Friend, Not Foe? Monetary Policy and Energy Prices *

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Abstract

We empirically show that a central bank's ability to affect global energy prices crucially alters monetary policy transmission. We first provide novel evidence that euro area monetary policy significantly affects energy prices. Employing a Lucas critique-robust counterfactual framework, we find that this ability strengthens and accelerates transmission to inflation and substantially alleviates the inflation-output trade-off. We further show that this ability materially shapes the mandate-optimal policy response to an energy supply shock: the optimal response implies a smaller interest rate increase and a more favorable inflation-output allocation than in a scenario where energy prices are unaffected by monetary policy.

Keywords: inflation, energy prices, monetary policy, monetary transmission mechanism
JEL Codes: C32, E31, E52, Q43

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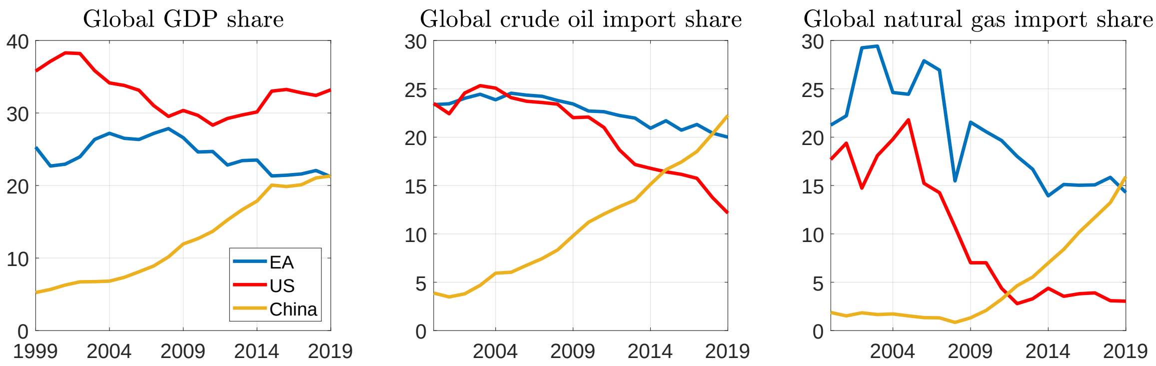
1 Introduction

Ever since the oil price shocks of the 1970s, the interaction between monetary policy and energy prices has been a central issue in macroeconomic analysis. More than forty years later, energy prices have reemerged as key drivers of inflation (Bernanke and Blanchard, 2024, 2025), bringing this issue back to the forefront of macroeconomics. In this paper, we empirically show that monetary transmission, and by extension the mandate-optimal policy response to an energy price shock, crucially depends on the extent to which the central bank can influence energy prices in the first place. We study this interaction in the euro area. As one of the world's largest economies and a major net energy importer (see Figure 1), it is both highly exposed to energy price fluctuations and accounts for a large share of global demand for energy commodities, making it a natural setting for our analysis.

First, drawing on high-frequency event-study evidence and a Bayesian proxy structural VAR (BPSVAR), we find that an unexpected tightening by the European Central Bank (ECB) leads to a strong and persistent decline in global oil prices and in energy prices faced by euro area consumers. We then assess the importance of this finding for the monetary transmission mechanism by studying a counterfactual scenario in which ECB policy does not influence global oil prices. Recently developed methods (McKay and Wolf (2023)) enable us to conduct this analysis empirically in a way that is robust to the Lucas critique and to model misspecification. Under this counterfactual, consumer prices and inflation expectations react considerably less to changes in the policy stance, as the response is reduced by more than half. Furthermore, we empirically show that the ability to affect energy prices substantially lowers the sacrifice ratio: the output cost of stabilizing inflation is roughly halved when the central bank can influence global energy prices. The intuition is that, because energy prices are considerably less sticky than prices of other consumer goods, their sensitivity to monetary policy amplifies the response of aggregate consumer prices. Therefore, when energy prices are not exogenous to decisions of the central bank, monetary policy is characterized by a faster transmission to inflation and a more favorable inflation-output trade-off. In this sense, energy prices can be considered a friend, not a foe, to the central bank.

Second, to illustrate the policy relevance of this finding, we revisit the classic question of how monetary policy should respond to a supply-driven surge in global energy prices. To do so, we combine the approach to empirically analyzing counterfactual scenarios of McKay and Wolf (2023) with their method of estimating impulse responses under optimal policy. With this approach, we show that the ability to affect global energy prices crucially alters the mandate-optimal policy prescription. When a central bank can affect global energy prices, a stylized single-mandate loss function, mirroring the ECB's primary objective of medium-term price stability, calls for a front-loaded tightening to directly counteract the rise in global energy prices. Whereas, under a more realistic loss function that balances inflation and output deviations, the mandate-optimal response is closer to a classical "looking-through" strategy and closely aligns with the ECB's observed response in the data. Crucially, under both loss functions, absent the ability to affect global energy prices, the optimal response requires a substantially stronger increase in interest rates and entails a significantly less favorable inflation–output allocation.

Figure 1: Role of the euro area in the global economy and energy markets



Notes: Share of global real GDP, share of global crude oil imports, and share of global natural gas imports for the euro area (EA), the United States (US), and China in percent. GDP data (in US dollars) from the IMF's World Economic Outlook database. Oil and gas import data are from the UN Comtrade database.

In more detail, the paper first examines whether the ECB influences energy prices. As a motivating exercise, we follow the monetary policy event study literature (Gürkaynak et al. (2005); Altavilla et al. (2019); and many others) and use intra-day data to uncover the causal effects of changes in the ECB's monetary policy stance on the global oil price. Throughout much of the paper, the Brent crude oil price, the dominant energy price in the consumer basket, acts as a stand-in for the price of energy goods traded on global financial markets – we refer to it as global energy price for short.[1] Our findings indicate that ECB policy decisions are rapidly transmitted to global energy prices, resulting in sizable and immediate effects.

To further investigate these dynamics, we employ a BPSVAR model with high-frequency identification to analyze the business cycle and the dynamic effects of euro area monetary policy shocks on energy prices, as well as their role in monetary transmission. Importantly, our analysis shows that a contractionary monetary policy shock results in a significant reduction in both globally traded energy prices and the energy prices faced by euro area

[1]We show in the Appendix that the same effects also materialize for other energy goods such as natural gas (see Appendix B and E), therefore, this is not a critical assumption for our analysis. In addition, the Brent crude oil price is highly correlated with other major energy benchmarks, according to the IMF's Primary Commodity Prices database: its unconditional correlation with WTI crude is 0.99, with Dubai crude it is 0.99, and even with Dutch TTF natural gas it is 0.88.

consumers. We rationalize this result through the lens of state-of-the-art theoretical models and provide empirical evidence for the proposed mechanism, which is centered around the effect of monetary policy on energy demand. In particular, since the euro area is one of the world's largest economies and the largest energy importer (see Figure 1), changes in its monetary policy stance directly influence global oil and energy demand, which, in line with the theoretical work of Auclert et al. (2023) and Bayer et al. (2023), results in lower energy prices. Notably, these reductions in energy prices occur more quickly and are substantially more pronounced than the changes in headline consumer price indices. This is consistent with microdata evidence showing that energy goods prices are updated considerably more frequently than those of other consumer goods (Aucremanne and Dhyne (2004)).

Having established that European monetary policy indeed influences energy prices, we conduct a counterfactual exercise to assess the significance of this effect for monetary policy transmission. Our analysis is based on an empirical counterfactual scenario in which ECB monetary policy decisions do not affect global energy prices. Specifically, in this counterfactual, the Organization of the Petroleum Exporting Countries (OPEC) adjusts supply to keep the global oil price at its preferred level, thereby neutralizing any impact of euro area monetary policy on global oil prices. We estimate this scenario using the method recently developed by McKay and Wolf (2023), which accounts for the anticipatory effects of such an OPEC policy rule change, and thus is robust to the Lucas critique. To implement this approach, we build on the literature on high-frequency identification of oil supply shocks (Känzig, 2021) to jointly identify both short-term and medium-term oil supply news shocks within our BPSVAR model. In the scenario where ECB monetary policy does not influence the global oil price, the response of energy prices faced by euro area consumers to a monetary tightening is substantially dampened. Crucially, this also results in a much weaker transmission of monetary policy to both consumer price inflation and inflation expectations.

A comparison of the counterfactual and baseline responses highlights that, by influencing rapidly adjusting energy prices, monetary policy exerts significantly greater control over inflation dynamics—particularly in the short to medium term. This echoes the results of Aoki (2001) and Guerrieri et al. (2025), who theoretically show that the slope of the aggregate consumer price Phillips curve depends on the ability to affect (flexible) energy prices. Building on the non-parametric "Phillips Multiplier" approach of Barnichon and Mesters (2021), we study this mechanism empirically and show that the ability of a central bank to influence energy prices reduces the inflation–output trade-off by around 50%, even at medium horizons.

Given that our findings indicate that a central bank's ability to influence energy prices shapes monetary transmission, we next assess and quantify the policy implications of our findings by studying how this ability shapes the optimal conduct of monetary policy in response to a surge in energy prices. Using the framework of McKay and Wolf (2023), we compute impulse responses to an oil supply shock under mandate-optimal policy by combining an identified oil supply shock (Känzig, 2021) with euro area monetary policy shocks. Following Barnichon and Mesters (2023, 2024), we consider two mandate-based loss functions: a primary-mandate specification that targets medium-term price stability, and a more realistic dual-mandate specification that assigns equal weight to inflation and output deviations. In both cases, we compare the optimal response to an oil supply shock when the ECB can influence global energy prices with the optimal response in a counterfactual scenario in which it cannot.

When the ECB can influence global energy prices, the primary-mandate loss function implies that the optimal policy entails a modest, front-loaded tightening along the yield curve that curbs the rise in inflation at the cost of only a slightly deeper but short-lived contraction in output, reflecting the rapid adjustment of relatively flexible energy prices. Under the dual-mandate loss function, the mandate-optimal response instead aligns with a classical "looking-through" strategy and closely mirrors the ECB's estimated response. We then combine the optimal policy approach of McKay and Wolf (2023) with their method to estimate counterfactual impulse responses. Our results show that when the central bank cannot influence global energy prices, irrespective of the loss function, optimal policy requires substantially stronger tightening — at both the short and long ends of the yield curve — and results in a markedly less favorable inflation–output allocation as inflation becomes harder to stabilize. Therefore, our analysis suggests that a central bank's ability to influence global energy prices materially affects the appropriate policy response, and thus is an important determinant of the optimal monetary policy response to an energy supply shock.

The rest of the paper is structured as follows. In Section 2, we present the high-frequency event study analysis. Section 3 describes the empirical BPSVAR framework used throughout the paper. Section 4 examines if euro area monetary policy can affect energy prices. Section 5 studies the role of energy prices in the transmission of monetary policy. Section 6 investigates how a central bank's ability to affect energy prices shapes the optimal conduct of monetary policy. The last section concludes.

Related literature. Our paper contributes to the literature that studies how monetary policy transmits to the economy (Christiano et al. (1999); Gertler and Karadi (2015); Miranda-Agrippino and Ricco (2021); and many others). While this literature is extensive, the specific role of energy prices has received little attention. We examine how the response of energy prices to a monetary policy shock shapes its transmission to the economy and show that this mechanism plays a key role. In particular, our findings contribute to the literature studying the transmission pace of monetary policy and provide further evidence against the notion that monetary policy mostly transmits with long and variable lags

(Buda et al. (2023)). The literature has documented that when monetary policy shocks are identified using high-frequency identification, monetary policy affects consumer prices in the short run (Miranda-Agrippino and Ricco (2021); Bauer and Swanson (2023)). We not only confirm this finding but also provide a more structural explanation for the quick response of consumer prices, which is tied to the ability of monetary policy to affect highly flexible energy prices.

Beyond its implications for the transmission pace, our findings also speak to the literature on the inflation–output trade-off, commonly summarized by the sacrifice ratio (Ball (1994); Mankiw (2001)). This literature studies the output costs associated with stabilizing inflation and typically emphasizes the role of expectations and central bank credibility (Ball (1995); Bomfim and Rudebusch (2000); Erceg and Levin (2003)). We identify an understudied mechanism shaping the sacrifice ratio: the response of energy prices to monetary policy. In particular, we show that when monetary policy affects relatively flexible energy prices, inflation responds more strongly for a given change in economic activity, a mechanism that quantitatively implies a substantially lower sacrifice ratio.

Furthermore, our work adds to the literature on the appropriate monetary policy response to energy supply shocks. Previous studies have relied on dynamic stochastic general equilibrium (DSGE) models, which are arguably more prone to model misspecification (Leduc and Sill (2004); Bodenstein et al. (2012); Natal (2012); Guerrieri et al. (2025)) or have employed empirical methods vulnerable to the Lucas critique (Bernanke et al. (1997), Kilian and Lewis (2011)). We contribute to this literature by empirically estimating the mandate-optimal monetary policy response within a framework that is robust to the Lucas critique and by studying how a central bank's ability to impact crude oil prices is crucial for the optimal policy reaction to an oil supply shock. In this scope, Castelnuovo et al. (2024) and Bjørnland et al. (2025) come closest to our analysis as they use the same Lucas-critique-robust empirical approach for a related question. However, while they focus on the role of the monetary policy response in the transmission of commodity price shocks, we study how the central bank's ability to impact energy prices shapes its mandate-optimal policy reaction to an oil supply shock, very much in the spirit of the theoretical analyses of Guerrieri et al. (2025) and Auclert et al. (2023).

Lastly, our paper is closely related to the literature that studies the effects of monetary policy on commodity prices. Existing work that utilizes the state-of-the-art approach of identifying monetary policy shocks in VARs using high-frequency monetary policy surprise series finds that contractionary US monetary policy shocks decrease commodity prices (Miranda-Agrippino and Rey (2020); Bauer and Swanson (2023)) and global oil prices specifically (Degasperi et al. (2023); Miranda-Pinto et al. (2023)).[2,3] Meanwhile, Gazzani and Ferriani (2024) document a similar transmission of Chinese monetary policy to commodity prices. Building on these findings, we show that the global energy commodity prices respond in a comparable manner to European monetary policy as well. Crucially, and in contrast to the existing work, we show that this response has important implications for the transmission of monetary policy to inflation and, importantly, the inflation-output trade-off. Additionally, we find that these effects extend to inflation expectations, further connecting our paper to the interplay between energy prices and inflation expectations (Aastveit et al. (2023); Wehrhöfer (2023); Jo and Klopack (2024)).

2 Motivating evidence: Monetary policy & energy prices at high frequency

To start the analysis, we utilize the high-frequency event study regression approach commonly employed in the literature to study the effects of monetary policy on asset prices. Using intraday data, we document that ECB monetary policy announcements impact global energy prices at high frequency.[4] For our baseline result, we use the Brent oil price as our preferred measure of global energy prices, but we show in Appendix B that the results are robust to using natural gas prices as well. To put the results for the euro area into perspective, we compare them with those for the U.S. and the U.K., which are a large open economy and a small open economy, respectively.

To ensure comparability, we measure unexpected changes in the interest rates — monetary policy surprises — using the intra-day changes in the three-month-ahead federal funds futures, the three-month overnight index swap (OIS) rate, and the three-month Libor rate in a narrow window around monetary policy announcements for the US, the euro area,

[2]Miranda-Agrippino and Ricco (2021) include the Commodity Research Bureau (CRB) commodity price index in their baseline VAR but do not report the IRFs. Therefore, using their replication files while keeping true to their baseline empirical specification, we produce the commodity price index IRFs and find that the commodity price index declines significantly in response to a contractionary US monetary policy shock (see Figure E.9 in the Appendix).

[3]A recent study that does not find this result is Gagliardone and Gertler (2023), who concludes that the real oil price does not respond to US monetary policy shocks. In Appendix C, we replicate their analysis and show that when the critique raised in Kilian (2024) regarding their aggregation of the monetary policy surprise series and the simultaneous use of the average-of-the-month crude oil price is addressed, the oil price does in fact strongly and significantly decline in response to a contractionary US monetary policy shock.

[4]Gürkaynak et al. (2005), Beechey and Wright (2009), and others have shown that intraday data yield more precise point estimates of announcement effects than lower-frequency (daily) data. Rosa (2014) investigates this premise for crude oil futures prices and finds that oil prices respond to a broader range of news announcements than other U.S. asset prices, highlighting the importance of using intraday data for our analysis.

and the UK, respectively.[5] We follow Jarociński and Karadi (2020) and purge monetary policy surprises from central bank information effects using changes in stock prices in the same window around the monetary policy announcements. Specifically, if stock prices and interest rates move in opposite directions, we label this a monetary policy shock. If not, we set the corresponding entry to zero. This corresponds to what Jarociński and Karadi (2020) call the "poor man's" identification approach. We use tick data from the Refinitiv Tick History database to compute the variation in the Brent crude oil price in the same narrow intra-day window around the monetary policy announcements. Precisely, we measure the price variation in the ICE Brent crude oil front-month futures (LCOc1), which is generally the benchmark global spot price quoted in financial news.

To study the effects of monetary policy on the global oil price, we estimate the following high-frequency event study regression for the ECB, the Federal Reserve, and the Bank of England separately:

$$p^{oil}_{i,t} = \alpha_i + \beta_i mps_{i,t} + \epsilon_{i,t} \quad i \in [EA, US, UK]. \tag{1}$$

$p^{oil}_{i,t}$ is the intraday percent variation in the Brent crude oil price (in US dollars) around the monetary policy announcement of country i on day t, and $mps_{i,t}$ represents the corresponding monetary policy surprise of country i. Sample for the euro area high-frequency event study regression starts from 2002 following the suggestions from Altavilla et al. (2019) and Andrade and Ferroni (2021) due to liquidity issues in the OIS during 1999-2001. We start the sample for the US regression in 1996 due to the availability of intraday Brent crude oil price data. The sample for the UK regression starts from June 1997 due to the availability of the UK monetary policy surprise series.

[5] Data sources are Gürkaynak et al. (2005), Altavilla et al. (2019), and Cesa-Bianchi et al. (2020). The choice of the interest rate maturity (three-month) is not only widely used in the literature (Jarociński and Karadi (2020), Cesa-Bianchi et al. (2020)) but also allows us to ensure comparability across countries, given data availability. Results are similar when using other maturities.

