,124.4 | 185 | 2,000.0 |
| Spain (ES) | 162 | 604.0 | 237 | 163.7 |
| Finland (FI) | 19 | 5,000.0 | 19 | 5,000.0 |
| France (FR) | 84 | 15,388.0 | 82 | 20,565.5 |
| Ireland (IE) | 23 | 4,941.4 | 29 | 4,023.0 |
| Italy (IT) | 117 | 14,878.8 | 138 | 14,891.3 |
| Netherlands (NL) | 30 | 13,876.9 | 32 | 13,765.1 |
| Portugal (PT) | 35 | 600.0 | 39 | 1,000.0 |

We split domestic purchases into "own purchases" (purchases by country $j$'s central bank of a specific bond $b$ issued by country $j$) and "other domestic purchases" (purchases by country $j$'s central bank of bonds other than bond $b$ issued by the same country $j$). Let $Q_{bjt}$ denote the nominal amount of central bank purchases of bond $b$ in month $t$, issued in country $j$, $OA_{bjt}$—the nominal outstanding amount issued of bond $b$ in country $j$. Then own purchases ($own\_purch_{bjt}$) are constructed as follows:

$$own\_purch_{bjt} = \frac{Q_{bjt}}{OA_{bjt}} \times 100. \tag{3}$$

"Other domestic purchases" are further divided into close and distant substitutes. For this purpose, we group bonds in each country into six mutually exclusive maturity segments $K$ based on the bond's remaining time to maturity in years, using the following intervals: 0–1 year, 1–2 years, 2–5 years, 5–10 years, 10–20 years, and over 20 years. The upper bounds of the intervals (except for the last one) are closed, so that the same bond cannot appear in two segments at the same time. "Domestic purchases of close substitutes" are defined as all purchases by country $j$'s central bank of all bonds other than bond $b_0$, issued in the same country $j$ and located in the same maturity segment $K$ as bond $b_0$. "Domestic purchases of distant substitutes" are defined as all purchases by country $j$'s central bank of all bonds other than bond $b_0$, issued in the same country $j$ and located in different maturity segments $K$ than bond $b_0$. Let $N_j$ denote the universe of bonds issued in country $j$. "Other domestic purchases" ($oth\_dom\_purch_{bjt}$) are then constructed in the formulas (4)–(5) as follows:

$$close\_substitutes_{bjt} = \frac{\sum_{\substack{b=1\\b\neq b_0}}^{N_j} Q_{bjt}}{\sum_{\substack{b=1\\b\neq b_0}}^{N_j} OA_{bjt}} \times 100 \text{ if } K_{bjt} = K_{b_0jt}, \quad (4)$$

$$distant\_substitutes_{bjt} = \frac{\sum_{\substack{i=1\\b\neq b_0}}^{N_j} Q_{bjt}}{\sum_{\substack{b=1\\b\neq b_0}}^{N_j} OA_{bjt}} \times 100 \text{ if } K_{bjt} \neq K_{b_0jt}. \quad (5)$$

Next, we construct purchase variables indicating non-domestic purchases. We start from "total non-domestic purchases" ($nondom\_purch_{bjt}$), denoting all monthly net relative purchases by other central banks than the central bank in country $j_0$, formalized as

$$nondom\_purch_{bjt} = \frac{\sum_{\substack{j=1\\j\neq j_0}}^{J} \sum_{b=1}^{N_j} Q_{bjt}}{\sum_{\substack{j=1\\j\neq j_0}}^{J} \sum_{b=1}^{N_j} OA_{bjt}} \times 100. \quad (6)$$

We decompose total non-domestic purchases using two dimensions: risk group and bonds' maturity segment. First, we distinguish lower/higher credit risk groups and assign each country in our sample to one of them. For this purpose, we allocate countries to one of the five credit rating categories, using S&P ratings of individual EA countries during 2015–18: (i) AAA (Germany, the Netherlands); (ii) AA (Austria, Belgium, Finland, France); (iii) A (Ireland); (iv) BBB (Italy, Spain); and (v) BB (Portugal). The lower credit risk group includes rating categories (i) and (ii) with six countries (Austria, Belgium, Finland, France, Germany, and the Netherlands); the higher credit risk group includes rating categories (iii)–(v) and consists of the four remaining countries (Ireland, Italy, Portugal, and Spain). We use this distinction to construct "same group (SG) non-domestic purchases" (all purchases by other countries that are within the same risk group $R$ as country $j_0$) and "different group (DG) non-domestic purchases" (all purchases by other countries that are in the different risk group $R$ than country $j_0$), formalized as follows:

$$SG\_nondom\_purch_{bjt} = \frac{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} Q_{bjt}}{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} OA_{bjt}} \text{ if } R_{bjt} = R_{bj_0t} \tag{7}$$

$$DG\_nondom\_purch_{bjt} = \frac{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} Q_{bjt}}{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} OA_{bjt}} \text{ if } R_{bjt} \neq R_{bj_0t}. \tag{8}$$

Finally, we use the bond grouping by maturity segments, as described above, and decompose total non-domestic purchases into "same maturity (SM) non-domestic purchases" (all purchases of bonds issued by other countries and located in the same maturity segment $K$ as bond $b_0$ issued by country $j_0$), and "different maturity (DM) non-domestic purchases" (all purchases of bonds issued by other countries and located in the different maturity segments $K$ than bond $b_0$ issued by country $j_0$), constructed as

$$SM\_nondom\_purch_{bjt} = \frac{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} Q_{bjt}}{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} OA_{bjt}} \text{ if } K_{bjt} = K_{b_0j_0t} \tag{9}$$

$$DM\_nondom\_purch_{bjt} = \frac{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} Q_{bjt}}{\sum_{\substack{j=1 \\ j \neq j_0}}^{J} \sum_{b=1}^{N_j} OA_{bjt}} \text{ if } K_{bjt} \neq K_{b_0j_0t}. \tag{10}$$

Note that each purchases variable is normalized by the nominal outstanding amount of a corresponding bond (group of bonds), hence all purchase variables have different denominators.[16] This

[16]The numerator and the denominator for all purchases variables are taken at the same month $t$. To check whether variation in the denominator might be

implies that the purchases variables (e.g., domestic and non-domestic) and their estimated effects on the bond return cannot be summed up to calculate the combined impact. To gauge and compare the economic size of the effect across different purchases, we use one standard deviation in the purchases variables based on their descriptive statistics for the estimation sample. Figure 2 provides an overview of the constructed purchases variables.