Table 1: Results of the event study regression for the euro area, US, and UK

	EA	US	UK
$\widehat{\beta}^{std}$	-0.056^{**}	-0.078^{**}	0.019
	(0.026)	(0.037)	(0.037)
Sample	2002:1-2019:12	1996:1-2019:12	1997:6-2019:12
N	182	198	246
R^2 (%)	3.37	2.64	0.38

Notes: Coefficient estimates $\widehat{\beta}^{std}$ measure the percentage change in the front month future of the Brent crude oil price following a 1 standard deviation increase in the country-specific monetary policy surprise. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** represent statistical significance levels at 10%, 5%, and 1%, respectively.

The intra-day responses of the Brent crude oil price to a one standard deviation – i.e., an average – contractionary monetary policy shock are presented in Table 1.[6] The results show that the Brent oil price declines immediately in response to an unexpected interest rate increase in both the euro area and the US, while it remains unaffected by a similar increase in the UK.[7]

This suggests that financial market participants update their expectations of the global oil market in light of surprise policy actions by the ECB and the Federal Reserve. In turn, this implies that, like the United States, the euro area functions as a large open economy in the global energy market. Such behavior is consistent with the fact that, for much of our sample period, the euro area was the world's largest oil importer —— surpassed only by China more recently (see Figure 1).

3 The empirical framework

The high-frequency event study shows that the ECB's monetary policy has an immediate and significant effect on global energy prices. Motivated by this evidence, the rest of the paper studies the dynamics of this relationship, allowing us to trace out the entire effect at

[6] Appendix B offers additional material and robustness along several dimensions such as sample period, instrument choice and choice of the energy price.

[7] Our findings for the US are similar to the results in the relevant literature that makes use of intraday data (Rosa (2014); Basistha and Kurov (2015)). However, there are two papers focusing on the euro area that have contradicting results to ours (Torro (2019); Soriano and Torró (2022)). These two papers do not control for central bank information effects, which is arguably a more prominent issue in the euro area rather than in the US (Jarociński and Karadi (2020)). Furthermore, Torro (2019) uses daily data against the recommendation of Rosa (2014) specific to crude oil prices.

a lower frequency. Therefore, this section presents our time series model of monetary policy and energy prices in the euro area. We first outline the general Bayesian proxy structural vector-autoregressive (BPSVAR) model framework of Arias et al. (2021) that allows us to identify dynamic causal effects with the use of instrumental variables. Next, we discuss our model specification and endogenous variables. Finally, we present our identifying assumptions in detail. Our empirical analysis in later sections requires the identification of up to two structural shocks simultaneously. Therefore, we discuss our approach to identifying both a single, as well as two shocks in the BPSVAR model. Note, however, that although the type and the number of structural shocks we identify vary according to the application, all shocks are identified in one consistent model with a constant set of endogenous variables.

3.1 Bayesian proxy SVAR model

We lay out the BPSVAR model for the general case with $k \geq 1$ proxy variables and k structural shocks of interest. Following the notation of Rubio-Ramirez et al. (2010), the structural VAR model with one lag and without deterministic terms can be written as:

$$\boldsymbol{y}_t' \boldsymbol{A}_0 = \boldsymbol{y}_{t-1}' \boldsymbol{A}_1 + \boldsymbol{\epsilon}_t', \qquad \boldsymbol{\epsilon} \sim N(\boldsymbol{0}, \boldsymbol{I}_n), \tag{2}$$

where $\boldsymbol{y}_t$ is an $n \times 1$ vector of endogenous variables and $\boldsymbol{\epsilon}_t$ an $n \times 1$ vector of structural shocks. The BPSVAR framework identifies k structural shocks of interest $\boldsymbol{\epsilon}_t^*$ using $k \times 1$ proxy variables $\boldsymbol{m}_t$ that are correlated with $\boldsymbol{\epsilon}_t^*$ and orthogonal to the remaining structural shocks $\boldsymbol{\epsilon}_t^o$:

$$E[\boldsymbol{\epsilon}_t^* \boldsymbol{m}_t'] = \underset{(k \times k)}{\boldsymbol{V}}, \tag{3a}$$

$$E[\boldsymbol{\epsilon}_t^o \boldsymbol{m}_t'] = \underset{((n-k) \times k)}{\boldsymbol{0}}, \tag{3b}$$

These represent the relevance and the exogeneity conditions, respectively.

We estimate the BPSVAR model using the algorithm developed in Arias et al. (2021). In this algorithm, the model in (2) is augmented by the equations for the proxy variables. More precisely, denote by $\tilde{\boldsymbol{y}}_t' \equiv (\boldsymbol{y}_t', \boldsymbol{m}_t')$, by $\tilde{\boldsymbol{A}}_\ell$ the corresponding $\tilde{n} \times \tilde{n}$ coefficient matrices with $\tilde{n} = n+k$, and by $\tilde{\boldsymbol{\epsilon}}' \equiv (\boldsymbol{\epsilon}_t', \boldsymbol{\eta}_t') \sim N(\boldsymbol{0}, \boldsymbol{I}_{n+k})$, where $\boldsymbol{\eta}_t$ is a $k \times 1$ vector of measurement errors. The augmented structural VAR model is then given by

$$\tilde{\boldsymbol{y}}_t' \tilde{\boldsymbol{A}}_0 = \tilde{\boldsymbol{y}}_{t-1}' \tilde{\boldsymbol{A}}_1 + \tilde{\boldsymbol{\epsilon}}_t'. \tag{4}$$

In the estimation of the model in (4), the algorithm by Arias et al. (2021) imposes the assumptions (3a) and (3b) to identify the structural shocks.

3.2 Data and model specification

Our baseline BPSVAR model for the euro area includes nine endogenous variables. Our starting point is a standard monetary model featuring the 1-year constant maturity yield on German Bunds as a monetary policy indicator, the industrial production index (excluding construction) as a measure of economic activity, the Harmonised Index of Consumer Prices (HICP) as a measure of the price level, and the BBB corporate bond spread to capture financial conditions (Gertler and Karadi (2015)). To this setup, we add the energy component of the HICP as a measure of energy prices in the euro area, the Brent crude oil price, and one-year-ahead inflation forecasts from Consensus Economics to capture inflation expectations. Since the euro area is a major energy importer, we also add the EUR-USD exchange rate, as oil and other energy commodities are generally traded in US dollars. Finally, we add the 5-year constant maturity yield on German Bunds since our analysis is going to include the identification of forward guidance shocks later on. The sources and more details on the data can be found in Appendix A.

The variables are measured in monthly frequency. Furthermore, all variables except interest rates and credit spreads enter the SVAR in log levels ($\times 100$), so that the impulse responses can be interpreted as percentage deviations. The BPSVAR model is estimated on a sample from January 2002 to December 2019. As in our high-frequency event study, we exclude the period $1999 - 2001$ due to liquidity issues in the OIS contracts, which, as discussed below, will serve as a proxy to identify monetary policy shocks. The model has 12 lags and includes a constant. We follow Arias et al. (2021) and use flat priors for estimating the BPSVAR parameters.[8]

3.3 Identifying assumptions

Our empirical strategy to identify structural shocks relies on an instrumental variables (or proxy) approach. Define matrices containing all 12 lags of the endogenous variables and the proxy as $\boldsymbol{Y}'_{t-1} = (\boldsymbol{y}'_{t-1}, \ldots, \boldsymbol{y}'_{t-12})$ and $\boldsymbol{M}'_{t-1} = (m_{t-1}, \ldots, m_{t-12})$. For the identification of a single structural shock with a single proxy, we can derive the Equation governing the (scalar) proxy variable from Equation (4):[9]

$$m_t = (\boldsymbol{Y}'_{t-1}, \boldsymbol{M}'_{t-1})\boldsymbol{b} + v_{1,1}\epsilon^*_t + c\eta_t, \tag{5}$$

[8]As in Born and Pfeifer (2021) and many other studies, we impose the dogmatic prior that the SVAR is stable, implying that, after being hit by an exogenous shock, the endogenous variables eventually converge back to their steady state. In addition, a relevance threshold is imposed to express the prior belief that the proxy is informative to identify monetary policy shocks. In particular, we assume that the identified structural monetary policy shocks account for at least 10% of the variance in the proxy. This is a weak requirement compared to the 20% threshold of Arias et al. (2021) and the 'high-relevance' prior of Caldara and Herbst (2019). As shown in Figure E.5 in the Appendix, our results are robust to reducing the relevance condition to 0 and increasing it to 20%.

[9]See Appendix D for details.

where $v_{1,1} \neq 0$ by the relevance condition (3a). All remaining structural shocks, $\boldsymbol{\epsilon}_t^o$, are unrelated to m_t by means of the exogeneity condition (3b). Note that relative to the standard frequentist external instrument procedure as in Mertens and Ravn (2013), Equation (5) illustrates that here the proxy variable is allowed to be serially correlated, predictable, and affected by measurement error.

For the case of identifying two shocks with two proxies, define the structural shocks as $\boldsymbol{\epsilon}_t^* \equiv (\epsilon_{1,t}^*, \epsilon_{2,t}^*)'$. In this case, we need additional identifying assumptions. Specifically, we rely on relatively weak magnitude restrictions to obtain set-identification, thereby circumventing recursive ordering as in Mertens and Ravn (2013). The identifying assumptions in the two-shock scenario are then given by:

$$m_{1,t} = (\boldsymbol{Y}_{t-1}', \boldsymbol{M}_{t-1}')\boldsymbol{b}_1 + v_{1,1}\epsilon_{1,t}^* + v_{1,2}\epsilon_{2,t}^* + \boldsymbol{\eta}_t'\boldsymbol{c}_1, \tag{6}$$

$$m_{2,t} = (\boldsymbol{Y}_{t-1}', \boldsymbol{M}_{t-1}')\boldsymbol{b}_2 + v_{2,1}\epsilon_{1,t}^* + v_{2,2}\epsilon_{2,t}^* + \boldsymbol{\eta}_t'\boldsymbol{c}_2, \tag{7}$$

$$|v_{1,1}| > |v_{1,2}|, \quad |v_{2,2}| > |v_{2,1}|. \tag{8}$$

For example, we later identify a conventional monetary policy shock and a forward guidance shock with high-frequency surprises in short- and long-maturity OIS contracts, assuming each proxy loads more strongly on its corresponding shock.

Relative to the standard frequentist two-step estimation, the algorithm and the Bayesian approach, in general, have the following advantages. First, we refrain from imposing potentially contentious recursiveness assumptions between the endogenous variables when multiple structural shocks are identified. Second, the single-step estimation of the BPSVAR model is more efficient than the standard two-stage least squares estimation of proxy SVAR and facilitates coherent inference. In fact, the Bayesian set-up allows exact finite sample inference and does not require an explicit theory to accommodate potentially weak instruments. Third, the BPSVAR framework allows the proxy variables to be serially correlated, predictable, and affected by measurement error. Lastly, Bayesian inference is particularly convenient in the presence of set identification, which arises in our applications with two proxies.[10]

[10]We fully acknowledge the concerns that in the case of set identification, our uniform prior for the rotation matrix, which is embedded in the approach of Arias et al. (2021), may even asymptotically influence our results as forcefully raised by Baumeister and Hamilton (2019) and Giacomini and Kitagawa (2021). But recent contributions by Inoue and Kilian (2021) and Arias et al. (2025) called into question the empirical relevance of this concern in applied research with tightly identified sets as is the case in our applications. Therefore we conduct standard Bayesian inference along the lines of Rubio-Ramirez et al. (2010) and the subsequent literature.

4 Monetary policy and energy prices: SVAR evidence

The event study in Section 2 demonstrated that the ECB's policy decisions impact energy prices at high frequency. We now investigate whether this effect also materializes at a monthly frequency and how it influences the economy using high-frequency changes in interest rate futures around monetary policy announcements for identification of monetary policy shocks (similarly to Gertler and Karadi (2015); Jarociński and Karadi (2020); Miranda-Agrippino and Ricco (2021)).

4.1 Dynamic response to monetary policy shock

We construct the monetary policy shock in three steps. First, we compute the first principal component of OIS surprises from the Altavilla et al. (2019) dataset with maturities from one month up to one year. This "generic" monetary policy shock (Nakamura and Steinsson (2018); Bauer and Swanson (2023)) has the advantage that it captures a combination of conventional monetary policy surprises and forward guidance surprises, and it does not depend on one specific maturity. Second, we purge the resulting surprise series from central bank information effects (see Section 2). Third, we employ the approach proposed by Kilian (2024) to aggregate the surprises to monthly frequency. We denote this proxy by $m^{MP}_{t,PC1}$. It enters the framework in Section 3 Equation (5) in the following way: $m_t \equiv m^{MP}_{t,PC1}$ with $\epsilon^*_t \equiv \epsilon^{MP}_{t,generic}$ as the corresponding structural shock. The shock represents a linear combination of monetary policy shocks at different maturities, which, in combination, move the term structure of interest rates (Inoue and Rossi (2021) and McKay and Wolf (2023)).

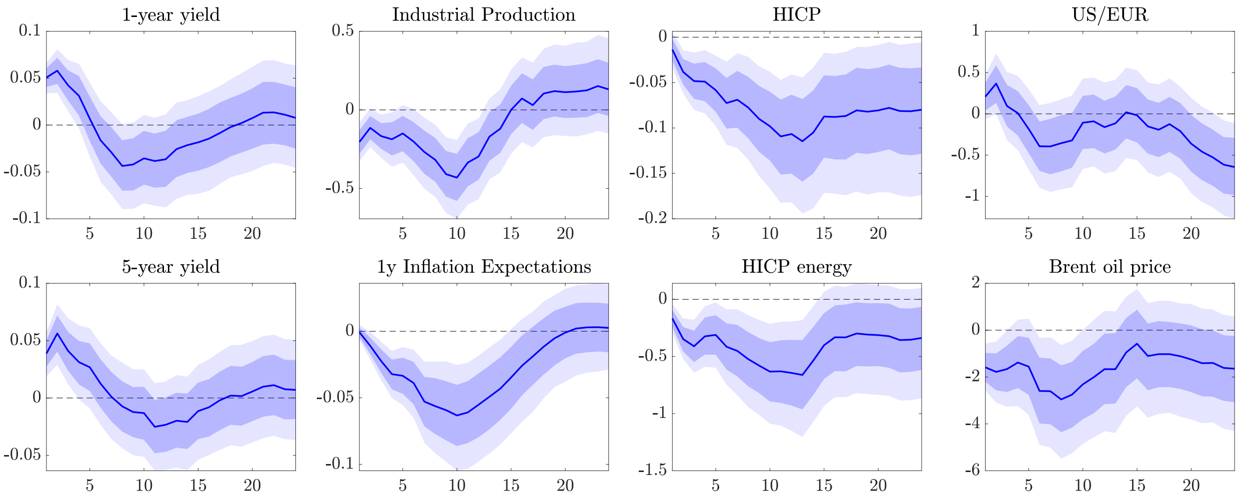
Figure 2 shows the impulse responses to a one standard deviation contractionary monetary policy shock. Both the 1-year and 5-year Bund yields increase by approximately 5 basis points on impact before reverting to zero. Industrial production experiences a slight decline initially, reaching its lowest point after 10 months. Similarly, the domestic headline consumer price index quickly declines, dropping by about 0.12% after a year and remaining depressed. Concurrently, the euro appreciates against the dollar by just under 0.4% in the short term, financial conditions tighten, and inflation expectations decline significantly and persistently. Overall, the estimated dynamics for the endogenous variables align with standard theory and previous findings in the literature.

The main result of this section is the substantial decline in global crude oil prices and the energy prices faced by euro area consumers (HICP energy). The oil price drops sharply on impact and remains subdued for over a year, with a trough response of -3%.[11] Additionally, the HICP energy price index falls by 0.65%, a much larger decline than that

[11] The oil price response in the high-frequency event study differs from the impact response in the monthly BPSVAR. This reflects that the event study isolates the immediate, intra-day reaction to a monetary policy surprise. Since macroeconomic responses are typically hump-shaped, the peak effect on oil prices may materialize only gradually.

observed in the overall HICP basket. Given that energy prices constitute about 10% of the overall HICP basket, a back-of-the-envelope calculation suggests that the majority of the decline in the overall HICP in the short- and medium-term can be attributed to the contractionary monetary policy shock's effect on oil prices and, subsequently, energy prices in the euro area.

Figure 2: Transmission of a generic EA monetary policy shock



Notes: Impulse responses to a one standard deviation monetary policy shock. Point-wise posterior means along with 68% and 90% point-wise credible sets. Horizon in months. Impulse responses for variables that do not correspond to interest rates or inflation rates are expressed in percent. Impulse responses for inflation rates and interest rates are expressed in annualized percentage points. Response of the credit spread is omitted to save space (see Figure E.1).

Importantly, our finding that energy prices adjust more rapidly and significantly than other goods is supported by the micro-data literature on price changes. For instance, Aucremanne and Dhyne (2004) analyze the micro-data used to compute the Belgian HICP and find that the average price duration for energy goods is approximately one month. This contrasts sharply with the median price duration of all goods in the basket, which is around 14 months. From the perspective of a standard New-Keynesian Model, this implies that, all else being equal, the Phillips curve for energy goods is steeper compared to that for the average consumer good. Consistent with this theoretical intuition, energy-intensive subcomponents of the HICP all exhibit a significant decline in their prices (see Figure E.8 in the Appendix). Among these, the consumer prices of fuels, which are more flexible, contract the most.

Discussion of the results The pronounced decline in the Brent crude oil price is consistent with the low short-run elasticity of substitution for energy goods and the near-vertical short-run supply curve for energy: for a given policy-induced contraction in demand, the price must fall sharply to clear the energy market. In Appendix F, we formalize this mechanism and verify it in the Bayer et al. (2023) general equilibrium model, which generates an oil price decline of similar magnitude to our baseline estimate. Moreover, we show that, when measured in terms of standard deviations, a 2% surprise fall in the oil price is less rare than a 5 basis point unanticipated increase in the one-year yield, consistent with the well-known high volatility of energy prices (Figure F.2).

Furthermore, the implied industrial production elasticity to a 100 basis point increase in the one-year yield is larger than typically found in proxy-SVAR studies of monetary policy (Miranda-Agrippino and Ricco (2021); Bauer and Swanson (2023)). These estimates generally are based on US data, with samples beginning in the early 1970s. However, as we extensively show in Table E.1 in Appendix E, once differences in sample periods are accounted for, our estimate aligns closely with existing evidence for the US, the UK, and the euro area. A larger industrial production elasticity to exogenous interest rate changes also appears to be a feature of modern high-frequency identification, particularly in the euro area.