As a robustness check, we use duration risk-weighted net purchases instead of unweighted purchases, to test if purchases of government bonds with a higher duration risk have a stronger effect on returns than purchases of bonds with a lower duration risk (see Section 6.3).

### *5.3 Descriptive Statistics*

Table 3 presents the descriptive statistics of the variables used in our empirical analysis. For the average bond, monthly own purchases of a specific bond by individual EA central banks constituted on average 0.245 percent of the nominal outstanding amount of this bond. Monthly domestic purchase volumes of close substitutes, relative to their nominal amount outstanding, were somewhat larger than domestic purchases of distant substitutes (0.574 percent compared to 0.526 percent). Regarding the total non-domestic purchases, during 2015–18 on average monthly they were equal to 0.531 percent of total outstanding amount of the corresponding bonds in our sample.[17] The largest in terms of relative monthly volume were non-domestic purchases by countries of bonds within the same maturity segments as bond $b$ purchased by country $j$'s central bank. The univariate unit-root Fisher-type tests for unbalanced panel data show that all variables are stationary (results available on request).

driving results, as a robustness test, we lag the denominator by one month. The estimated coefficients are very similar to the baseline ones (available on request). Thus, we are confident that it is the variation in the numerator (the purchases) that drives the empirical results, and not the denominator.

[17]Purchases of bonds, conducted abroad, range between 0.49 percent and 0.53 percent of the total outstanding amount of these bonds, from a perspective of an individual country in our sample.

**Figure 2. Overview of Purchases Variables Constructed for the Model Estimation**

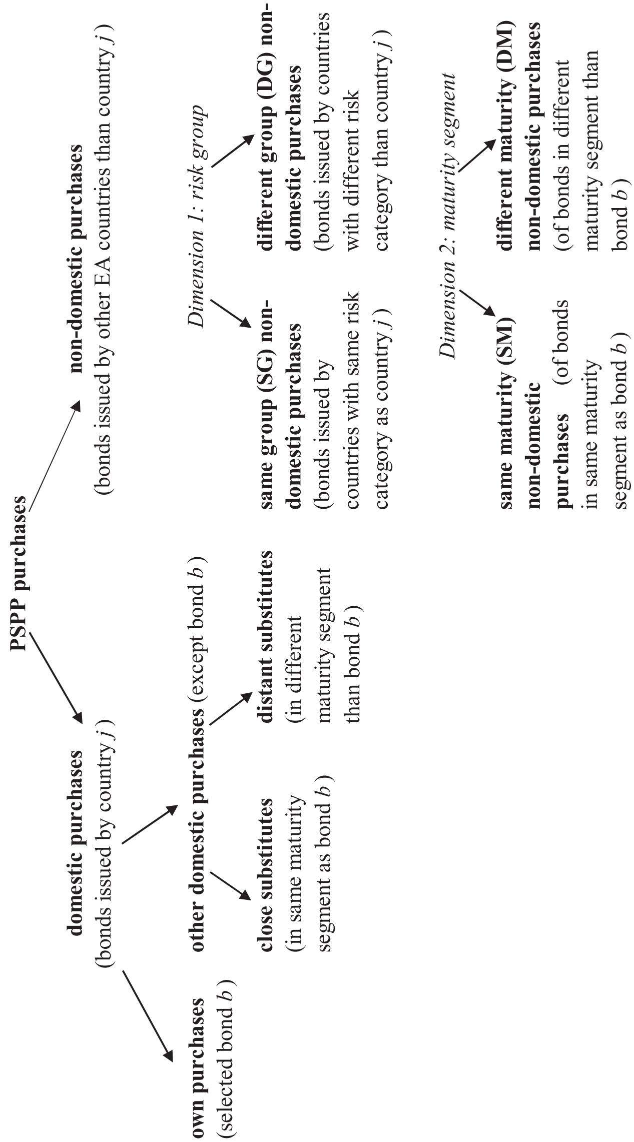


**Table 3. Descriptive Statistics for 10 EA Countries over March 2015–December 2018**

| Variable | Mean | St. Dev. | 25th Percentile | 75th Percentile |
|---|---|---|---|---|
| Bond Return (in %) | –0.098 | 2.357 | –0.595 | 0.541 |
| Own Purchases | 0.245 | 0.754 | 0.000 | 0.024 |
| Domestic Close Substitutes | 0.574 | 0.579 | 0.089 | 0.851 |
| Domestic Distant Substitutes | 0.525 | 0.303 | 0.334 | 0.681 |
| Non-domestic Purchases | 0.531 | 0.256 | 0.420 | 0.642 |
| Same Risk Group Non-domestic Purchases | 0.534 | 0.264 | 0.414 | 0.674 |
| Different Risk Group Non-domestic Purchases | 0.525 | 0.254 | 0.412 | 0.667 |
| Same Maturity Non-domestic Purchases | 0.556 | 0.392 | 0.251 | 0.808 |
| Different Maturity Non-domestic Purchases | 0.513 | 0.257 | 0.390 | 0.631 |

**Note:** The table reports the descriptive statistics for the variables used in the 2SLS regressions reported in Table 4, columns 3–6. The mean, standard deviation (St. Dev.), and 25th and 75th percentiles are reported for the sample included in these regressions. N=32,683. All purchases are measured in percent of the nominal amount outstanding of a corresponding bond (group of bonds) issued by EA countries in the sample.