4.2 Transmission channels

To shed further light on the transmission mechanisms through which ECB policy influences global oil prices, we augment the baseline VAR one-by-one with variables capturing potential channels. We consider the oil market as a standard demand–supply equilibrium with flexible prices (Kilian (2009); Bodenstein et al. (2012)). Therefore, to affect the oil price, monetary policy has to either shift global oil demand or global oil supply. [12]

Four channels emerge from the literature. First, a higher interest rate directly reduces domestic energy demand (Auclert et al., 2023). Given that the euro area accounts for $\approx$ 23% share of global energy imports (Figure 1), this contraction in euro area demand for energy goods has sizable global effects (Panel 1 of Figure 3). Second, a euro area monetary tightening also implies global spillovers to other countries (Corsetti et al., 2024). In particular, we document that global industrial production and thus demand for oil falls significantly after an ECB monetary tightening, implying a further fall in global energy demand (see Panel 2 of Figure 3).[13] Third, tighter financial conditions raise risk premia

[12]For instance, in Appendix F.3 we show that, under standard assumptions regarding the functional form of the demand and supply curve and given market-clearing, the equilibrium price of a generic energy good is (up to first order) given by

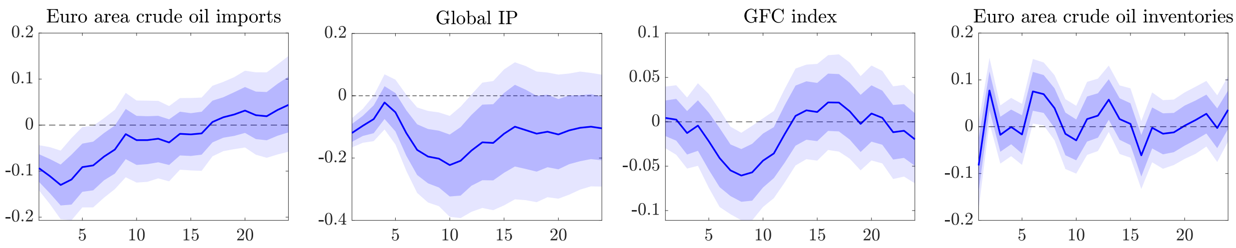
$$\widehat{p}^{E}_{t,r} = \frac{1}{\sigma + \varphi_s} \widehat{y}^{W}_t . \tag{9}$$

where $\widehat{p}^{E}_{t,r}$ are deviations of the (real) energy price, σ corresponds to the demand elasticity of substitution and φ the supply elasticity of production. $\widehat{y}^{W}_t$ corresponds to deviations of global aggregate spending. Thus, to rationalize the observed movement in the oil price, the ECB would need to be able to affect $\widehat{y}^{W}_t$, with the size of the oil price effect being inversely related to the elasticities of demand and production.

[13]A back of the envelope calculation using the share of the euro area in global GDP (see Figure 1) implies that the observed fall in global industrial production is not only due to the fall in euro area industrial

(Miranda-Agrippino and Rey, 2020) and curb speculative oil demand (Hamilton and Wu, 2014). We, in fact, find that risk appetite decreases, potentially further reducing demand for risky assets such as oil futures (see Panel 3 of Figure 3). Fourth, higher interest rates increase the cost of carry and storage costs, reducing inventory holdings and thus oil demand (Frankel, 2014). We do not find conclusive evidence for this channel (see Panel 4 of Figure 3).

Figure 3: Inspecting the transmission channels of a euro area monetary tightening



Notes: Impulse responses to a one standard deviation monetary policy shock. Point-wise posterior means along with 68% and 90% point-wise credible sets. Horizon in months. The variables were included in the baseline BPSVAR one by one. See notes to Figure 2 for scaling of variables.

All four channels shift oil demand downward in response to higher interest rates. To rule out supply effects, Appendix Figure E.2 shows global oil production slightly contracts, confirming the oil price decline reflects reduced demand rather than increased supply. While Figure 3 provides suggestive evidence for all four channels, we do not quantify their relative contributions—nor need we do so. For our counterfactual analysis, it suffices that ECB policy lowers oil prices through general equilibrium effects, regardless of the specific channel.

4.3 Robustness of the results

Our baseline results are robust to a wide range of alternative specifications, as detailed in Appendix E. To address concerns about the relevant information set for the global oil market (Baumeister and Hamilton, 2019), we augment the model with global oil production, global industrial production, and crude oil inventories. The resulting impulse responses remain essentially unchanged (Figure E.2). As the BPSVAR identification relies on (partial) invertibility, we additionally report impulse responses based on the internal instrument approach of Plagborg-Møller and Wolf (2021), which is robust to non-invertibility. These estimates are very similar to our baseline results (Figure E.3).

We further show that gas prices decline markedly following a monetary policy shock, indicating that our use of Brent oil prices as the baseline measure of global energy prices

production documented in Figure 2.

does not drive the results (Figure E.4). The findings are also robust to removing the prior on proxy relevance (Figure E.5) and to incorporating the pandemic (Figure E.6). Finally, following Bauer and Swanson (2023), we purge high-frequency monetary policy surprises of any predictability from Brent oil prices. We find no statistically meaningful predictability, and our baseline results remain unchanged when using the purged series (Figure E.7).

5 The role of energy prices in monetary transmission

The impulse response functions from Section 4 suggest that energy prices play an important role in the monetary transmission mechanism. We now conduct an empirical counterfactual where global oil prices do not to respond to ECB monetary policy shocks. We first outline the general framework, then identify the required structural shocks to implement the counterfactual methodology, and lastly examine the counterfactual transmission of monetary policy and its inflation-output trade-off.

5.1 Structural policy counterfactuals: the MW-framework

McKay and Wolf (2023, henceforth MW) show how to construct Lucas Critique-robust counterfactual impulse response functions by combining the impulse response function to the structural shock of interest —estimated under the baseline policy rule— with a particular sequence of impulse responses to policy (news) shocks.

Formally, MW consider a linear, perfect-foresight, infinite-horizon economy in terms of deviations from the deterministic steady state for periods $t = 0, 1, 2, \dots$. In sequence-space notation, this economy can be described by a set of equations

$$\boldsymbol{\mathcal{H}}_x \boldsymbol{x} + \boldsymbol{\mathcal{H}}_z \boldsymbol{z} + \boldsymbol{\mathcal{H}}_\epsilon \boldsymbol{\epsilon} = \boldsymbol{0}, \tag{10}$$

$$\boldsymbol{\mathcal{A}}_x \boldsymbol{x} + \boldsymbol{\mathcal{A}}_z \boldsymbol{z} + \boldsymbol{\nu} = \boldsymbol{0}, \tag{11}$$

where $\boldsymbol{x} \equiv (\boldsymbol{x}_1', \boldsymbol{x}_2', \dots, \boldsymbol{x}_{n_x}')'$ stacks the time paths of the n_x endogenous variables over n_h periods, analogously $\boldsymbol{z}$ stacks the time path of the n_z policy instruments. The matrices $\boldsymbol{\mathcal{H}}$ summarize the behavior of agents in the non-policy block, while the matrices $\boldsymbol{\mathcal{A}}$ describe the baseline policy rule of interest. $\boldsymbol{\epsilon}$ represents the n_ϵ non-policy structural shocks and $\boldsymbol{\nu}$ the n_ν policy (news) shocks; the latter are deviations from the policy rule announced at date t but implemented only in some future period $t + i$, $i \geq 0$. The key assumption reflected in Equations (10) and (11) is that $\{\boldsymbol{\mathcal{H}}_x, \boldsymbol{\mathcal{H}}_z, \boldsymbol{\mathcal{H}}_\epsilon\}$ do not depend on the coefficients of the policy rule $\{\boldsymbol{\mathcal{A}}_x, \boldsymbol{\mathcal{A}}_z\}$, implying that private agents respond to the expected path of $\boldsymbol{z}$, not the rule itself.

Under the assumption that the solution exists and is unique, the solution to Equations

(10) and (11) can be written in impulse response space as

$$\begin{pmatrix} \boldsymbol{x} \\ \boldsymbol{z} \end{pmatrix} = \boldsymbol{\Theta}_{\mathcal{A}} \times \begin{pmatrix} \boldsymbol{\epsilon} \\ \boldsymbol{\nu} \end{pmatrix}, \quad \boldsymbol{\Theta}_{\mathcal{A}} \equiv (\boldsymbol{\Theta}_{\epsilon,\mathcal{A}}, \boldsymbol{\Theta}_{\nu,\mathcal{A}}) \equiv \begin{pmatrix} \boldsymbol{\Theta}_{x,\epsilon,\mathcal{A}} & \boldsymbol{\Theta}_{x,\nu,\mathcal{A}} \\ \boldsymbol{\Theta}_{z,\epsilon,\mathcal{A}} & \boldsymbol{\Theta}_{z,\nu,\mathcal{A}} \end{pmatrix}. \tag{12}$$

where $\boldsymbol{\Theta}_{\mathcal{A}}$ collects the impulse responses of the policy instrument $\boldsymbol{z}$ and the non-policy variables $\boldsymbol{x}$ under the baseline policy rule summarized by $\boldsymbol{\mathcal{A}}$.

In the counterfactual analysis below, we study impulse responses to a non-policy shock ϵ under a counterfactual policy rule $\{\tilde{\boldsymbol{\mathcal{A}}}_x, \tilde{\boldsymbol{\mathcal{A}}}_z\}$:

$$\tilde{\boldsymbol{\mathcal{A}}}_x \boldsymbol{x} + \tilde{\boldsymbol{\mathcal{A}}}_z \boldsymbol{z} = \mathbf{0}. \tag{13}$$

where $\tilde{\boldsymbol{\mathcal{A}}}_x$ and $\tilde{\boldsymbol{\mathcal{A}}}_z$ contain the corresponding coefficients of the counterfactual rule. MW show that the baseline impulse responses $\boldsymbol{\Theta}_{\mathcal{A}}$ are sufficient to recover the counterfactual impulse responses under any alternative policy rule, without knowing the true underlying structural model. Specifically:

$$\boldsymbol{x}_{\tilde{\mathcal{A}}}(\boldsymbol{\epsilon}) = \boldsymbol{\Theta}_{x,\epsilon,\mathcal{A}} \times \boldsymbol{\epsilon} + \boldsymbol{\Theta}_{x,\nu,\mathcal{A}} \times \widetilde{\boldsymbol{\nu}}, \qquad \boldsymbol{z}_{\tilde{\mathcal{A}}}(\boldsymbol{\epsilon}) = \boldsymbol{\Theta}_{z,\epsilon,\mathcal{A}} \times \boldsymbol{\epsilon} + \boldsymbol{\Theta}_{z,\nu,\mathcal{A}} \times \widetilde{\boldsymbol{\nu}} \tag{14}$$

where $\widetilde{\boldsymbol{\nu}}$ are a sequence of policy news shocks chosen such that the counterfactual policy rule holds:

$$\tilde{\boldsymbol{\mathcal{A}}}_x \left[\boldsymbol{\Theta}_{x,\epsilon,\mathcal{A}} \times \boldsymbol{\epsilon} + \boldsymbol{\Theta}_{x,\nu,\mathcal{A}} \times \widetilde{\boldsymbol{\nu}}\right] + \tilde{\boldsymbol{\mathcal{A}}}_z \left[\boldsymbol{\Theta}_{z,\epsilon,\mathcal{A}} \times \boldsymbol{\epsilon} + \boldsymbol{\Theta}_{z,\nu,\mathcal{A}} \times \widetilde{\boldsymbol{\nu}}\right] = \mathbf{0}. \tag{15}$$

Intuitively, as long as agents respond to the expected path of the policy instrument rather than the rule itself, it does not matter whether this path arises from systematic policy or from news shocks.

In practice, impulse responses to the full set of shocks $\boldsymbol{\nu}$ are not available. MW show that a small identified subset $\boldsymbol{s} \subseteq \boldsymbol{\nu}$ suffices, as long as each shock implies a different future path of the policy instrument. In particular, the (counterfactual) realizations of those shocks $\widetilde{\boldsymbol{s}}$ solve:

$$\min_{\widetilde{\boldsymbol{s}}} \ ||\tilde{\boldsymbol{\mathcal{A}}}_x \left[\boldsymbol{\Theta}_{x,\epsilon,\mathcal{A}} \times \boldsymbol{\epsilon} + \boldsymbol{\Theta}_{x,s,\mathcal{A}} \times \widetilde{\boldsymbol{s}}\,\right] + \tilde{\boldsymbol{\mathcal{A}}}_z \left[\boldsymbol{\Theta}_{z,\epsilon,\mathcal{A}} \times \boldsymbol{\epsilon} + \boldsymbol{\Theta}_{z,s,\mathcal{A}} \times \widetilde{\boldsymbol{s}}\,\right]||, \tag{16}$$

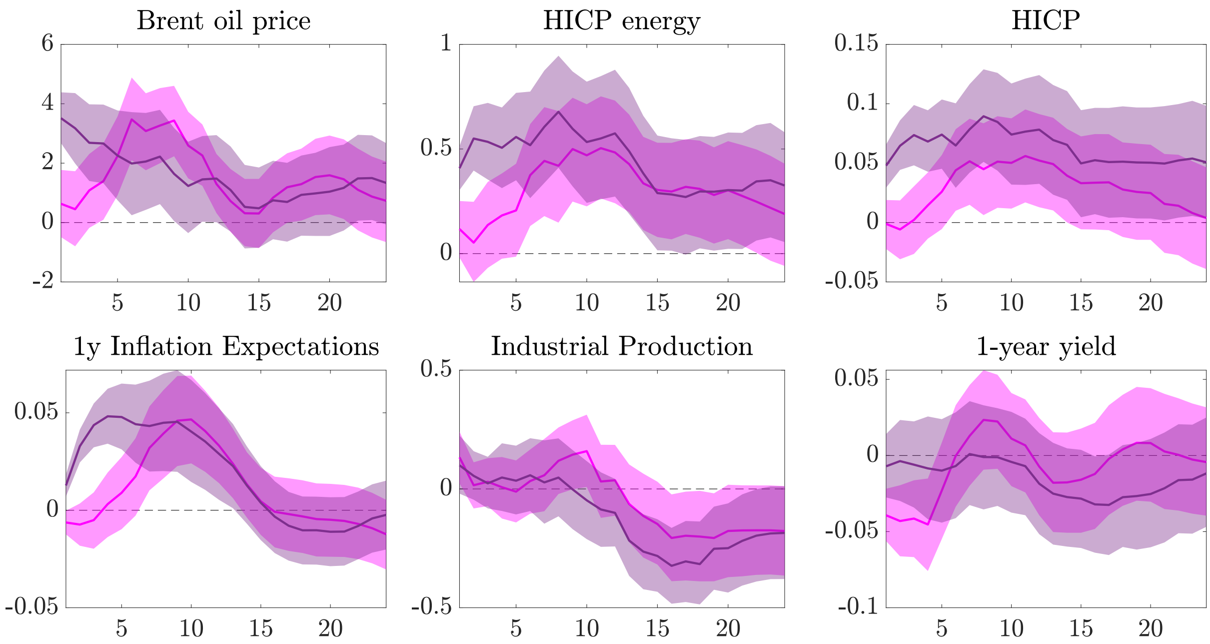
delivering a reliable "best Lucas-critique-robust approximation".[14]

[14] We compute this solution as follows: We first stack the system in Equation (15) across all the responses of all the $n = n_x + n_z$ endogenous variables $\boldsymbol{x}$ and the policy instrument $\boldsymbol{z}$ in Equation (15) and all horizons $n_H = n \times n_h$ in order to arrive at $\tilde{\boldsymbol{\mathcal{A}}}\boldsymbol{\Theta}_{\epsilon,A} \times \boldsymbol{\epsilon} + \tilde{\boldsymbol{\mathcal{A}}}\boldsymbol{\Theta}_{\nu,\mathcal{A}} \times \widetilde{\boldsymbol{\nu}} = 0$. Then we collect all impulse response functions to the n_s identified policy (news) shocks in $\boldsymbol{\Theta}_{s\mathcal{A}}$, and build $\boldsymbol{\Theta}_{\nu,\mathcal{A}} = [\boldsymbol{\Theta}_{s,\mathcal{A}}, \mathbf{0}_{(n \times n_h) \times (n_h - n_s)})]$. We then solve for the subset of shocks as $\widetilde{\boldsymbol{s}}$ as the non-zero entries in $\widetilde{\boldsymbol{\nu}} = \left(\tilde{\boldsymbol{\mathcal{A}}}\boldsymbol{\Theta}_{\nu,\mathcal{A}}\right)^{\star} \tilde{\boldsymbol{\mathcal{A}}}\boldsymbol{\Theta}_{A,\epsilon} \times \boldsymbol{\epsilon}$ with $\left(\tilde{\boldsymbol{\mathcal{A}}}\boldsymbol{\Theta}_{\nu,\mathcal{A}}\right)^{\star}$ as the Moore-Penrose inverse of $\tilde{\boldsymbol{\mathcal{A}}}\boldsymbol{\Theta}_{\nu,\mathcal{A}}$.

5.2 Identifying two oil supply shocks

To estimate $\mathbf{\Theta}_{z,s,\mathcal{A}}$ and $\mathbf{\Theta}_{x,s,\mathcal{A}}$, we identify OPEC-related oil supply news shocks using the proxy variables of Känzig (2021), which capture high-frequency changes of oil price futures around OPEC meetings. To improve the approximation accuracy of Equation (16), we depart from Känzig (2021), who use only the first principal component of futures price changes across maturities to identify a single oil supply news shock. Instead, we use high-frequency changes in the 3-month ($m^{oil}_{t,3m}$) and 24-month ($m^{oil}_{t,24m}$) futures to identify short-term ($\nu^{oil}_{t,short}$) and medium-term ($\nu^{oil}_{t,medium}$) oil supply news shocks. Both proxies are aggregated to monthly frequency following Kilian (2024) and purged of oil demand shocks following Degasperi (2023). In the context of our general identifying assumptions framework in Equation (6), this implies that we set $\boldsymbol{\epsilon}^*_t \equiv (\epsilon^*_{1,t}, \epsilon^*_{2,t})' = (\nu^{oil}_{t,short}, \nu^{oil}_{t,medium})'$ and $\boldsymbol{m}_t \equiv (m_{1,t}, m_{2,t})' = (m^{oil}_{t,3m}, m^{oil}_{t,24m})'$.

Figure 4: Transmission of short-run (purple) and medium-run (magenta) oil supply news shocks



Notes: Impulse responses to the short-term oil supply news shock and corresponding 68% credible sets in magenta. Impulse responses to the medium-term oil supply news shock and term 68% credible sets in purple. Horizon in months. We normalize the short-term (medium-term) oil supply news shock to increase the oil price on impact (after twelve months). Responses of the credit spread, exchange rate, and 5-year government bond yield are omitted to save space. See notes to Figure 2 for scaling of variables.

Figure 4 shows the impulse responses to these two oil supply news shocks.[15] Both shocks raise oil prices persistently, pass through to euro area consumer energy prices, and generate

[15]To maximize the number of observations, we start the estimation in 1999, as the proxies proposed in Känzig (2021) do not suffer from the liquidity issues affecting OIS contracts used to compute high-frequency monetary policy surprises in the early years of the euro area.

a significant rise in HICP and a delayed contraction in industrial production. The short-term oil supply shock produces a strong and immediate response in oil prices and most endogenous variables, while the medium-term shock generates more delayed, yet equally persistent, effects on oil prices and the broader economy. Together, these two shocks span a richer set of future oil price paths than a single shock, improving the counterfactual approximation in Section 5.3.

5.3 What if OPEC stabilizes the oil price?

We now construct a counterfactual in which the ECB cannot influence the global oil price in order to study the role of energy prices in euro area monetary transmission. Specifically, we consider a scenario in which OPEC stabilizes the oil price at its steady-state level by adjusting supply accordingly, i.e. $E_t[\widehat{p}^{oil}_{t+s}] = 0 \, \forall t, s \geq 0$.[16]

Under this rule, $\tilde{\boldsymbol{\mathcal{A}}}$ becomes a selection matrix that selects the entries in $\boldsymbol{\Theta}_{\epsilon,A}$ and $\boldsymbol{\Theta}_{\nu,A}$ corresponding to the oil price. We combine the estimated impulse responses to a generic monetary policy shock (Figure 2) and the two oil supply news shocks (Figure 4) to approximate the counterfactual impulse responses to a one standard deviation monetary policy shock in a scenario where OPEC stabilizes the oil price.[17]

The results are shown in Figure 5. In the counterfactual scenario (depicted as gold impulse responses), the muted oil price response leads to a substantially smaller reaction of euro area consumer energy prices, headline inflation, and inflation expectations — the transmission of monetary policy to consumer prices is more than halved. Conversely, industrial production declines more than in the baseline, as the fall in the oil price no longer plays a stabilizing role. This points to the smaller inflation response in the counterfactual being driven by the ECB's inability to influence global oil prices, rather than by changes in the prices of domestically produced goods.[18]

Lastly, note that, to the extent that a structural model such as the one discussed in F.2 matches our empirical impulse responses, the counterfactual result obtained by changing the energy supply side rule would yield identical counterfactual results (see Caravello et al. (2023) for a discussion).

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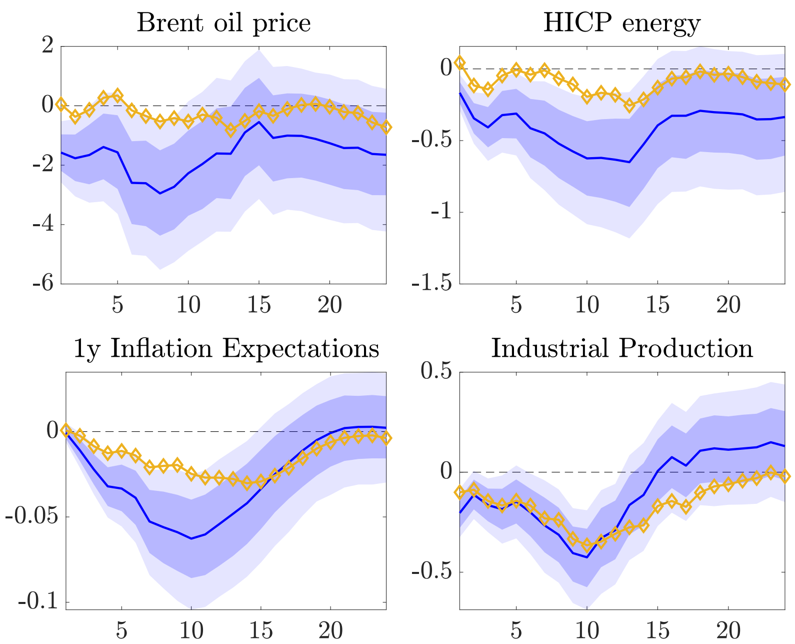
[16] It is important to note that the existence of such a policy rule for OPEC is not a new assumption in the literature. As already discussed by Leeper et al. (1996), the assumption that OPEC-related shocks, such as those identified for instance by Känzig (2021), exist is equivalent to the assumption that there is a policy rule that characterizes the systematic part of the corresponding equation (see Caldara and Herbst (2019) for a discussion).

[17] This implies that we condition on the point-estimates in Figure 2, which is consistent with standard practice in the policy counterfactual literature, which tends to take initial point estimates as given (see, e.g., Rotemberg and Woodford (1997), Eberly et al. (2020), Wolf (2023), McKay and Wolf (2023)). Given the results in Plagborg-Møller and Wolf (2021), we could equivalently run local projections for each identified shock and then combine these as done in Broer et al. (2024).

[18] Note that, in response to a one standard deviation shock, the one-year yield rises less than in the baseline because the transmission of the shock and the endogenous policy response differ in the counterfactual economy.

Figure 5: Monetary transmission if EA MP can (blue) and cannot (gold) affect oil prices



Notes: Impulse response functions to a one standard deviation monetary policy shock showing the point-wise posterior means along with 68% point-wise credible sets in blue. Horizon in months. The golden line with diamonds shows the point-wise posterior means of the counterfactual where EA monetary policy does not affect the oil price. We approximate the solution to the counterfactual using the "best Lucas-Critique-robust approximation" of McKay and Wolf (2023) (see Equation (16)), where we follow McKay and Wolf (2023) and condition on the point estimate to the monetary policy shock depicted in Figure 2. We report corresponding credible sets in Figure G.1 of the Appendix. Responses of the credit spread, exchange rate, and 5-year government bond yield are omitted to save space. See notes to Figure 2 for scaling of variables.

5.4 Energy prices and the inflation–output trade-off

To quantify how the ability to move energy prices affects the inflation–output trade-off, we follow a strategy very much akin to the non-parametric "Phillips-Multiplier" approach of Barnichon and Mesters (2021). In particular, we define the " Output-Phillips-Multiplier " as

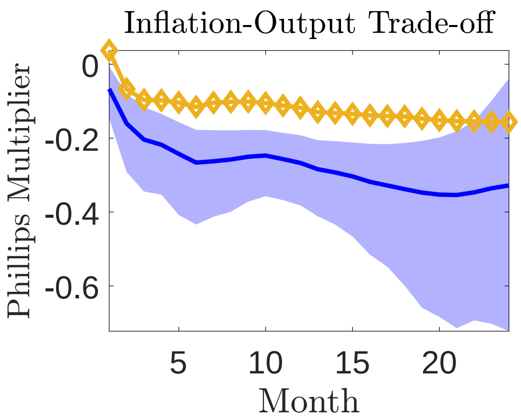
$$\mathcal{P}^h = -\frac{\Theta^h_{\bar{\pi},\nu^{mp}}}{\Theta^h_{\bar{\mathcal{Y}},\nu^{mp}}}, \tag{17}$$

where $\Theta^h_{\bar{\mathcal{Y}},\nu^{mp}}$ ($\Theta^h_{\bar{\pi},\nu^{mp}}$) is the horizon h impulse response of the average of industrial production (consumer price inflation) to a monetary policy shock ν^{mp}. The statistic measures the average disinflation achieved by engineering a 1% decline in industrial production over the next h periods (see Appendix G.1 for details). It can thus be considered a non-parametric estimate of the (inverse) sacrifice ratio (see Ball (1994) for a definition). We compute $\mathcal{P}^h$

for the baseline and the counterfactual scenario of Section 5.3.

The results from this exercise are shown in Figure 6. The ability to influence global energy prices substantially alleviates the inflation-output trade-off. Under the baseline, engineering a 1% decline in industrial production over the next year reduces average inflation by 0.27%. In the counterfactual, the same output cost yields only a 0.12% reduction in average inflation — meaning the ECB's leverage over energy prices alleviates the inflation–output trade-off by approximately 55%.

Figure 6: Inflation-Output Trade-off if EA MP can (blue) and cannot (gold) affect oil prices



Notes: Point-wise median of the Output-Phillips-Multiplier in blue (see Equation (17)). Counterfactual Output-Phillips-Multiplier under the assumption that EA monetary policy does not affect energy prices is depicted in gold. We compute the IRFs of year-on-year inflation by transforming the impulse responses of the HICP accordingly. We only plot 68% credible sets to not distort the scale of the figure as the posterior distribution is very much skewed to the left.

Barnichon and Mesters (2021) demonstrates that if the true underlying model were characterized by a New-Keynesian Phillips Curve, this method would recover (the negative of) its slope with respect to industrial production. Thus, when viewed through the lens of this model, our estimates suggest that this slope is much steeper when monetary policy can affect energy prices. Intuitively, and consistent with the microdata and the intuition outlined above, energy prices are updated much more frequently than other goods, which implies that the slope of the aggregate Phillips curve is steeper when monetary policy affects these goods. This echoes the results in the theoretical analyses of Aoki (2001) and Guerrieri et al. (2025), who show that the slope of the aggregate consumer price Phillips curve depends on the ability to affect (flexible) energy prices.

6 Implications for the optimal policy response to supply shocks

The inflation-output trade-off faced by a central bank is particularly important when monetary policy faces a supply-side shock (Woodford (2003), Blanchard and Galí (2007), Galí (2015), Fornaro and Wolf (2023)). Our findings show that the ECB's ability to influence energy prices is a critical factor shaping this trade-off. To illustrate the significance of this result, we examine its implications for the mandate-optimal conduct of monetary policy. Specifically, we focus on a scenario in which the euro area faces an exogenous, supply-driven increase in oil prices. In this context, we consider two types of policy mandates: one focused solely on medium-term inflation stabilization, and another that targets the joint stabilization of both inflation and output. In both cases, we demonstrate how the ECB's mandate-optimal response depends on its capacity to affect global energy prices. Following MW, we approach this question empirically.

6.1 Computing optimal policy counterfactuals

In this section, we outline the setup for computing the mandate-optimal policy responses to an exogenous shock. After setting up the framework, we discuss how we specify the ECB's loss function, and identify the supply shock and two monetary policy shocks.

The framework. The approach of McKay and Wolf (2023) to estimating policy-rule counterfactuals, introduced in Section 5.1, extends naturally to the computation of impulse responses under mandate-optimal policy. Specifically, in line with Barnichon and Mesters (2023), MW define the optimal policy response as the one that implements an allocation allowing the policymaker to optimally achieve its mandate. More precisely, we follow Barnichon and Mesters (2023) and McKay and Wolf (2022) and assume that the central bank minimizes the quadratic loss function of the form

$$\mathcal{L} = \frac{1}{2}\sum_{i=1}^{n_x} \lambda_i \boldsymbol{x}_i' W \boldsymbol{x}_i' = \frac{1}{2}\boldsymbol{x}'(\Lambda \otimes W)\boldsymbol{x} \tag{18}$$

where $\boldsymbol{x}_i$ represents the time path of the endogenous variable i, λ_i describes the policy weights attached to that variable with $\Lambda = diag(\lambda_1, \lambda_2 .... \lambda_{n_x})$, and W summarizes time discounting in the policymaker's preferences, parameterized by a single discount factor β.

MW show that this problem can be stated in impulse-response space: the implementable space of allocations for $\boldsymbol{x}$ and the policy instrument z is fully characterized by the impulse responses $\Theta_{\nu,A}$ to the sequence of policy shocks ν:

$$\begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{z} \end{bmatrix} = \Theta_{\nu,\mathcal{A}} \times \boldsymbol{\nu}. \tag{19}$$

Minimizing the loss function Equation (18) subject to Equation (12) yields the following optimality condition (see Appendix H.1):

$$\begin{aligned} \mathcal{A}^{\star}_{\boldsymbol{x}} &= (\lambda_1 \Theta'_{x_1,\nu,\mathcal{A}} W, \lambda_2 \Theta'_{x_2,\nu,\mathcal{A}} W, \ldots, \lambda_{n_x} \Theta'_{x_{n_x},\nu,\mathcal{A}} W), \\ \mathcal{A}^{*}_{\boldsymbol{z}} &= \mathbf{0}, \end{aligned} \tag{20}$$

which is substituted into the policy block of Equation (11) and where $\Theta_{x_i,\nu,\mathcal{A}}$ is the matrix of impulse responses of variable i to all shocks in $\boldsymbol{\nu}$ under the estimated policy rules ($\boldsymbol{\mathcal{A}}$). Although numerically equivalent to previous approaches in the literature (e.g., Svensson (1997)), the optimal policy rule here is fully characterized by impulse responses to policy (news) shocks, all of which can be, in theory, estimated from the data.

In practice, researchers may not be able to identify the entire menu of policy shocks $\boldsymbol{\nu}$ but only a subset ($\widetilde{\boldsymbol{s}} \subset \boldsymbol{\nu}$). In this case, the set of hypothetical, feasible allocations is no longer described by Equation (19) but is instead given by

$$\boldsymbol{y} = \Theta_{s,\mathcal{A}} \times \widetilde{\boldsymbol{s}} \tag{21}$$

with $\boldsymbol{y} = (\boldsymbol{x}', \boldsymbol{z}')'$. The monetary policy authority then chooses the optimal policy rule (Equation (20)) and the corresponding allocation of $\boldsymbol{y}$ that minimizes the loss function in Equation (18) within the empirically identified space described by Equation (21).

Two loss functions. The first key ingredient in the framework is the specification of the central bank loss function. The ECB's primary mandate is to maintain price stability, defined as a (consumer price) inflation target of 2% over the medium term.[19] Following the evidence in Paloviita et al. (2021) that the ECB's relevant medium-term horizon corresponds to 6–8 quarters, we assign higher weights to inflation deviations at those horizons. The resulting loss function takes the form:

$$\mathcal{L} = \lambda_\pi \boldsymbol{\pi}' W \boldsymbol{\pi}, \tag{22}$$

with $\lambda_\pi = 1$ and $W = (\text{diag}(\beta^{24}, \ldots \beta^2, \beta, 1))$, where β is set such that the corresponding annualized real interest rate equals 2% in a standard New Keynesian model.[20] Additionally,

[19] Dietrich (2024) shows that, targeting headline inflation instead of sticky price/core-inflation (Aoki (2001)) may even be optimal from a welfare theoretic point when allowing for empirically realistic deviations from full information rational expectations.

[20] This is only a linear approximation to the weighting problem, where the deviation at the last horizon (24 months) has the highest weight and the weight of deviations increases linearly. A quadratic approximation would not change the result significantly.

$\boldsymbol{\pi} = \mathcal{D}\boldsymbol{P}^{\text{HICP}}$ represents the transformed impulse responses of the (log) level of the HICP, denoted as $\boldsymbol{P}^{\text{HICP}}$ with the operator $\mathcal{D}$ converting them to year-on-year inflation rates.

While instructive for isolating the key mechanism, a loss function based solely on the primary mandate abstracts from the economic costs of policy tightening. We therefore also consider a dual mandate loss function that incorporates the ECB's secondary objective of supporting balanced economic growth by adding a term penalizing deviations of output from trend:

$$\mathcal{L} = \lambda_\pi \boldsymbol{\pi}' W \boldsymbol{\pi} + \lambda_y \boldsymbol{\mathcal{Y}}' W \boldsymbol{\mathcal{Y}}, \tag{23}$$

To best flesh out the differences between the two loss functions, we set $\lambda_y = \lambda_\pi$, implying equal weight on inflation and output stabilization.[21]

An oil supply shock and two monetary policy shocks. The second key ingredient is the identification a supply-side shock. As in Section 5.2, we follow Känzig (2021) and use high-frequency changes in oil price futures to identify OPEC-related oil supply news shocks. This time, however, we use only the first principal component ($m^{OIL}_{t,PC1}$) of the changes in oil price futures from one month up to one year to identify a single "generic" oil supply news shock, rather than distinguishing between short- and medium-run oil supply news. Within our identifying assumptions framework in Equation (5) we set $\epsilon^*_t \equiv \epsilon^{oil}_{t,generic}$ and $m_t \equiv m^{OIL}_{t,PC1}$. We interpret this shock as news about oil supply policies at different maturities that, in combination, shift the current and expected future price of oil (Inoue and Rossi (2021), McKay and Wolf (2023)).

The resulting impulse responses, depicted in blue in Figure 8, illustrate the transmission of an average, one standard deviation oil supply news shock. They generate a persistent increase in the Brent oil price, higher consumer energy prices, rising inflation and inflation expectations, and a delayed but significant contraction in industrial production. In line with the conventional wisdom that "in the past, central banks have typically looked through energy shocks" (Schnabel (2022)), the estimated monetary policy response does not appear to counteract the inflationary pressures.