## 6. Empirical Results

### *6.1 Main Analysis*

Table 4 presents our main results for the full sample. The findings from the 2SLS IV estimates point to statistically significant effects of all types of purchases on bond returns. Based on the specification including only the own purchases, time and bond fixed effects as explanatory variables (column 2), monthly central bank purchases of a specific bond equal to 1 percent of its outstanding amount raise this bond's return by 0.13 percentage point (pp) on average over the sample.[18] This result is in line with De Santis and Holm-Hadulla (2020, Table 1, columns 1–3), although the magnitude of the estimated coefficient on the own purchases variable is smaller in our case. This is plausibly due to methodological and sample differences: unlike the cited paper based on daily data over March 2015–June 2016, we use monthly data over a longer period (March 2015–December 2018) as well as different instruments in the IV approach.

Next, we add other domestic purchases as explanatory variables, that is, domestic purchases of close and distant substitutes (column 3). The estimated coefficient on the own purchases variable remains significant, albeit smaller in magnitude (0.104). Purchases of close substitutes—bonds in the same maturity segment as a specific bond $b$—have a similar direction of impact as own purchases, implying an increase in the bond's return, while purchases of distant substitutes are associated with lower return on the bond in a different maturity segment. Price elasticities differ also in terms of size, with the coefficient on distant substitutes purchases being statistically significantly larger in absolute value compared to the coefficient on close substitutes purchases.

[18]Note that it is not possible to evaluate the cumulative effect of purchases over the entire sample period using our empirical setting. That is, the average monthly effects cannot be simply summed up over 46 months to produce the total effect of the PSPP on bond returns. In order to estimate a cumulative effect of the PSPP, one would need a different model with cross-sectional data on total purchased stocks as of the end of 2018 and a bond return change between the start and the end of the first phase of the PSPP implementation. Such analysis is beyond the scope of our paper, as we investigate the market arbitrage due to the PSPP and not the total effectiveness of the PSPP.

## Table 4. Main Estimation Results—Effects of PSPP Purchases on Bond Returns

| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Own Purchases | 0.028** | 0.130*** | 0.104** | 0.106** | 0.106** | 0.078* |
| | (0.011) | (0.048) | (0.047) | (0.048) | (0.047) | (0.047) |
| Close Substitutes | | | 0.044* | 0.118*** | 0.109*** | 0.054** |
| | | | (0.027) | (0.037) | (0.034) | (0.029) |
| Distant Substitutes | | | –0.665*** | –0.252* | –0.300** | –0.384*** |
| | | | (0.100) | (0.154) | (0.136) | (0.109) |
| Non-domestic Purchases | | | | 5.354*** | | |
| | | | | (1.020) | | |
| Same Group Non-domestic Purchases | | | | | 1.391*** | |
| | | | | | (0.329) | |
| Different Group Non-domestic Purchases | | | | | 3.699*** | |
| | | | | | (0.504) | |
| Same Maturity Non-domestic Purchases | | | | | | 1.153*** |
| | | | | | | (0.118) |
| Different Maturity Non-domestic Purchases | | | | | | 2.090*** |
| | | | | | | (0.338) |
| No. of Observations | 32,819 | 32,809 | 32,683 | 32,683 | 32,683 | 32,683 |
| No. of Bonds | 997 | 997 | 995 | 995 | 995 | 995 |
| R-squared (Overall) | 0.279 | 0.278 | 0.278 | 0.276 | 0.276 | 0.272 |
| Kleibergen-Paap rk Wald F-statistic | — | 256.81 | 248.78 | 246.08 | 246.19 | 245.46 |
| Stock-Yogo Critical Values | — | 19.93 | 19.93 | 19.93 | 19.93 | 19.93 |

**Note:** The table reports the estimation results of Equation (1) where a monthly bond return is a dependent variable. Standard errors in parentheses are clustered on the bond level. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively. Column 1 shows the results of the fixed-effects panel OLS regression, while columns 2–6 show the second-stage results of the 2SLS IV regressions where own purchases variable is instrumented in the first-stage equation (2). Stock-Yogo critical values are reported for 10 percent maximal Wald test size distortion.

Column 4 includes total non-domestic purchases to control for spillovers from purchases by the rest of the Eurosystem. The coefficient estimate on the non-domestic purchases variable is sizable and statistically significant at the 1 percent level. Purchases of bonds by other EA countries amounting to 1 percent of total outstanding amount issued of these bonds increase a specific bond's $b$ return by 5.35 pp on average over the sample. This implies that bond returns are significantly affected by both domestic and non-domestic purchases, which provides evidence for rebalancing within the EA government bond markets. Noteworthy, the coefficient on own purchases (0.106) is much smaller in magnitude and statistically significantly different from the coefficient on non-domestic purchases (5.354), indicating a substantially higher price elasticity of a bond to non-domestic spillovers than to own purchases.

To interpret the economic size of the coefficient, we use a one standard deviation (st. dev.) increase in purchases variables as reported in descriptive statistics in Table 3. Based on the data and the estimated coefficients in our baseline specification (Table 4, column 4), a one st. dev. increase in monthly own purchases under the PSPP raised a bond return by 7.99 bps, ceteris paribus. In addition, during a typical month a one st. dev. increase in domestic purchases of close substitutes further increased the bond $b$'s return by 6.83 bps. The effects of own and close substitutes purchases were somewhat offset by domestic purchases of distant substitutes—one st. dev. increase in the latter reduced the bond return by 7.64 bps. Lastly, monthly non-domestic purchases equal to one st. dev. of total outstanding amount of purchased bonds raised the return of a specific bond $b$ by 137 bps (1.37 pp), which is a relatively large economic impact, accounting for over half of a standard deviation in the bond return variable (Table 3).