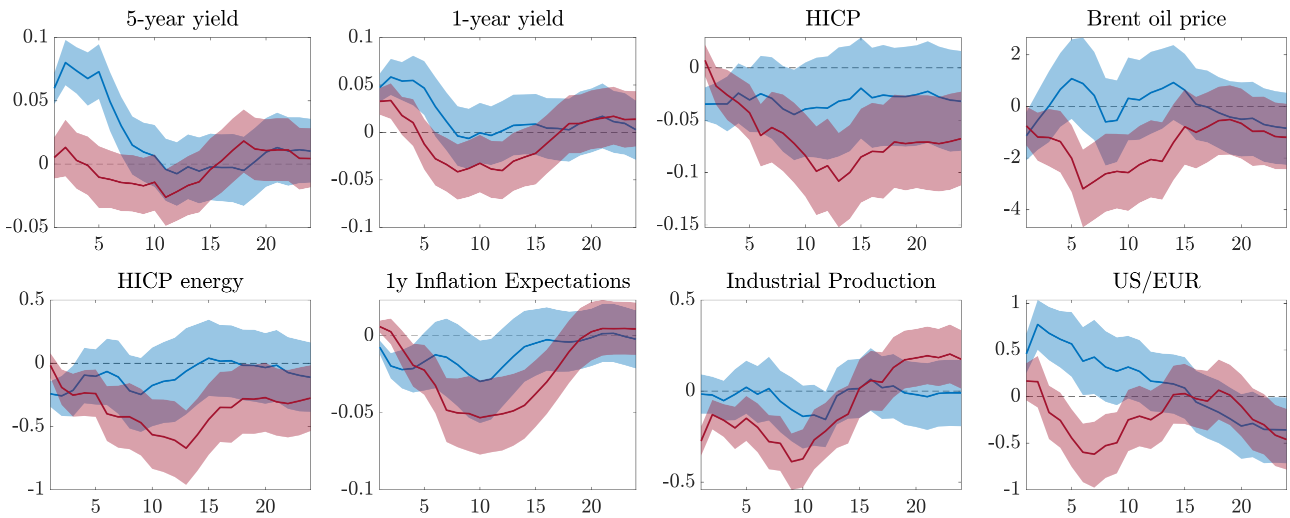
As the third ingredient, we identify two euro area monetary policy shocks to approximate the solution to the optimal policy counterfactual in Equation (21). Specifically, we utilize high-frequency changes in the 3-month ($m^{MP}_{t,3m}$) and 24-month ($m^{MP}_{t,24m}$) futures to identify a short-term ($\nu^{MP}_{t,short}$) and a medium-term ($\nu^{MP}_{t,medium}$) monetary policy news shock. These shocks can be interpreted as shifting different segments of the yield curve.[22] Both

[21] To map industrial production deviations from our SVAR into GDP deviations, we scale the hypothetical equal weight that we want to give to GDP (λ_{GDP}) by the relative variance of GDP and industrial production (IP) such that $\lambda_y = \lambda_{\text{IP}} = \lambda_{\text{GDP}} \times \frac{\sigma^2(\text{GDP})}{\sigma^2(\text{IP})}$. See Georgiadis et al. (2024) for a similar approach.

[22] Given our identifying assumptions, the "generic" monetary policy shock that we identify in Section 4 should best be thought of as a linear combination of these two shocks. See Inoue and Rossi (2021) and Caravello et al. (2023) for a similar interpretation of identified monetary policy shocks as a linear

shocks are incorporated into the framework in Section 3, Equation (5), as follows: we define $\boldsymbol{\epsilon}_t^* \equiv (\epsilon_{1,t}, \epsilon_{2,t})' = (\nu_{t,short}^{MP}, \nu_{t,medium}^{MP})'$ and $\boldsymbol{m}_t^* \equiv (m_{1,t}, m_{2,t})' = (m_{t,3m}^{MP}, m_{t,24m}^{MP})'$. The impulse responses to these monetary policy shocks are presented in Figure 7 and align with the existing empirical literature (Swanson (2024), Ricco et al. (2025), Miranda-Agrippino and Ricco (2023), Lakdawala (2019); see Rossi (2021) for a comprehensive literature review).

Figure 7: Response to a short-run (crimson red) and medium-run (sky blue) EA MP shock



Notes: Impulse responses to a short-run (medium-run) EA monetary policy shock in crimson red (sky blue) alongside 68% credible sets. We normalize the responses such that the 1-year (5-year) yield increases on impact. Response of the credit spread is omitted to save space. See notes to Figure 2 for scaling of variables.

6.2 Mandate-optimal policy response to an oil supply shock

Equipped with the oil-supply shock $\epsilon_t = \epsilon_{t,generic}^{oil}$ and the two policy shocks $\widetilde{\boldsymbol{s}} = [\nu_{t,short}^{MP}, \nu_{t,medium}^{MP}]$ we estimate the transmission of an oil supply shock under the policies described in Equations (22) and (23). The results are depicted in Figure 8: the blue lines show the impulse responses under the observed (empirical) policy rule, the black circled lines show the primary-mandate-optimal responses, and the magenta crossed lines show the dual-mandate-optimal responses.

The mandate-optimal response under the primary mandate (black) stands in contrast to the empirically observed response (blue): rather than leaving rates broadly unchanged, the ECB should promptly raise interest rates to directly counteract the inflationary effects of the oil price increase. This result is in line with the "expansionary bias" emphasized by Guerrieri et al. (2025), who show theoretically that when a central bank treats the

combination of underlying shocks.

energy price as exogenous, the resulting policy response is likely too accommodative.[23] Importantly, however, our estimates do not support an excessive rate hike: a modest, front-loaded tightening is sufficient to stabilize more than halve of the oil-supply-shock-induced deviations of inflation from target. The cost relative to the empirical policy rule is a front-loaded output contraction, but this is partly offset by higher output in the medium term, so that the average economic contraction is close to the baseline. The relatively benign inflation stabilization cost traces back to the role of energy prices for inflation: a large share of the disinflation is borne by the flexible energy price component, which on average remains 50% below the corresponding path under the empirical rule (second row, third panel in Figure 8).

Under the dual mandate (magenta), the ECB additionally aims to limit the output contraction induced by the supply shock. As a result, the optimal response calls for only a slight tightening at the short end of the yield curve, rather than an immediate and decisive rate increase. In fact, this dual-mandate-optimal response closely mirrors the ECB's actual estimated historical response, suggesting that observed ECB behaviour during oil supply episodes is broadly consistent with a dual-mandate interpretation. By construction, this strategy accepts a somewhat less favourable path for inflation in exchange for a shallower recession. The comparison of the two optimal responses illustrates the inflation–output trade-off: the primary-mandate prescription leans against the inflationary impulse more aggressively, while the dual-mandate prescription is closer to a classical "looking-through" strategy in the short run.

6.3 Energy prices and mandate-optimal monetary policy

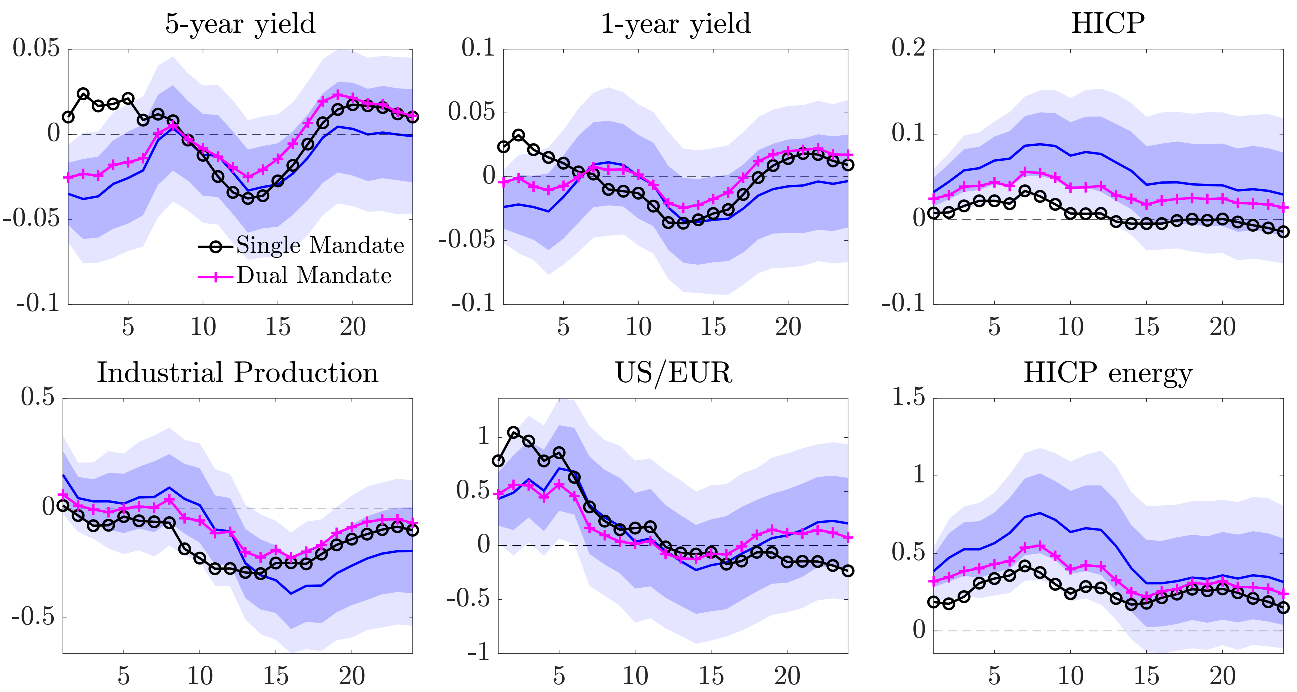
In this section, we now ask how the mandate-optimal responses change in the counterfactual scenario in which the ECB cannot influence global energy prices. Specifically, we are interested in the optimal allocation $\boldsymbol{y}$ when the empirically identified, implementable space of possible allocations is not described by Equation (21), but rather by

$$\boldsymbol{y} = \Theta_{s,\widetilde{\mathcal{A}}} \times \widetilde{\boldsymbol{s}} \tag{24}$$

Here, the subscript $\widetilde{\mathcal{A}}$ indicates that the space is now characterized by counterfactual impulse responses, where the ECB does not affect oil prices. We construct these counterfactual impulse responses for the two identified monetary policy shocks $\widetilde{\boldsymbol{s}}$ in a manner

[23] For example, at the press conference on February 3, 2022, Christine Lagarde responded to a question on this topic by stating: "If the ECB was to ... then raise interest rates in short order, do you think it would have any impact on energy prices? No, it is not in the ambit of monetary policy to decide the price of the barrel that is organized predominantly outside of Europe." (Lagarde (2022)) The assumption that ECB policy does not affect global energy prices is not only embedded in theoretical models used for policy analysis, but is also part of the ECB's forecasting process (see Coenen et al. (2018) for an example and discussion)

Figure 8: Oil supply shock transmission under different (optimal) monetary policy rules



Notes: Impulse response functions to a one standard deviation oil supply shock, showing the point-wise posterior means along with 68% and 90% point-wise credible sets in blue. The black circled lines (magenta crossed lines) show the responses of the endogenous variables under optimal policy with a single mandate (dual mandate) loss function described in Equation (22) ((23)). Figure H.1 of the Appendix contains the responses of the remaining variables. See notes to Figure 2 for scaling of variables.

analogous to our approach in Section 5.1.[24]

The results are shown in Figure 9. For ease of exposition, we compare and summarize the allocation under optimal policy relative to the baseline allocation depicted by the blue lines in Figure 8. For the case where the central bank can affect global oil prices, the results are given by the black bars (single mandate) and magenta bars (dual mandate). Crucially, for each loss function, we also compute the optimal allocation for the case when the central bank cannot affect global oil prices, shown by the green bars (single mandate) and purple bars (dual mandate).

The first column quantifies the cumulated additional tightening required to implement the optimal policy relative to the baseline. For both loss functions, the second column depicts the fraction of inflation deviations that can be stabilized under optimal policy. For reference, the black dashed line corresponds to perfect stabilization, which would imply that switching to the optimal policy would offset all inflation deviations that occur under the baseline policy rule, implying that the impulse response of inflation is zero at all

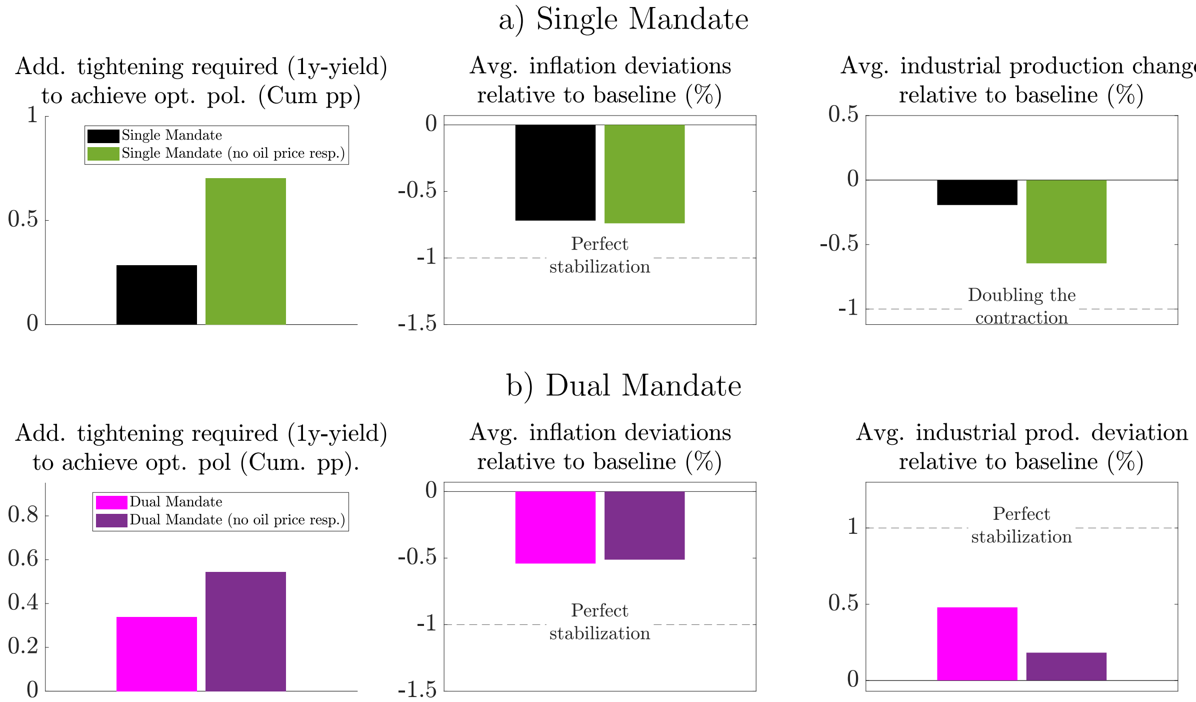
[24] A detailed step-by-step summary of our approach to estimating the optimal monetary policy response to an oil supply shock, under the assumption that the ECB's decisions do not affect global oil prices, can be found in Appendix H.2.

horizons. Likewise, the bottom panel in the third column shows that much of the output deviations are stabilized under the optimal policy response under a dual mandate. Because under a single mandate, monetary policy does not aim to minimize deviations of output, the top panel in the third row shows the average *change* in output relative to the baseline that occurs if monetary policy optimally aims to stabilize inflation. For reference, the black dashed line corresponds to the case where switching to the optimal policy doubles the oil supply shock-induced contraction relative to the baseline.

A coherent picture emerges for both loss functions. Focusing on the first column, it becomes apparent that, under both loss functions, the inability to move energy prices forces the ECB to tighten substantially more to achieve the mandate optimal allocation. Under the primary mandate, the cumulative additional tightening required to implement optimal policy is more than three times as large as when the ECB cannot affect oil prices. As shown in the second column, the ECB can still stabilize 72% of the inflation deviations from target, which would otherwise occur under the baseline (empirical) policy rule. But, as shown in the third row, the economic costs are far higher: the average output contraction is around 65% more severe relative to the baseline ECB response, and the total cost of achieving optimal inflation stabilization is more than three times as large compared to the scenario where the ECB could affect oil prices.

Under the dual mandate, the picture is qualitatively identical. Even though the loss function explicitly penalizes output losses, both the additional tightening required and the residual loss — measured as combined deviations of inflation and output from target — are significantly higher when the central bank cannot affect oil prices. The comparison across both mandate specifications, therefore, leads to the same conclusion: it is precisely the ECB's ability to move fast-adjusting energy prices that allows it to achieve its objectives at comparatively low cost. Absent this channel, the central bank must rely exclusively on the slower and costlier mechanism of domestic demand compression, substantially worsening the inflation–output allocation under both mandate specifications. This result underscores that the ability to influence energy prices not only crucially shapes monetary transmission but also is of particular importance for policymaking in the face of an energy supply shock.

Figure 9: The role of energy prices for mandate-optimal monetary policy



Notes: See notes to Figure 8. We measure the additional tightening required in cumulative percentage points relative to the baseline. In the single (dual) mandate case, the central bank aims to stabilize inflation (inflation and output). Therefore, measure deviations relative to the baseline and express the resulting stabilization in percent. That is, for each scenario, we compute $\sum(|z_{t,\mathcal{A}^\star}| - |z_{t,\mathcal{A}}|)/\sum|z_{t,\mathcal{A}}|$, where z_t is the impulse response of the policy target variable. The superscript $\mathcal{A}$ refers to the baseline impulse response, while $\mathcal{A}^\star$ indicates the impulse responses under the corresponding (optimal) policy rule. For industrial production under the single mandate the bars measure the average policy implied change relative to the baseline impulse response $\sum(x_{t,\mathcal{A}^\star} - x_{t,\mathcal{A}})/\sum|x_{t,\mathcal{A}}|$, where x_t is the impulse response of of industrial production. Note that, if the central bank cannot affect oil prices, the oil price response should be independent of the policy change, implying that the policy-induced change in the oil price should be zero relative to the baseline. As we approximate the solution, this is not exactly the case, but the approximation error is small, as shown in Figure H.2. The impulse responses underlying these bar charts can be found in Figures H.3 and Figures H.4 of the Appendix.

7 Conclusion

A central bank's ability to influence energy prices fundamentally shapes both monetary policy transmission and mandate-optimal policy design. Using euro area data, we show that European monetary policy shocks significantly lower global energy prices, amplifying and accelerating the transmission to headline inflation and inflation expectations because energy prices adjust more rapidly than other consumer prices. We study the importance of monetary policy's influence on energy prices using an empirical counterfactual approach that is robust to the Lucas critique and model misspecification (McKay and Wolf (2023)). We find that when monetary policy can not affect global energy prices, its transmission to inflation is more than halved, and the inflation–output trade-off deteriorates substantially:

the sacrifice ratio roughly doubles. In this sense, energy prices can be considered a friend, not a foe, to the central bank. This finding has important policy implications for the response to energy price shocks. The ability to affect energy prices materially alters the mandate-optimal policy response, requiring more moderate tightening and delivering a more favorable inflation–output allocation. Absent this ability, stabilizing inflation requires substantially stronger tightening at significantly higher output costs.