Several observations can be made based on these findings. First, coefficient estimates differ substantially in size across the variables. This suggests that the price elasticity of bond returns to PSPP purchases depends on the type of purchases considered. Second, the size of the effect of own purchases on the return of a specific purchased bond is rather small. Third, purchases of close and distant substitutes seem to push the bond return in opposite directions, in some way offsetting each other. Fourth, the coefficients for non-domestic purchases as well as their economic effect are considerably larger than for own purchases of a specific bond. These findings suggest that the general purchase pace under the PSPP across all involved EA countries was of great relevance for the effect on all bond returns. Moreover, it points to an important role of arbitrage in the EA government bond markets.

Distinguishing non-domestic purchases by different dimensions does not alter our conclusions about their importance. We observe that purchases by countries from a different risk group raise the return of a domestic bond $b$ stronger than purchases by countries in the same risk group, which is visible both from the coefficients (column 5) and from the calculated economic effect (94 bps for different group purchases versus 37 bps for same group purchases). The same holds when we compare non-domestic purchases by maturity—a one st. dev. increase in non-domestic purchases in a different maturity segment raised a bond $b$'s return slightly more (54 bps) than purchases in the same maturity segment (45 bps).

### *6.2 First-Stage Regression and Alternative Instruments*

This section discusses the results of the first-stage regressions in the 2SLS IV estimation of the own purchases variable on exogenous instruments and a full set of month and bond fixed effects, formalized in Equation (2). For each specification we report model diagnostics that indicate if included instruments are strong and valid, based on Sanderson-Windmeijer (S-W) weak IV statistic (conditional F-test), Stock-Yogo (S-Y) critical values, and Hansen's J test of overidentifying restrictions.

We start by including only the eligibility dummy as an instrument in Table 5, column 1, which comes out significant with an expected positive sign. In column 2 we estimate a first-stage equation with the eligibility dummy and the deviation from 33 percent limit included as instruments. The results confirm the significance of both instruments. In line with our conjecture, the larger the distance is of cumulative purchases in a specific bond $b$ up to current month from the 33 percent allowed limit—that is, the less scarce a bond is in the market—the more of this bond a central bank can buy in the next month. The conditional F-test statistic (S-W) improves substantially; it is high and well above the S-Y critical values for relative bias and Wald-test size distortions, indicating that the instruments are strong. In addition, a test of overidentifying restrictions fails to

**Table 5. First-Stage Regression of PSPP Purchases on Instrumental Variables**

| | (1) | (2) | (3) |
|---|---|---|---|
| $\text{Eligible}_{bjt-1}$ | 0.279*** | 0.283*** | |
| | (0.037) | (0.033) | |
| $\text{Eligible}_{bjt-1}$ (Excluding Criterion 2) | | | 0.268*** |
| | | | (0.036) |
| $\text{Deviation}_{bjt-1}$ | | 0.046*** | 0.046*** |
| | | (0.002) | (0.002) |
| Bond-Specific Fixed Effects | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes |
| No. of Observations | 32,813 | 32,809 | 32,809 |
| No. of Bonds | 997 | 997 | 997 |
| R-squared (Overall) | 0.053 | 0.023 | 0.023 |
| Sanderson-Windmeijer Weak IV Statistic | 57.32 | 256.81 | 250.40 |
| Stock-Yogo Critical Values | 16.38 | 19.93 | 19.93 |
| Hansen's J Test of Overidentifying Restrictions | 0.00 | 1.10 | 21.49 |
| P-value | Exactly Identified | 0.29 | 0.00 |

**Note:** The table reports the first-stage estimation results of the 2SLS IV regression, with the first-stage regression specified in Equation (2) where own purchases is a dependent variable. Standard errors in parentheses are clustered on the bond level. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively. Sanderson-Windmeijer weak IV statistic corresponds to Sanderson-Windmeijer conditional F-statistic for the endogenous regressor; Stock-Yogo critical values are reported for 10 percent maximal Wald test size distortion.

reject the null hypothesis of joint instrument validity. Thus, we find no evidence of consistency problems in the IV estimates and can conclude that the selected instruments are valid. This assessment is supported by high Kleibergen-Paap rk Wald F-statistic, reported in Table 4 for the second-stage regressions. The validity of instruments is also reflected in the size of the coefficient on the instrumented own purchases variable, which becomes five times larger in absolute value in the 2SLS regression (Table 4, column 2) compared to the OLS estimate (Table 4, column 1). This indicates that not addressing the endogeneity problem leads to the underestimation bias in the OLS specification, which is effectively alleviated by our IV approach.

As a robustness check, we constructed an alternative instrumental variable for eligibility, excluding the second restriction which mandates the yield level to be higher than the DFR. This restriction might be less exogenous as yields at the end of a previous period determine whether a bond is eligible or not but could also be correlated with yields in the next period. In addition, the DFR restriction became ineffective from January 2017 onwards.[19] The results of the first-stage regression using this alternative specification (Table 5, column 3) are very similar to the baseline IV specification in column 2, with the coefficient estimate for the eligibility dummy in column 3 becoming slightly smaller in absolute value. The model diagnostics is worse in this robustness check, as a Hansen's J test of overidentifying restrictions rejects the null hypothesis of joint instrument validity. The results of the second-stage regressions based on different instrumental specifications used in Table 5 show that dropping the DFR restriction in the eligibility dummy does not qualitatively change our findings about the impact of purchases on bond returns (results available on request). We conclude that using the eligibility instrument excluding the DFR restriction does not offer a better and stronger (econometrically) IV identification. Therefore, the baseline IV specification in Table 5, column 2 remains our preferred choice.