Consequently, standard frameworks treating energy prices as exogenous therefore mischaracterize both the transmission and the mandate-optimal policy response of monetary policy to energy price shocks. Accounting for their endogenous response reveals that central banks may have more leverage over energy-driven inflation than previously thought.

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A Data description

Table A.1: Detailed description of data used in the high-frequency event study regressions

Variable	Description	Notes	Source
Global oil price	Brent crude oil front-month futures (LCOc1) price (in US dollars)	Computed the percent price change around monetary policy announcements (ECB, Fed and BoE)	Refinitiv Tick History database
ECB monetary policy surprise	3-month OIS rate changes around ECB monetary policy announcements	Computed based on methodology of Jarociński and Karadi (2020)	EA-MPD from Altavilla et al. (2019)
Fed monetary policy surprise (baseline)	3-month-ahead federal funds future rate changes around FOMC announcements	Computed based on methodology of Jarociński and Karadi (2020)	Gürkaynak et al. (2005) and Marek Jarocinski's website
Fed monetary policy surprise (robustness)	The first principal component of the changes in ED1–ED4 around FOMC announcements	Orthogonalized monetary policy surprises uncorrelated with macroeconomic and financial data observed before FOMC announcements	Bauer and Swanson (2023)
Bank of England monetary policy surprise	3-month Libor rate changes around Bank of England monetary policy announcements	Computed based on methodology of Jarociński and Karadi (2020)	Cesa-Bianchi et al. (2020)
FTSE 100 index	FTSE 100 index price changes around Bank of England monetary policy announcements	Computed from tick data	Refinitiv Tick History database
Dutch TTF natural gas price	Daily (closing) price changes of 1-month and 1-year Dutch TTF futures around ECB monetary policy announcements		Bloomberg

Table A.2: Detailed description of data used in the VAR analysis

Variable	Description	Notes	Source
1-year yield	Germany Government 1 year yield	Monthly average of daily values	Macrobond Financial AB
5-year yield	Germany Government 5 year yield	Monthly average of daily values	Macrobond Financial AB
US/EUR	US-Dollar per Euro, spot rate	Monthly average of daily values	Macrobond Financial AB
Industrial Production	Euro Area Industrial Production excl. Construction		Eurostat
Brent oil price	Brent crude Europe Spot price FOB, US-Dollar per barrel	Monthly average of daily values	Energy Information Administration
CPI (headline)	Euro Area Harmonized Index of Consumer Prices	Seasonally adjusted using X13	Eurostat
HICP housing	Euro Area, HICP, Housing, Water & Electricity & Gas & Other Fuels	Seasonally adjusted using X13	Eurostat
HICP transport	Euro Area, HICP, Transport	Seasonally adjusted using X13	Eurostat
HICP heating	Euro Area, HICP, Housing, Water, Electricity, Fuel, Electricity, Gas	Seasonally adjusted using X13	Eurostat
HICP fuels	Euro Area, HICP, Fuels & Lubricants for Personal Transport Equipment	Seasonally adjusted using X13	Eurostat
HICP energy	Euro Area, HICP, Energy	Seasonally adjusted using X13	Eurostat
Credit spread	ICE BofA Euro High Yield Index Option-Adjusted Spread	Monthly average of daily values	FRED
Euro area crude oil imports	Sum of imports in barrels of crude oil by Germany, France, Italy, Spain, and the Netherlands instead of imports from the whole euro area, due to data limitations	3-month trailing moving average	Joint Organization Data Initiative (Jodi)
Euro area crude oil inventories	The same description as for imports applies		Joint Organization Data Initiative (Jodi)
GFC index	Global Financial Cycle index - Miranda-Agrippino and Rey (2020) call it the Global Factor		Miranda-Agrippino and Rey (2020)
Euro Area short-run monetary policy proxy	3 month (monetary event window) OIS surprise	Calculated based on data and methodology by Jarociński and Karadi (2020) (“poor-man” approach), aggregated to monthly frequency according to Kilian (2024)	Jarociński and Karadi (2020) and authors’ calculations
Euro Area medium-run monetary policy proxy	2 year (monetary event window) OIS surprise	The same notes apply to all monetary policy proxies	Jarociński and Karadi (2020) and authors’ calculations
Euro Area generic monetary policy proxy	First principle component of 1 month to 1 year (monetary event window) OIS surprises	The same notes apply to all monetary policy proxies	Jarociński and Karadi (2020) and authors’ calculations
Global oil production	Global oil production (million barrels/day)		Baumeister and Hamilton (2019)
Global IP	Global industrial production		Baumeister and Hamilton (2019)
Consensus 1-year ahead inflation expectations	(GDP-) Weighted average of Germany, France, Italy, and Spain	We use the largest four euro area countries’ data since the euro area aggregate data is only available starting from December 2002. The (monthly) 1-year ahead expectation is a weighted average of the “Current year” and “Next year” inflation forecasts, as in Miranda-Agrippino and Ricco (2021).	Consensus economics
Oil supply news proxy	Suprise in oil futures prices around OPEC announcements	Monthly sum of daily values	Känzig (2021)

As in Born and Pfeifer (2021), we demean the variables to avoid numerical problems arising from under/overflow during the posterior computations that involve the sum of squares.

B High-frequency event study robustness results

Table B.1: Additional results for the event study regression for the euro area, US and UK (Equation 1) for a 100 basis points monetary policy surprise

	EA	EA	US	US	UK	UK
	(1)	(2)	mps_{FF4}^{pm}	$mps^{\perp}$	(1)	(2)
$\widehat{\beta}^{100\text{bps}}$	-3.20^{**}	-3.34^{**}	-2.24^{**}	-2.23^{***}	0.37	0.36
	(1.31)	(1.54)	(1.04)	(0.83)	(0.67)	(0.68)
R^2 (%)	3.75	3.37	2.64	3.21	0.33	0.38
N	198	182	198	197	257	246
Sample	2002:1	2002:1	1996:1	1996:1	1997:6	1997:6
	2021:12	2019:12	2019:12	2019:12	2021:3	2019:12

Note: Coefficient estimates $\widehat{\beta}^{100\text{bps}}$ from the Brent crude oil price event study regression equation $p_{i,t}^{oil} = \alpha_i + \beta_i mps_{i,t} + \epsilon_{i,t}$, where t indexes monetary policy announcements and i denotes country (EA, US, UK). Coefficient represents the percentage change in the Brent crude oil price in response to a 100 basis points increase in the country-specific monetary policy surprise measure. Each column represents the results for a different country-sample combination. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, *** represent statistical significance levels at 10%, 5% and 1% respectively.

Table B.2: Additional results for the event study regression for the euro area, US and UK (Equation 1) for a 1 standard deviation monetary policy surprise

	EA	EA	US	US	UK	UK
	(1)	(2)	mps^{pm}_{FF4}	$mps^{\perp}$	(1)	(2)
$\widehat{\beta}^{\text{std}}$	-0.054^{**}	-0.056^{**}	-0.078^{**}	-0.078^{***}	0.020	0.019
	(0.022)	(0.026)	(0.037)	(0.029)	(0.035)	(0.037)
R^2 (%)	3.75	3.37	2.64	3.21	0.33	0.38
N	198	182	198	197	257	246
Sample	2002:1	2002:1	1996:1	1996:1	1997:6	1997:6
	2021:12	2019:12	2019:12	2019:12	2021:3	2019:12

Note: Coefficient estimates $\widehat{\beta}^{\text{100bps}}$ from the Brent crude oil price event study regression equation $p^{oil}_{i,t} = \alpha_i + \beta_i mps_{i,t} + \epsilon_{i,t}$, where t indexes monetary policy announcements and i denotes country (EA, US, UK). Coefficient represents the percentage change in the Brent crude oil price in response to a one standard deviation increase in the country-specific monetary policy surprise measure. Each column represents the results for a different country-sample combination. Heteroskedasticity-consistent standard errors are reported in parentheses. *, **, *** represent statistical significance levels at 10%, 5% and 1% respectively.

Table B.3: Coefficient estimates $\widehat{\beta}^{100\text{bps}}$ from the natural gas price (Dutch TTF) event study regressions.

	1-month TTF	1-year TTF	1-month TTF	1-year TTF
$\widehat{\beta}^{100\text{bps}}$	-17.42^{***}	-12.32^{***}	-13.85^{***}	-13.41^{***}
	(4.50)	(3.12)	(3.92)	(3.23)
R^2 (%)	2.68	2.61	1.39	2.69
Sample	2007:10-2019:12	2007:10-2019:12	2007:10-2021:12	2007:10-2021:12
N	127	127	143	143

Note: Event study regressions are of the form $p^{gas}_{i,t} = \alpha_i + \beta_i mps_{i,t} + \epsilon_{i,t}$, where t indexes monetary policy announcements and i denotes country (EA, US, UK), $p^{gas}_{i,t}$ is the daily change of the relevant natural gas futures price, computed as the difference between the closing price of the ECB policy announcement day and the closing price of the previous day. Coefficient represents the percentage change in the Dutch TTF natural gas price in response to a 100 basis points increase in the country-specific monetary policy surprise measure. Each column presents the event study regression for the combination of a different TTF maturity and a different sample period. mps_t is the high frequency change in the three month Overnight Index Swap (OIS) rate with poor man's sign restrictions as in Jarociński and Karadi (2020). Daily Dutch TTF price data is available from October 2007. Heteroskedasticity-consistent standard errors are reported in parentheses.

Table B.4: Coefficient estimates $\widehat{\beta}^{\text{std}}$ from the natural gas price (Dutch TTF) event study regressions.

	1-month TTF	1-year TTF	1-month TTF	1-year TTF
$\widehat{\beta}^{\text{std}}$	-0.33^{***}	-0.24^{***}	-0.25^{***}	-0.24^{***}
	(0.09)	(0.06)	(0.07)	(0.06)
R^2 (%)	2.68	2.61	1.39	2.69
Sample	2007:10-2019:12	2007:10-2019:12	2007:10-2021:12	2007:10-2021:12
N	127	127	143	143

Note: Event study regressions are of the form $p^{gas}_{i,t} = \alpha_i + \beta_i mps_{i,t} + \epsilon_{i,t}$, where t indexes monetary policy announcements and i denotes country (EA, US, UK), $p^{gas}_{i,t}$ is the daily change of the relevant natural gas futures price, computed as the difference between the closing price of the ECB policy announcement day and the closing price of the previous day. Coefficient represents the percentage change in the Dutch TTF natural gas price in response to a one standard deviation increase increase in the country-specific monetary policy surprise measure. Each column presents the event study regression for the combination of a different TTF maturity and a different sample period. mps_t is the high frequency change in the three month Overnight Index Swap (OIS) rate with poor man's sign restrictions as in Jarociński and Karadi (2020). Daily Dutch TTF price data is available from October 2007. Heteroskedasticity-consistent standard errors are reported in parentheses.

C Revisiting Gagliardone and Gertler (2023)

In a VAR using high-frequency identification of monetary policy shocks, Gagliardone and Gertler (2023) do not find that the real oil price declines in response to a contractionary US monetary policy shock. This contradicts our findings and much of the related literature showing that contractionary US monetary policy shocks decrease commodity and/or oil prices (Anzuini et al. (2012); Miranda-Agrippino and Ricco (2021); Bauer and Swanson (2023); Degasperi et al. (2023); Miranda-Pinto et al. (2023)).[25]

In order to understand the source of their different result regarding the crude oil price impulse response, we replicate the VAR in Gagliardone and Gertler (2023). There are two limitations of this replication exercise. First, the authors are not explicit about whether they run separate VARs for the monetary policy shock and the oil supply shock. Therefore, since there is no explanation of a joint identification procedure, we assume they estimate two separate VAR models. Second, the authors also measure "surprises around non-FOMC dates on which the Federal Reserve revealed information", but they neither specify these dates nor grant access to the corresponding data. As a result, we cannot precisely replicate their approach to identifying shocks across the full event set.

Through our replication analysis, we find that the different result reported by Gagliardone and Gertler (2023) may be driven by certain empirical choices that can affect the validity of the estimates. First, the authors aggregate monetary policy surprises from a higher frequency to a monthly frequency by summing the surprises in a given month, yet, in the VAR, they use average-of-period monthly data for variables available at a daily frequency. Kilian (2024) shows that such practice can bias the impulse response estimates. Instead, he proposes using end-of-period data, if one wishes to simply sum over the high-frequency surprises. In our replication of their monetary policy VAR, we find that using end-of-month oil prices (see Figure C.1), or the average price over the last three or five trading days of each month (see Figure C.2), leads to a significant decline in real crude oil prices following a contractionary monetary policy shock. Second, if instead one prefers average-of-period monthly prices, it is crucial to construct the monthly surprises in line with the methodology in Kilian (2024); adopting that approach in the VAR replication of Gagliardone and Gertler (2023) again produces a decline in the real oil price in line with the results from our VAR framework (see Figure C.3).[26]

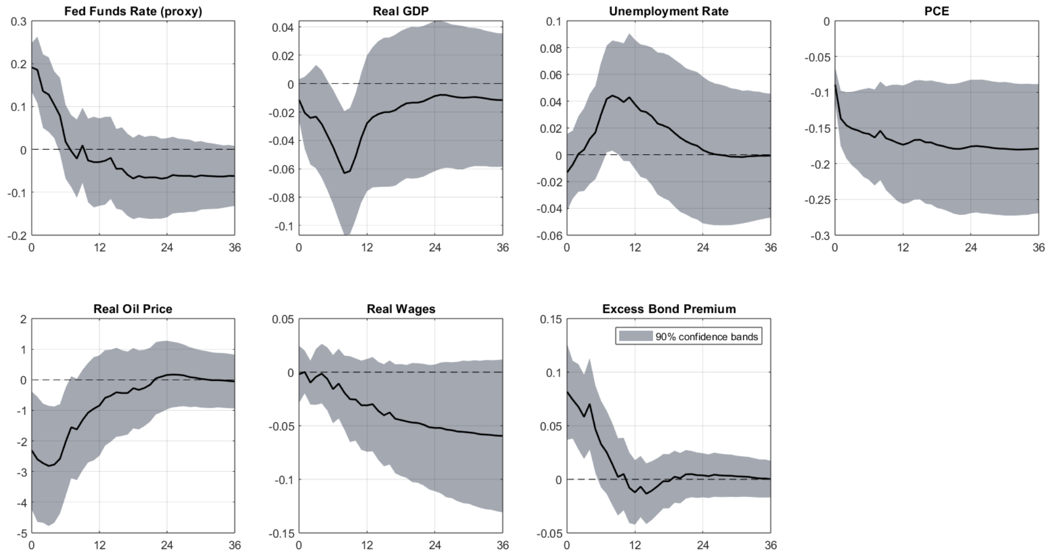
Moreover, the oil price series used by the authors (FRED code: WTISPLC) is not

[25]Miranda-Agrippino and Ricco (2021) include the Commodity Research Bureau (CRB) commodity price index in their baseline VAR but do not report the IRFs. Therefore, using their replication files while keeping true to their baseline empirical specification, we produce the commodity price index IRFs and find that the commodity price index declines significantly in response to a contractionary US monetary policy shock (see Figure E.9).

[26]The BPSVAR framework we employ allows the proxy variable to be serially correlated and predictable. Therefore, any serial correlation or predictability arising from the aggregation scheme does not pose a problem in our empirical framework.

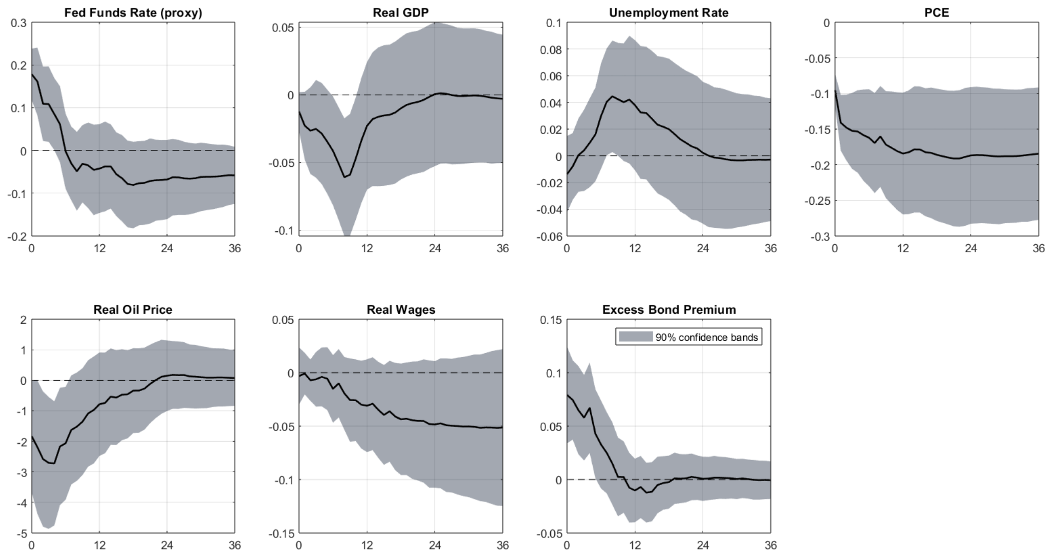
continuous during the first six years of their sample, remaining constant over prolonged intervals.

Figure C.1: Replication of Gagliardone and Gertler (2023) with end-of-month real oil price



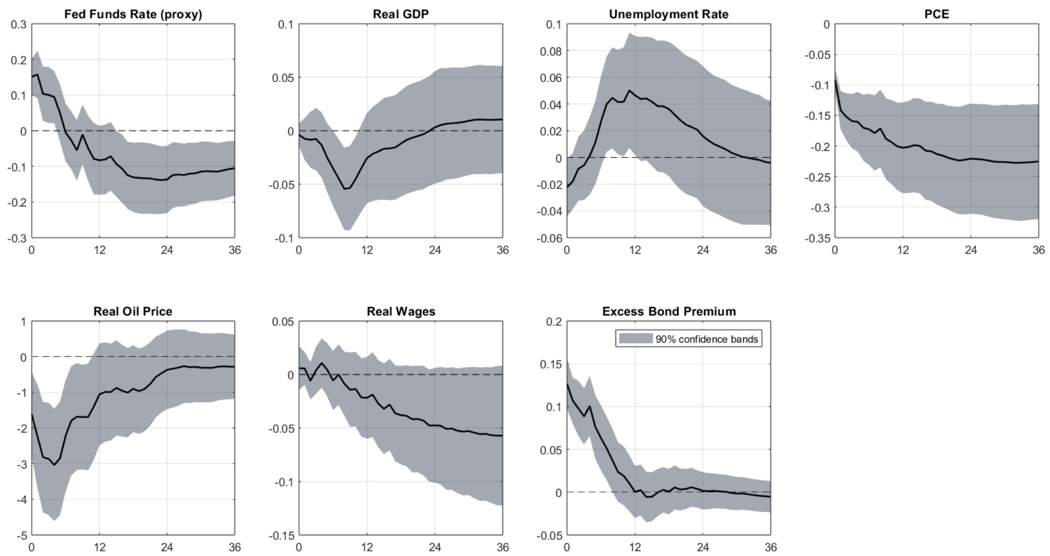
Notes: Baseline seven-variable VAR from Gagliardone and Gertler (2023). Sample is 1973M1–2019M12. The solid line is the point estimate and the shaded areas are the 90 percent confidence bands, computed using the wild bootstrap.

Figure C.2: Replication of Gagliardone and Gertler (2023) with real oil price as the average of the last 5 days in a month



Notes: Baseline seven-variable VAR from Gagliardone and Gertler (2023). Sample is 1973M1–2019M12. The solid line is the point estimate and the shaded areas are the 90 percent confidence bands, computed using the wild bootstrap.

Figure C.3: Replication of Gagliardone and Gertler (2023) average-of-month real oil price and monetary policy surprises aggregated following Kilian (2024)



Notes: Baseline seven-variable VAR from Gagliardone and Gertler (2023). Sample is 1973M1–2019M12. The solid line is the point estimate and the shaded areas are the 90 percent confidence bands, computed using the wild bootstrap.

D Details on the Bayesian Proxy SVAR model

In this appendix we give more details on the implementation of the algorithm of Arias et al. (2021) and derive equations (5) and (6). For convenience, we reproduce the VAR Equation (4), augmented with proxies:

$$\tilde{\boldsymbol{y}}_t'\tilde{\boldsymbol{A}}_0 = \tilde{\boldsymbol{y}}_{t-1}'\tilde{\boldsymbol{A}}_1 + \tilde{\boldsymbol{\epsilon}}_t'. \tag{D.1}$$

To ensure that the augmentation with equations for the proxy variables does not affect the dynamics of the endogenous variables, the coefficient matrices $\tilde{\boldsymbol{A}}_\ell$ are specified as

$$\tilde{\boldsymbol{A}}_\ell = \begin{pmatrix} \underset{(n\times n)}{\boldsymbol{A}_\ell} & \underset{(n\times k)}{\boldsymbol{\Gamma}_{\ell,1}} \\ \underset{(k\times n)}{\boldsymbol{0}} & \underset{(k\times k)}{\boldsymbol{\Gamma}_{\ell,2}} \end{pmatrix}, \qquad \ell = 0, 1. \tag{D.2}$$

The zero restrictions on the lower left-hand side block imply that the proxy variables do not enter the equations of the endogenous variables. The reduced form of the model is

$$\tilde{\boldsymbol{y}}_t' = \tilde{\boldsymbol{y}}_{t-1}'\tilde{\boldsymbol{A}}_1\tilde{\boldsymbol{A}}_0^{-1} + \tilde{\boldsymbol{\epsilon}}_t{}'\tilde{\boldsymbol{A}}_0^{-1}. \tag{D.3}$$

Because the inverse of $\tilde{\boldsymbol{A}}_0$ in Equation (D.2) is given by

$$\tilde{\boldsymbol{A}}_0^{-1} = \begin{pmatrix} \boldsymbol{A}_0^{-1} & -\boldsymbol{A}_0^{-1}\boldsymbol{\Gamma}_{0,1}\boldsymbol{\Gamma}_{0,2}^{-1} \\ 0 & \boldsymbol{\Gamma}_{0,2}^{-1} \end{pmatrix}, \tag{D.4}$$

the last k equations of the reduced form of the VAR model in Equation (D.3) read as

$$\boldsymbol{m}_t' = \tilde{\boldsymbol{y}}_{t-1}'\tilde{\boldsymbol{A}}_1 \begin{pmatrix} -\boldsymbol{A}_0^{-1}\boldsymbol{\Gamma}_{0,1}\boldsymbol{\Gamma}_{0,2}^{-1} \\ \boldsymbol{\Gamma}_{0,2}^{-1} \end{pmatrix} - \boldsymbol{\epsilon}_t'\boldsymbol{A}_0^{-1}\boldsymbol{\Gamma}_{0,1}\boldsymbol{\Gamma}_{0,2}^{-1} + \boldsymbol{\eta}_t'\boldsymbol{\Gamma}_{0,2}^{-1}, \tag{D.5}$$

which is the generalization for k proxies of equations (5) and (6), with

$$\boldsymbol{B} = \tilde{\boldsymbol{A}}_1 \begin{pmatrix} -\boldsymbol{A}_0^{-1}\boldsymbol{\Gamma}_{0,1}\boldsymbol{\Gamma}_{0,2}^{-1} \\ \boldsymbol{\Gamma}_{0,2}^{-1} \end{pmatrix}, \quad \boldsymbol{C} = \boldsymbol{\Gamma}_{0,2}^{-1}.$$

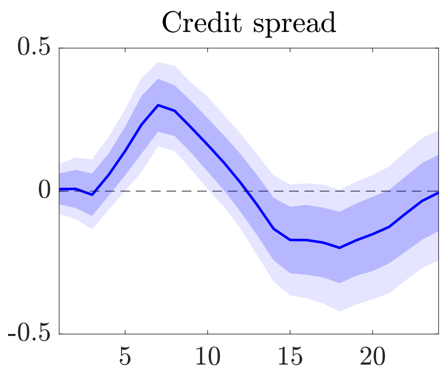
To see that only $\boldsymbol{\epsilon}_t^{*\prime}\boldsymbol{V}$ enters the equation, we order the structural shocks so that $\boldsymbol{\epsilon}_t = (\boldsymbol{\epsilon}_t^{o\prime}, \boldsymbol{\epsilon}_t^{*\prime})'$, which yields

$$E\left[\boldsymbol{\epsilon}_t\boldsymbol{m}_t'\right] = -\boldsymbol{A}_0^{-1}\boldsymbol{\Gamma}_{0,1}\boldsymbol{\Gamma}_{0,2}^{-1} = \begin{pmatrix} \underset{((n-k)\times k)}{\boldsymbol{0}} \\ \underset{(k\times k)}{\boldsymbol{V}} \end{pmatrix}. \tag{D.6}$$

The first equality is obtained using Equation (D.5) and because the structural shocks $\boldsymbol{\epsilon}_t$ are by assumption orthogonal to $\boldsymbol{y}_{t-1}$ and $\boldsymbol{\eta}_t$. The second equality is due to the exogeneity and relevance conditions in Equations (3a) and (3b). Equation (D.6) shows that the identifying assumptions imply restrictions on the last k columns of the contemporaneous structural impact coefficients in $\tilde{\boldsymbol{A}}_0{}^{-1}$. In particular, if the exogeneity condition in Equation (3b) holds, the first $n-k$ rows of the upper right-hand side sub-matrix $\boldsymbol{A}_0^{-1}\boldsymbol{\Gamma}_{0,1}\boldsymbol{\Gamma}_{0,2}^{-1}$ of $\tilde{\boldsymbol{A}}_0{}^{-1}$ in Equation (D.4) are zero. From the reduced form in Equation (D.3) it can be seen that this implies that the first $n-k$ structural shocks do not impact contemporaneously the proxy variables. In turn, if the relevance condition in Equation (3a) holds, the last k rows of the upper right-hand side sub-matrix $\boldsymbol{A}_0^{-1}\boldsymbol{\Gamma}_{0,1}\boldsymbol{\Gamma}_{0,2}^{-1}$ of $\tilde{\boldsymbol{A}}_0{}^{-1}$ are different from zero. From the reduced form in Equation (D.3) it can be seen that this implies that the last k structural shocks impact the proxy variables contemporaneously. The Bayesian estimation algorithm of Arias et al. (2021) determines the estimates of $\boldsymbol{A}_0$ and $\boldsymbol{\Gamma}_{0,\ell}$ such that the restrictions on $\tilde{\boldsymbol{A}}_0{}^{-1}$ implied by Equations (3a) and (3b) as well as on $\tilde{\boldsymbol{A}}_\ell$ in Equation (D.2) are simultaneously satisfied, and hence the estimation identifies the structural shocks $\boldsymbol{\epsilon}_t^*$.

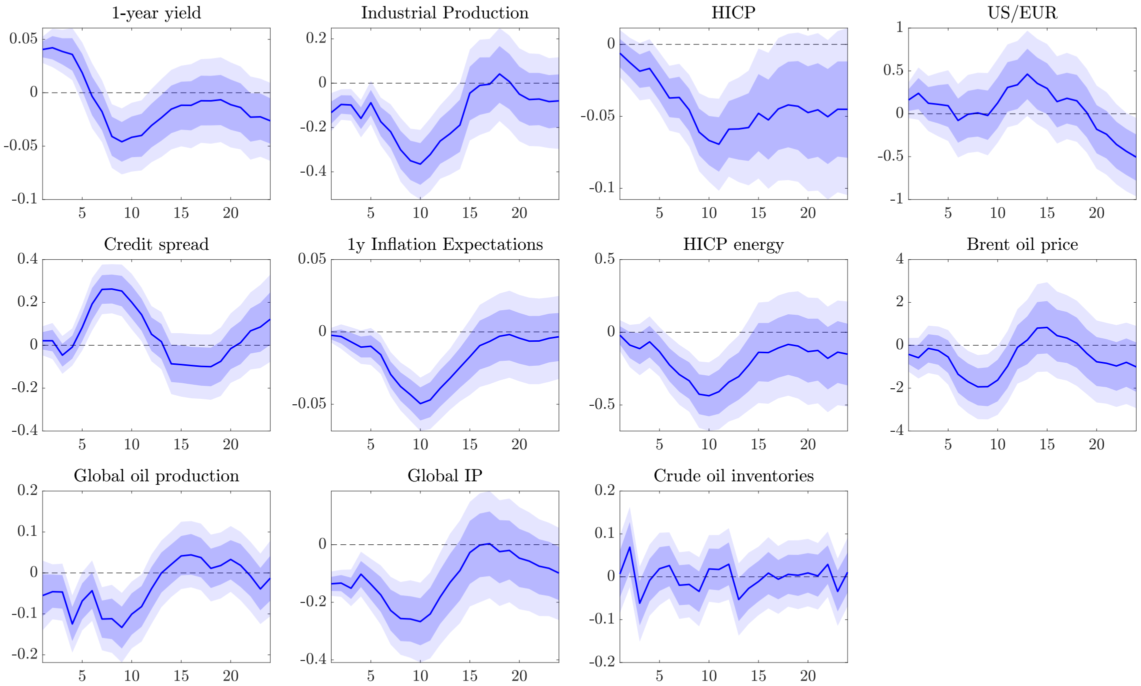
E BPSVAR robustness results

Figure E.1: Baseline Euro Area SVAR model: Response of the credit spread



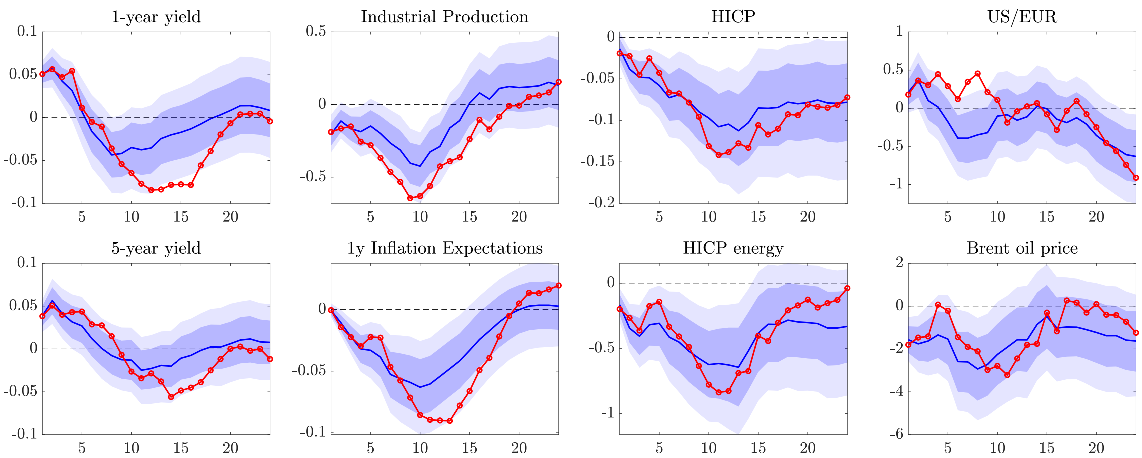
Notes: Impulse response functions to a one standard deviation monetary policy shock. Point-wise posterior means along with 68% and 90% point-wise probability bands. Response of the BBB corporate bond spread in percentage points.

Figure E.2: Euro Area SVAR model, robustness check with oil market variables



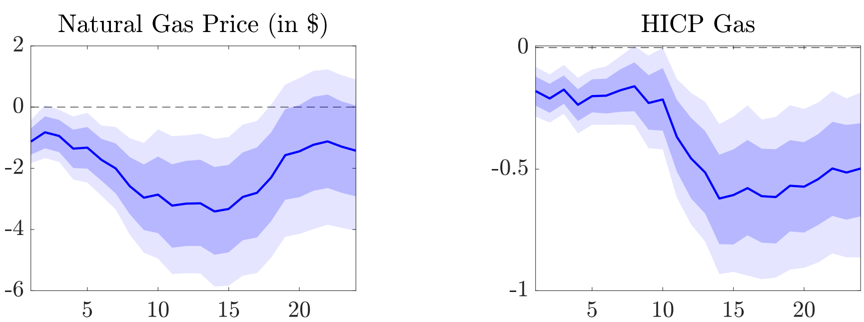
Notes: Euro Area model including additional variables that are typically used in models of the oil market. Impulse response functions to a one standard deviation monetary policy shock. Point-wise posterior means along with 68% and 90% point-wise probability bands. Horizon in months.

Figure E.3: Euro Area SVAR model, external vs. internal instrument identification



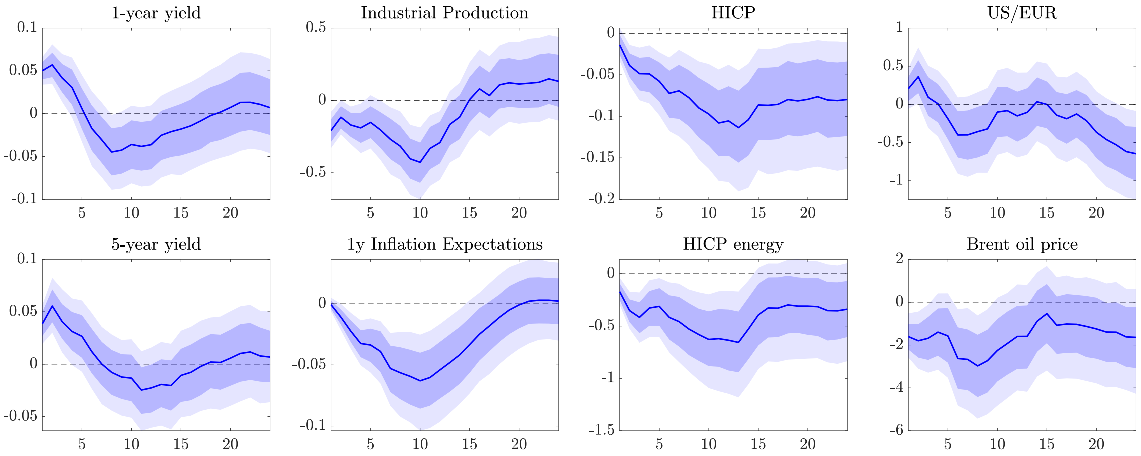
Notes: Posterior means of Impulse response functions to a one standard deviation monetary policy shock using the external-instrument BPSVAR identification alongside in blue 68% and 90% point-wise probability bands. Posterior mean impulse response functions to monetary policy shock identified using the internal-instrument approach of Plagborg-Møller and Wolf (2021) are depicted in red. To make the estimation of the IRFs using the internal instrument approach comparable to the BPSVAR approach we use a version of the conjugate normal-inverse-wishart prior. The impulse responses for the internal instrument approach are scaled such that they induce the same impact effect for the 1-year yield.

Figure E.4: IRFs of natural gas prices (in dollars) and EA consumer gas prices (in euros)



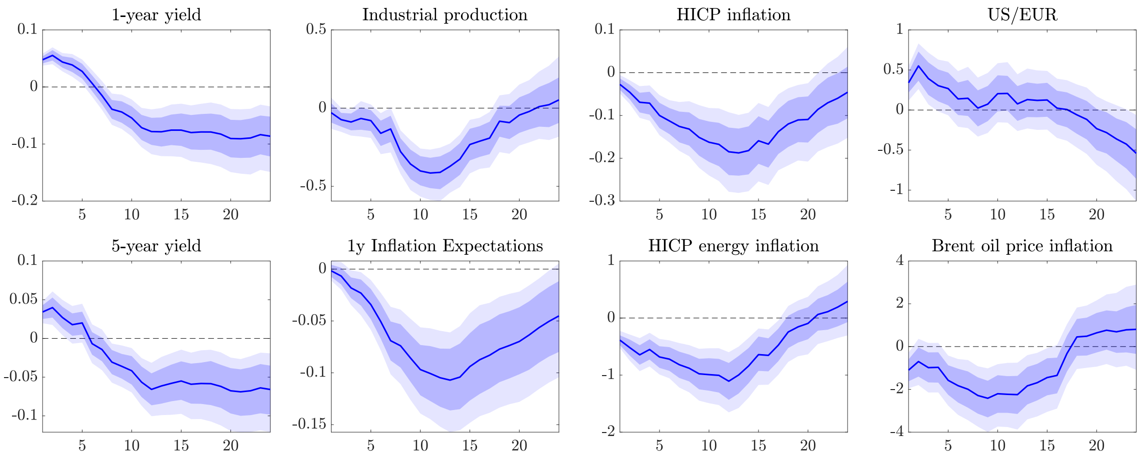
Impulse responses from the baseline BPSVAR model with (i) Worlds Bank's average, European natural gas primary commodity price (traded and quoted in US-$) and (ii) the natural gas component of the HICP (quoted in euros) as additional endogenous variables. Note that, even leaving aside differences in the currency in which the prices are quoted, these are not the same object. In particular, the HICP Gas series refers to gas prices faced by consumers (which naturally are more sticky) while the World Bank's average European natural gas price commodity price is the price traded on financial markets and faced by firms and consumers.