### *6.3 Robustness Analysis*

In order to test the robustness of our main results, we conduct several sensitivity checks by modifying the sample as well as the construction of our dependent and explanatory variables. The estimation results from all robustness checks using the baseline specification (Table 4, column 4) are reported in Table 6.

First, we apply winsorizing of bond returns variable at the 1st and 99th percentile of its distribution to prevent the outliers related to technical aspects (such as end-of-year effects, inflation-linked features, and other non-plain-vanilla bonds) from distorting the regressions. We include the winsorized bond returns as a dependent variable in column 1. The results are robust to outliers in the bond return, as the effects of purchases are very close to the baseline,

[19]We thank an anonymous referee for pointing this out.

**Table 6. Robustness Checks—Effects of PSPP Purchases on Bond Returns**

| | Winsorized Bond Return | Bond Yield Change | Excl. Days to Maturity ≤ 90 | Excl. Outstand. Amount < €100 mln | Risk-Weighted Purchases |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Own Purchases | 0.064* | –0.008** | 0.108** | 0.115** | 0.113** |
| | (0.045) | (0.004) | (0.048) | (0.053) | (0.050) |
| Close Substitutes | 0.087** | 0.003 | 0.115*** | 0.056 | 0.039* |
| | (0.035) | (0.003) | (0.037) | (0.039) | (0.024) |
| Distant Substitutes | –0.318** | 0.066*** | –0.274* | –0.400** | –0.159*** |
| | (0.147) | (0.014) | (0.156) | (0.169) | (0.061) |
| Non-domestic Purchases | 4.325*** | –0.277** | 5.339*** | 4.536*** | 5.844*** |
| | (0.936) | (0.089) | (1.032) | (1.098) | (0.621) |
| No. of Observations | 32,683 | 32,683 | 32,107 | 26,895 | 32,683 |
| No. of Bonds | 995 | 995 | 988 | 839 | 995 |
| R-squared (Overall) | 0.309 | 0.458 | 0.280 | 0.272 | 0.273 |
| Kleibergen-Paap rk Wald F-statistic | 246.08 | 246.08 | 242.87 | 226.81 | 135.89 |
| Stock-Yogo Critical Values | 19.93 | 19.93 | 19.93 | 19.93 | 19.93 |
| Hansen's J Test of Overid. Restrictions | 0.01 | 2.73 | 0.00 | 1.27 | 3.32 |
| P-value | 0.92 | 0.10 | 0.99 | 0.26 | 0.07 |

**Note:** The table reports the second-stage estimation results of the 2SLS IV regression specified in Equation (1) where the own purchases variable is instrumented in the first-stage equation (2). Standard errors in parentheses are clustered on the bond level. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively. Bond and month fixed effects are included (not shown). Column 1 uses as a dependent variable the winsorized bond returns variable with cutoffs at the 1st and 99th percentiles of its distribution. Column 2 replaces bond returns with bond yield changes as a dependent variable. Column 3 excludes observations for bonds with maturity up to 90 days. Column 4 drops observations for bonds with nominal outstanding amounts below €100 mln. Column 5 uses duration risk-weighted purchases instead of unweighted purchases. Stock-Yogo critical values are reported for 10 percent maximal Wald test size distortion.

although the coefficient estimate on the own purchases variable becomes smaller.

Second, we replace monthly bond returns with monthly bond yield changes as a dependent variable (column 2). The coefficients on own purchases and non-domestic purchases have the expected negative sign, suggesting that PSPP purchases—both domestic and by the rest of the Eurosystem—significantly reduced bond yields. These findings are consistent with our results for bond returns and in line with the related literature. Compared to De Santis and Holm-Hadulla (2020) the size of the estimated impact of own purchases is smaller in our case, likely due to the above-mentioned differences in the sample, data frequency, and IV approach.

Third, we exclude observations for bonds with a maturity of less than or equal to 90 days, as those are more likely to exhibit outliers or extreme bond returns. The estimation results for this modified sample shown in column 3 remain broadly unchanged compared to the baseline.

Fourth, we check sensitivity of outcomes to the inclusion of bonds with relatively small issuance volumes. For this purpose, we re-estimate the baseline specification while dropping bonds whose nominal outstanding amount is below €100 mln. The findings (Table 6, column 4) are close to the main ones. Thus, bonds with small issuance do not distort our estimates.

Lastly, we include duration risk-weighted net purchases instead of unweighted ones to test if purchases of bonds with a higher duration risk have a stronger effect on returns than purchases of bonds with a lower duration risk. We construct risk-weighted variables by multiplying net purchases with the remaining time to maturity in years (divided by 10 for comparability) and subsequently construct purchases variables using formulas (3)–(10). The coefficient estimates have similar signs as in the baseline specification, while magnitudes changed somewhat (column 5). Specifically, the effects of non-domestic and own purchases became larger, suggesting that duration risk extraction matters for the impact of PSPP on bond returns. Meanwhile, coefficients on other domestic purchases halved in size compared to the baseline.

These robustness checks confirm that the baseline results carry through in several modifications and do not alter the main conclusions. The model diagnostics for all 2SLS regressions in

Table 6 show that selected instruments remain strong and valid: the Kleibergen-Paap rk Wald F-statistics are well above the S-Y critical values, while the test of overidentifying restrictions does not reject the null hypothesis of joint instrument validity.

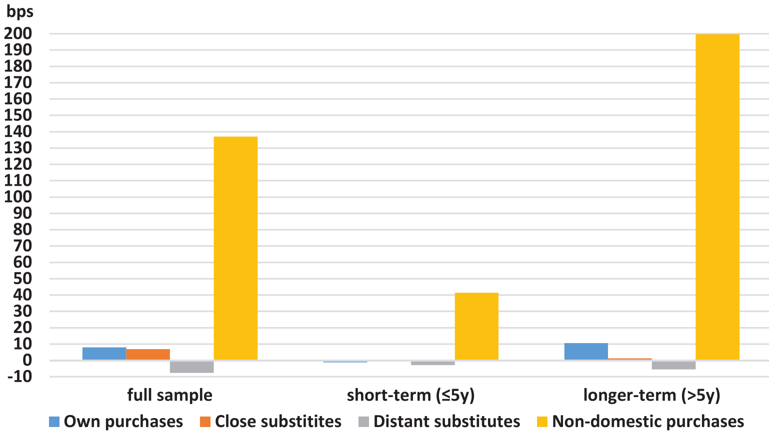
### *6.4 Extensions: Maturity Segments*

The effects of central bank asset purchases on bond returns may vary across maturity segments—for instance, due to preferred habitat investors. To test this prior we split the sample into two groups of government bonds based on their remaining time to maturity at month $t$. We distinguish short-term bonds (remaining maturity up to five years), capturing the short end of the yield curve, and the longer-term bonds (over five years), capturing the medium- and long-term parts of the curve. We re-estimate baseline specifications (4–6) as in Table 4 for each subsample.

The results (see Table A.2 in the appendix) offer several insights. First, the estimated effects of purchases on bond returns are more pronounced—both in absolute value and in statistical significance—for longer-term bonds, in line with a higher duration risk extracted from this market segment. This holds for both domestic (own and substitutes) purchases and non-domestic ones. Second, there is no evidence on the impact of own purchases on bond returns in the short-term subsample, while there is a positive significant effect from non-domestic purchases for this segment. Third, domestic purchases of close substitutes do not have a significant effect on bond returns in either subsample, while distant substitutes have a negative impact, albeit weakly significant.

Figure 3 shows that a one st. dev. increase in non-domestic purchases raises a return of a bond in the longer-term maturity segment by 200 bps (2 pp), which is almost five times as large as the impact for the bond return in the short-term maturity segment (41 bps). In terms of economic effect of own purchases, the estimated price elasticity implies that a one st. dev. increase in own purchases raises a bond return in the longer-term segment by 10.6 bps. Based on this analysis, we can deduce that the full sample results are mainly driven by bonds in the medium- and long-term parts of the yield curve, while the impact on bonds in the short-term end of the curve seems to be less pronounced.

**Figure 3. Effects of One St. Dev. Increase in Purchases, by Maturity Segments**




**Note:** The figure plots the effects (in bps) on a bond return of one st. dev. increase in own purchases, other domestic purchases (close and distant substitutes), and non-domestic purchases under the PSPP, calculated as coefficient estimate*1 st. dev. in purchases variable. The coefficient estimates are based on column 4 in Table 4 (full sample), and columns 1 and 4 in Table A.2 in the appendix (subsamples by maturity segment).

### *6.5 Extensions: Core versus Non-core Countries*

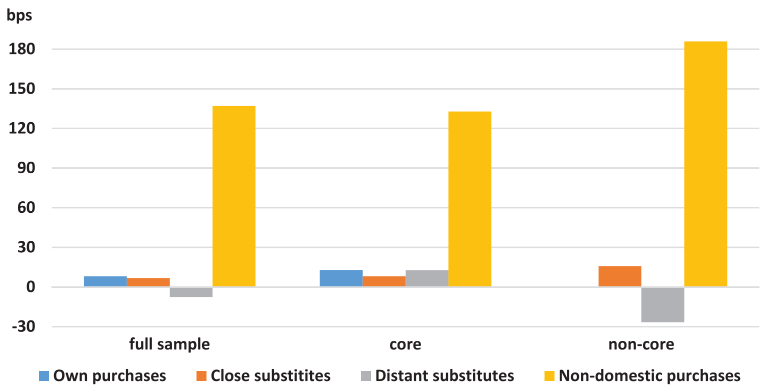
As another extension, we analyze whether the impact of bond purchases under the PSPP differs between country groups by estimating the models separately for the core (Austria, Belgium, France, Finland, Germany, the Netherlands) and the non-core EA countries (Italy, Ireland, Portugal, Spain). The results (Table A.3 in the appendix) show that the effects of purchases differ substantially between the core group (columns 1–3) and the non-core one (columns 4–6), both in terms of the sign and the magnitude. In particular, an increase in own purchases of bond $b$ issued by countries in the core group is associated with a much stronger rise in bond returns in this country group, while the impact of own purchases in the non-core group is insignificant. Such outcome may be related to the smaller credit risk component of bonds issued in the core jurisdictions, which increases the impact of own purchases. Moreover, better market liquidity in core countries can also contribute to stronger upward effects on the return of bonds that are being purchased. This is also in line with Kabaca et al. (2023), who find in a theoretical setting that a monetary union-wide QE reduces somewhat more term premiums of bonds issued in the core region than for bonds issued in the non-core region.

The estimated coefficients on close substitutes purchases for non-core countries are twice larger than for the core group. Perhaps this compensates for the weak effect of own purchases in the former group, with purchases in the same maturity segment having a stronger impact due to investors' portfolio rebalancing into similar bonds. The effect of distant substitutes differs across two subsamples: these purchases raise bond returns in the core countries, thus complementing the close substitutes purchases, while decreasing the bond returns in the non-core group, thus offsetting the effect of close substitutes.

The important result we find, which is novel in the empirical literature on PSPP, is the stronger impact of non-domestic purchases on bond returns in the non-core countries. Purchases by other countries equal to 1 percent of total outstanding amount of bought bonds raise the bond return by 5.2 pp in the core countries and by 7.2 pp in the non-core ones. The effect becomes particularly sizable when we split non-domestic purchases by the risk group (columns 2 and 5). The estimated coefficient on non-domestic different group purchases is almost three times larger in the non-core group than in the core one. The results for non-domestic purchases by bond maturity segment are rather comparable across the country groups.

Figure 4 shows the economic effects of a one st. dev. increase in purchases variables for two country groups. In line with the estimated coefficients, the economic size differs across the country groups, with a larger effect on a bond return of own purchases for the core jurisdictions (13 bps) than the non-core (–0.6 bps). Substantial differences in the economic impact are observed for non-domestic purchases: a one st. dev. increase in total non-domestic purchases raises a bond return in the core countries by 133 bps (1.3 pp) and by 186 bps (1.9 pp) in the non-core. These results suggest that the general pace of the PSPP was relatively more effective for raising bond returns in the EA non-core economies, in line with the observed data.

**Figure 4. The Effects of One St. Dev. Increase in Purchases, by Country Groups**




**Note:** The figure plots the effects (in basis points) on a bond return of one st. dev. increase in own purchases, other domestic purchases (close and distant substitutes), and non-domestic purchases under the PSPP, calculated as coefficient estimate*1 st. dev. in purchases variable. The coefficient estimates are based on column 4 in Table 4 (full sample), columns 1 and 4 in Table A.3 in the appendix (subsamples by country group).

This is also plausible from a theoretical point of view. When risk-free rates decrease, risk premiums are likely to decrease as well—for instance, because of improved debt sustainability. Since risk premiums are larger for non-core countries, the potential for increasing bond returns through the portfolio rebalancing channel is larger in these jurisdictions. The already low yields in the core countries may therefore trigger investors to rebalance their portfolios towards higher-yielding sovereign bonds issued by the non-core countries, thereby creating additional demand for those bonds and boosting their returns. In addition, the non-core jurisdictions may benefit relatively more than the core countries from the improved market liquidity and anticipation of increased European risk-sharing and reduced borrowing costs due to the PSPP. The latter can be partially due to the signaling channel of central bank purchases—PSPP signals a reduction of liquidity and credit risk in the entire EA and may be viewed as a commitment of the ECB to keep short-term interest rates at the effective lower bound for a longer time (e.g., King 2020).

## 7. Conclusions

This paper investigates cross-border spillover effects from the Eurosystem's PSPP on EA government bond returns. We provide evidence on how PSPP purchases of an individual bond, of bonds with a similar or different maturity, as well as purchases by the rest of the Eurosystem affected bond returns. The overall findings show that PSPP purchases had a significantly positive effect on bond returns. This holds not only for own purchases of a specific bond but also for other bond purchases within a particular country or across other EA countries.

The finding that the impact of bond purchases spreads across countries and maturity segments complements earlier research by showing the important role that arbitrageurs play in EA government bond markets. If these markets were completely fragmented, bond purchases in one EA country would have no effect on bond returns in other EA countries, ceteris paribus. The large cross-border effects, documented in this paper, suggest that arbitrageurs affect bond prices across EA government bond markets following large-scale PSPP bond purchases.

Our results have several policy implications. First, PSPP purchases have been effective in pushing down yields, while simultaneously raising bond returns, which is an important criterion for conducting central bank asset purchase programs in the first place. The effect appears to be most pronounced for bonds with longer maturities and lower credit ratings, which can be explained by the larger duration and credit risk extraction in these cases. The relatively large impact of non-domestic purchases in these market segments can be attributed to spillovers from higher-rated low-maturity bonds due to investors rebalancing their sovereign bond portfolio towards higher-yielding sovereign bonds.

Second, the results suggest that the precise distribution of government bond purchases over different countries may have a limited impact on the overall transmission of the ECB's monetary policy across EA countries as long as the arbitrage functions well in the bond markets. With arbitrageurs at work, it appears to be less relevant which bonds are being bought—as long as the overall volume is purchased. While not explicitly tested in this paper, the effect of the distribution of bond purchases might, however, also have an impact via the expectations channel after public ECB announcements. Moreover, the transmission of bond purchases across countries may depend on market liquidity and may be hampered in times of financial stress. There could also be limitations when purchases are concentrated in a few bond issues or in one particular maturity segment. In particular, price distortions would arise when purchases crowd out arbitrageurs and preferred habitat investors fully dominate these bond holdings. Preventing these potential market distortions can justify spreading bond purchases across a large number of bonds when conducting the PSPP.

Finally, our empirical framework can be applied for evaluating other (past, ongoing, and future) asset purchase programs in the EA. The important aspect that we add to the literature—i.e., considering spillover effects from bond purchases by central banks in other EA countries—potentially matters for the effectiveness of central bank purchase programs and, therefore, needs to be taken into account. In this sense, the Eurosystem's Pandemic Emergency Purchase Program (PEPP) can be an important testing ground for new research on the effectiveness of asset purchase programs in the EA.

## Appendix

### Table A.1. Effects of PSPP in the Euro Area: Empirical Evidence

| Study | Time Period | Country Sample | Empirical Approach | Estimated Effect |
|---|---|---|---|---|
| *PSPP Announcements—Effect on 10-Year Bond Yield* | | | | |
| Altavilla, Carboni, and Motto (2021) | 9/2014–3/2015 | Euro Area | Event Study<br>Daily Data | –65 bps |
| Andrade et al. (2016) | 3–12/2015 | Euro Area | Event Study<br>Daily Data | –45 bps |
| Eser et al. (2019) | 1/2015–6/2018 | Euro Area | Term Structure Model<br>Monthly Data | –50 bps (Initial Announcement)<br>–95 bps (Overall) |
| De Santis (2020) | 9/2014–10/2015 | 10 Euro Area Countries | Panel Error Correction Model<br>Daily Data | –72 bps |
| *PSPP Actual Purchases—Effect on 10-Year Bond Yield* | | | | |
| Arrata and Nguyen (2017) | 3/2015–3/2016 | France | OLS, IV Regressions<br>Cross-Sectional Data | Per 10% of Amount Outstanding Purchased:<br>–13 bps (OLS)<br>–26 bps (IV) |
| Koijen et al. (2021) | 2015:Q1–2017:Q4 | Euro Area | 2SLS Regressions<br>Quarterly Data | Per 10% of Amount Outstanding Purchased:<br>–63 bps on Average;<br>Between –38 and –83 bps across Countries |
| *PSPP Actual Purchases—Effect on Average Bond Return* | | | | |
| De Santis and Holm-Hadulla (2020) | 3/2015–6/2016 | Euro Area | 2SLS Regressions<br>Daily Data | Per 1% of Amount Outstanding Purchased:<br>+5.5 to +7.5 bps |
| Schlepper et al. (2020) | 9/2015–10/2016 | Germany | Panel Regressions<br>Intraday and Daily Data | Per €100 mln Purchased: +8.9 bps |

## Table A.2. Effects of PSPP Purchases on Bond Returns, by Maturity Segment

| | **Short Term (Up to Five Years)** | | | **Longer Term (Over Five Years)** | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Own Purchases | –0.016 | –0.009 | –0.008 | 0.138** | 0.133** | 0.167*** |
| | (0.023) | (0.022) | (0.023) | (0.065) | (0.063) | (0.068) |
| Close Substitutes | 0.002 | –0.002 | –0.016 | 0.022 | 0.007 | 0.064 |
| | (0.013) | (0.014) | (0.011) | (0.046) | (0.043) | (0.046) |
| Distant Substitutes | –0.090* | –0.113* | –0.148*** | –0.192 | –0.291 | –0.241 |
| | (0.055) | (0.059) | (0.039) | (0.243) | (0.206) | (0.183) |
| Non-domestic Purchases | 1.650** | | | 7.706*** | | |
| | (0.786) | | | (1.483) | | |
| Same Group Non-domestic Purchases | | 0.100 | | | 2.156*** | |
| | | (0.378) | | | (0.448) | |
| Different Group Non-domestic Purchases | | 1.287** | | | 4.898*** | |
| | | (0.556) | | | (0.667) | |
| Same Maturity Non-domestic Purchases | | | 0.076* | | | 2.835*** |
| | | | (0.040) | | | (0.257) |
| Different Maturity Non-domestic Purchases | | | 0.705*** | | | 6.359*** |
| | | | (0.258) | | | (0.630) |
| No. of Observations | 11,800 | 11,800 | 11,800 | 20,883 | 20,883 | 20,883 |
| No. of Bonds | 505 | 505 | 505 | 643 | 643 | 643 |
| R-squared (Overall) | 0.086 | 0.094 | 0.090 | 0.415 | 0.415 | 0.416 |
| Kleibergen-Paap rk Wald F-statistic | 79.74 | 78.27 | 77.81 | 140.66 | 141.59 | 139.16 |
| Stock-Yogo Critical Values | 19.93 | 19.93 | 19.93 | 19.93 | 19.93 | 19.93 |

**Note:** The table reports the second-stage estimation results of the 2SLS IV regression specified in Equation (1) where a monthly bond return is a dependent variable and the own purchases variable is instrumented in the first-stage equation (2). Standard errors in parentheses are clustered on the bond level. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively. Bond and month fixed effects are included (not shown). Stock-Yogo critical values are reported for 10 percent maximal Wald test size distortion.

**Table A.3. Effects of PSPP Purchases on Bond Returns, by Country Group**

| | Core Countries | | | Non-core Countries | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Own Purchases | 0.160*** | 0.158*** | 0.121** | –0.009 | –0.012 | –0.010 |
| | (0.057) | (0.057) | (0.059) | (0.077) | (0.076) | (0.075) |
| Close Substitutes | 0.133*** | 0.112*** | 0.087*** | 0.292*** | 0.279*** | 0.185** |
| | (0.028) | (0.026) | (0.024) | (0.095) | (0.095) | (0.074) |
| Distant Substitutes | 0.400*** | 0.286** | 0.309*** | –0.959*** | –1.033*** | –1.189*** |
| | (0.130) | (0.119) | (0.096) | (0.254) | (0.259) | (0.204) |
| Non-domestic Purchases | 5.232*** | | | 7.175*** | | |
| | (1.006) | | | (1.622) | | |
| Same Group Non-domestic Purchases | | 1.918*** | | | 1.631*** | |
| | | (0.413) | | | (0.492) | |
| Different Group Non-domestic Purchases | | 8.267*** | | | 23.386*** | |
| | | (1.556) | | | (2.985) | |
| Same Maturity Non-domestic Purchases | | | 1.267*** | | | 0.895*** |
| | | | (0.161) | | | (0.162) |
| Different Maturity Non-domestic Purchases | | | 2.144*** | | | 1.308*** |
| | | | (0.404) | | | (0.499) |
| No. of Observations | 18,454 | 18,454 | 18,454 | 14,229 | 14,229 | 14,229 |
| No. of Bonds | 556 | 556 | 556 | 439 | 439 | 439 |
| R-squared (Overall) | 0.326 | 0.327 | 0.322 | 0.316 | 0.318 | 0.316 |
| Kleibergen-Paap rk Wald F-statistic | 163.73 | 162.93 | 159.19 | 106.04 | 105.75 | 106.57 |
| Stock-Yogo Critical Values | 19.93 | 19.93 | 19.93 | 19.93 | 19.93 | 19.93 |

**Note:** The table reports the second-stage estimation results of the 2SLS IV regression specified in Equation (1) where a monthly bond return is a dependent variable and own purchases variable is instrumented in the first-stage equation (2). Standard errors in parentheses are clustered on the bond level. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent levels, respectively. Bond and month fixed effects are included (not shown). Stock-Yogo critical values are reported for 10 percent maximal Wald test size distortion.

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