Figure E.5: Euro Area SVAR model, zero proxy relevance prior threshold



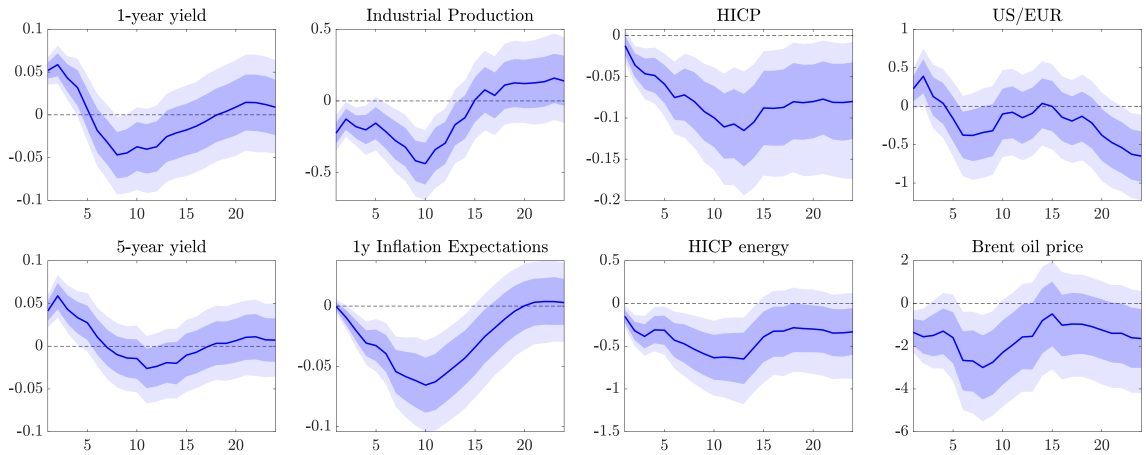
Notes: Impulse responses to a euro area monetary policy shock when the prior on the relevance of the shock for the proxy set to 0%. Impulse response functions to a one standard deviation monetary policy shock. Point-wise posterior means along with 68% and 90% point-wise probability bands. Horizon in months.

Figure E.6: Euro Area SVAR model including the Pandemic



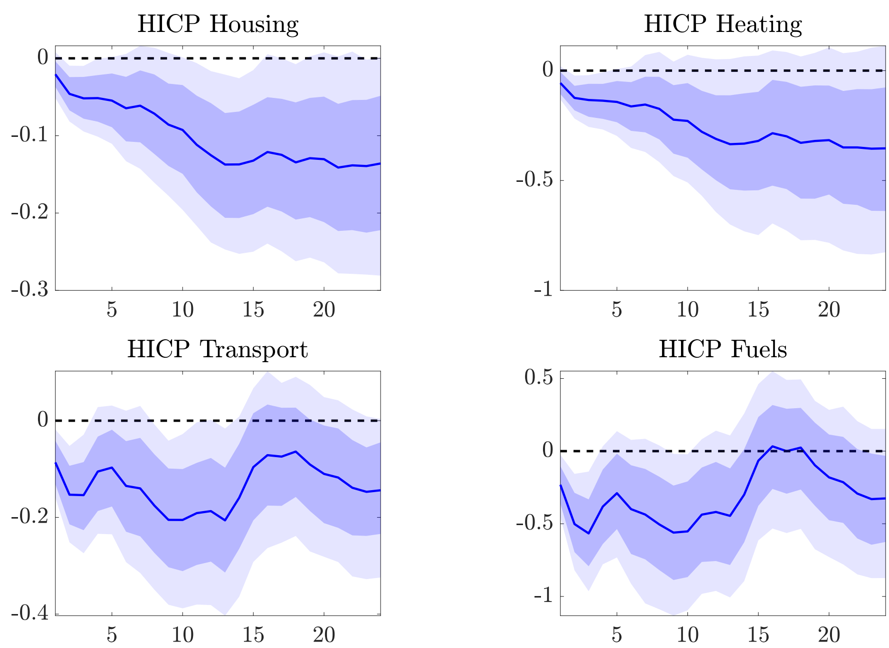
Notes: Impulse response functions to a one standard deviation monetary policy shock from the estimated BPVSAR model when including the pandemic period into the estimation sample. We model the pandemic using the "Pandemic-Priors" approach of Cascaldi-Garcia (2022) and transform prices to inflation rates to preserve stationarity. The extended sample ends in January 2023. Due to data availability, we follow Känzig (2023) and set to zero the values of the proxy starting in 2020. Point-wise posterior means along with 68% and 90% point-wise credible sets. Horizon in months.

Figure E.7: Euro Area SVAR model with purged high-frequency monetary surprises



Notes: Impulse response functions to a one standard deviation monetary policy shock, estimated using the baseline BPVSVAR specification with high-frequency monetary policy surprises purged of predictability from Brent oil prices (following Bauer and Swanson (2023)). Point-wise posterior means along with 68% and 90% point-wise credible sets. Horizon in months.

Figure E.8: Euro Area SVAR model including different energy-intensive subcomponents of the HICP



IRFs from the baseline BPSVAR model with the individual subcomponents of the HICP as additional endogenous variables. The official Eurostat categories are called "Housing, Water, Electricity, Gas & Other Fuels", "Transport", "Electricity, Gas & Other Fuels", and "Fuels & Lubricants for Personal Transport Equipment". Their weights in the headline HICP are, in percent, 16.5, 15.4, 5.9, and 4.3, respectively (2019 values).

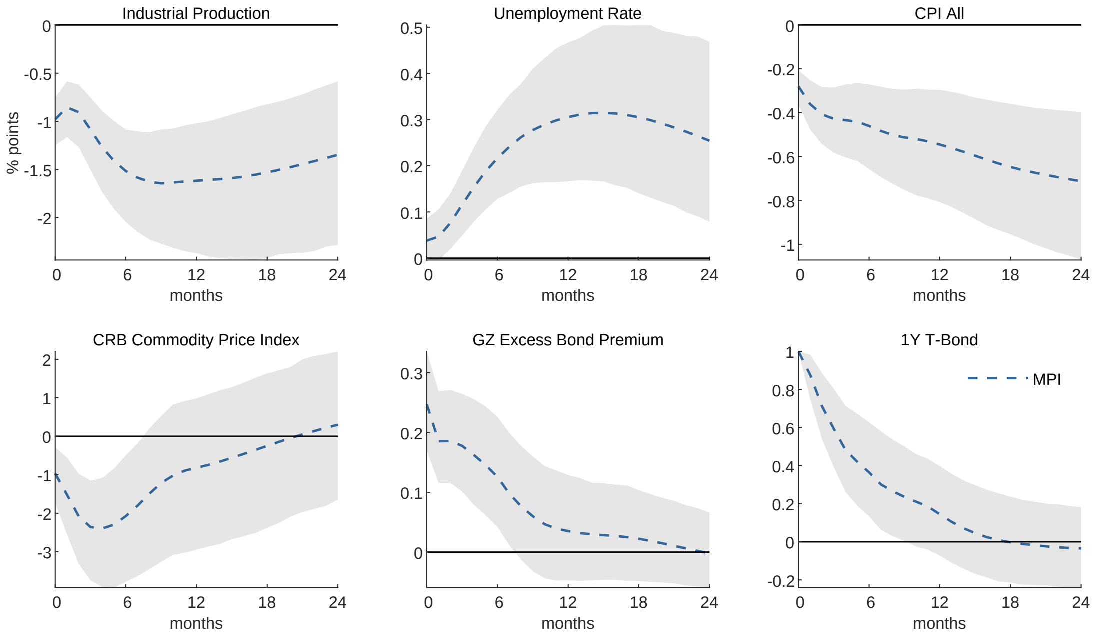
Table E.1: Literature review: Trough industrial production response to 100 bps tightening

Model	Sample period	Trough response
A. US Models		
Bauer and Swanson (2023) (Original sample)	1973:1 – 2020:2	−5.1%
Bauer and Swanson (2023) (Starting 2002)[a]	2002:1 – 2020:2	−10.5%
Miranda-Agrippino and Ricco (2021) (Original sample)	1979:1 – 2014:12	−1.7%
Miranda-Agrippino and Ricco (2021) (Starting 1999)	1999:1 – 2018:12	−9.2%
Jarociński and Karadi (2020) (Original Sample)	1984:2 – 2016:12	−3.6%
Jarociński and Karadi (2020) (Starting 1999)	1999:1 – 2016:12	−8.7%
IKKS US SVAR (starting 1990)	1990:1 – 2019:12	−1.3%
IKKS US SVAR (starting 1999)	1999:1 – 2019:12	−6.9%
B. EA Models		
Jarociński and Karadi (2020)	1999:1 – 2016:12	−17.4%
Corsetti et al. (2024)	1999:1 – 2021:12	−32%
Badinger and Schiman (2023)	1999:1 – 2019:12	−6.6%
This paper (main specification)	2002:1 – 2019:12	−9.3%
This paper (from 1999)	1999:1 – 2019:12	−6.1%
C. UK Models		
Braun et al. (2024)	1997:1 – 2019:12	≈ −6.6%
D. Summary		
Model average	Start < 1999	-3.7%
Model average	Start ≥ 1999	-11.9%

Notes: We report the trough Industrial Production response to a peak of one percentage point increase in the 1-year government bond yield of the respective country. As Braun et al. (2024) use monthly GDP instead of industrial production, we rescale their estimate to industrial production by taking into account the relative volatilities of the series (see Georgiadis et al., 2024 for a similar approach). For the euro area, the cited studies use the 1-year Bund yield. "IKKS" refers to the authors and "IKKS US SVAR" refers to the baseline SVAR model presented in Section 3 of this paper, where we replace the euro area data with the corresponding time series for the US. See Figures E.10 and E.11.

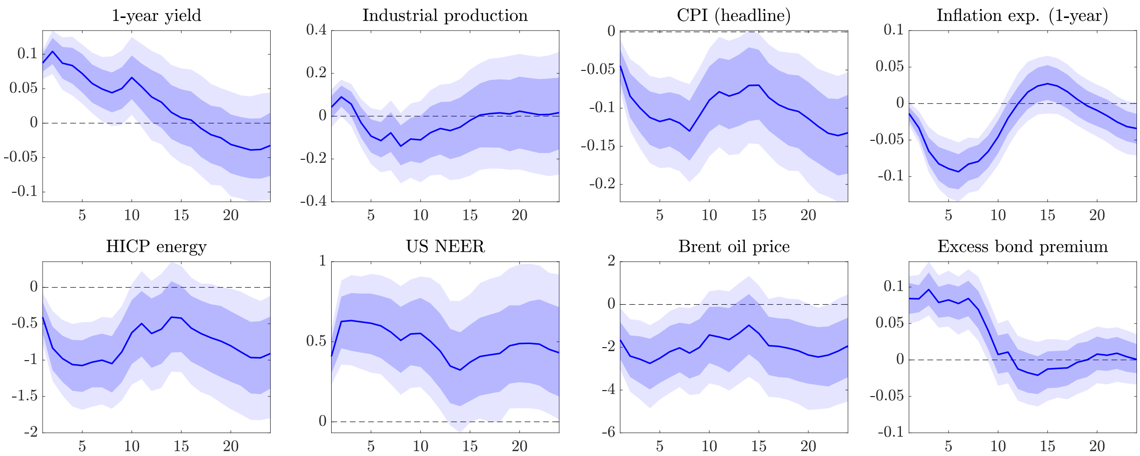
[a] The yield fails to increase in response to a contractionary monetary policy shock when starting the sample from 1999. Therefore, we chose to start the sample in 2002.

Figure E.9: Baseline VAR from Miranda-Agrippino and Ricco (2021)



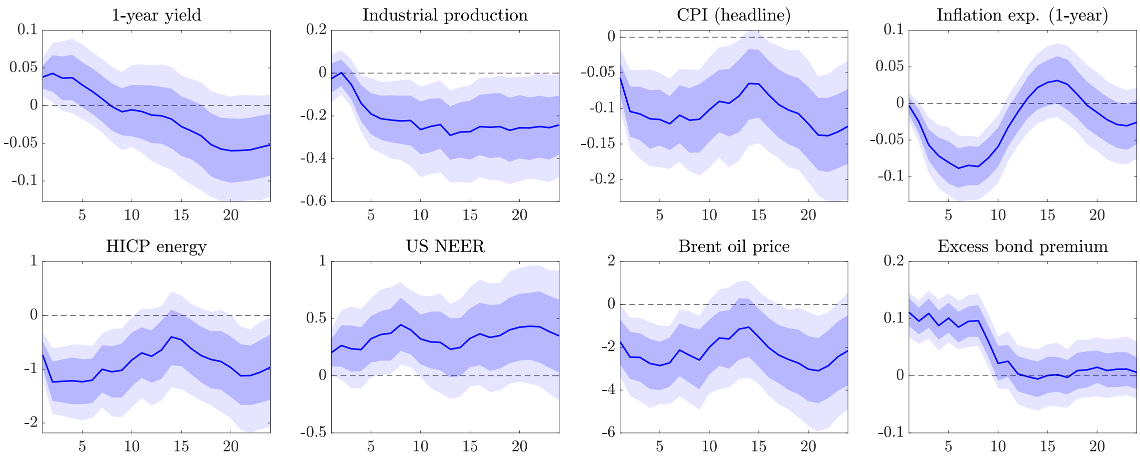
Notes: Baseline six-variable VAR from Miranda-Agrippino and Ricco (2021). MPI stands for the informationally robust monetary policy surprise series the authors construct. The shock is normalized to induce a 100 basis point increase in the 1-year rate. Sample is 1979M1–2014M12. Shaded areas are 90 percent posterior coverage bands.

Figure E.10: US SVAR model, starting 1990



Notes: Impulse responses to a one standard deviation monetary policy shock. Point-wise posterior means along with 68% and 90% point-wise credible sets. Horizon in months. Impulse responses for variables that do not correspond to interest rates or inflation rates are expressed in percent. Impulse responses for inflation rates and interest rates are expressed in annualized percentage points.

Figure E.11: US SVAR model, starting 1999



Notes: Impulse responses to a one standard deviation monetary policy shock. Point-wise posterior means along with 68% and 90% point-wise credible sets. Horizon in months. Impulse responses for variables that do not correspond to interest rates or inflation rates are expressed in percent. Impulse responses for inflation rates and interest rates are expressed in annualized percentage points.

F Discussion of the magnitude of the oil price response

F.1 A simple theoretical model

To rationalize why euro area monetary policy affects global energy prices and why energy prices are particularly sensitive to monetary policy induced changes in demand, we build a partial equilibrium model of the global market for energy goods. In particular, we assume that energy goods are traded globally, energy prices are flexible and energy supply is fixed at $\bar{E}$ in the short run as in Bayer et al. (2023).[27] Furthermore, we assume that world demand (Y_t^W) is allocated according to a standard CES aggregate of energy goods and non-energy goods, with α denoting the weight of energy goods in the aggregate basket.[28] Under these assumptions we can write the demand ($Y_{E,t}^D$) for and supply of energy goods ($Y_{E,t}^S$) as the following system of equations

$$Y_{E,t}^D = \alpha \left(\frac{P_t^E}{P_t^W} \right)^{-\sigma} Y_t^W, \qquad\qquad Y_{E,t}^S = \bar{E}, \tag{F.1}$$

with σ as the elasticity of substitution between energy and non-energy goods and P_t^E/P_t^W as the relative price of energy goods with respect to the world aggregate. Imposing market clearing ($Y_{E,t}^S = Y_{E,t}^D$) and log-linearizing, we can write the equilibrium relation as

$$\widehat{p}_{t,r}^E = \frac{\widehat{y}_t^W}{\sigma} \tag{F.2}$$

with $\widehat{y}_t^w$ denoting deviations of global demand from its steady state and ($\widehat{p}_{t,r}^E$) as the corresponding deviation of the relative price of energy goods.

Given that the euro area constitutes approximately 20% of global GDP and that the ECB's monetary policy decisions have sizable spillovers to other countries (Miranda-Agrippino and Nenova (2022), Ter Ellen et al. (2020)), an increase in the ECB's policy rate affects global demand $\widehat{y}_t^W$, which in turn affects the relative price of energy. In particular, recent estimates on the elasticity of substitution between energy and non-energy goods imply $\sigma \in [0.1, 0.2]$ (Bachmann et al. (2022) and Bayer et al. (2023)), i.e. an ECB-induced 1% decrease in demand causes the relative price of energy goods to fall by 5% to 10%. The intuition is that, given a low elasticity of substitution, the demand curve is very steep. When confronted with a vertical short-run supply curve, a change in demand will

[27] At the intraday frequency the assumption of flexible energy prices follows immediately from our high-frequency event study and at the monthly frequency this assumption is also in line with the micro-data underlying the computation of the HICP as for instance Aucremanne and Dhyne (2004) show that the prices of energy goods are on average updated every month.

[28] The aggregator is given by $Y_t^W = [\alpha^{\frac{1}{\sigma}} Y_{E,t}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)^{\frac{1}{\sigma}} Y_{NE,t}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$ with $Y_{NE,t}$ as non energy goods.

result in strong price adjustments in order to reach an equilibrium between supply and demand. This stylized mechanism not only rationalizes why ECB policy decisions affect energy prices but the assumptions on the energy market structure also offer one possible interpretation for why energy prices are more responsive to changes in monetary policy than prices of other goods. In the next section we discuss how this this partial equilibrium model of the energy market is embedded in the fully-fledged, state-of-the-art general equilibrium model of Bayer et al. (2023) and show that in this model, an increase in the ECB's policy rate of similar magnitude than the one estimated in our BPSVAR, indeed implies a similar drop in the price of energy goods.

F.2 The mechanism in general equilibrium

Figure 2 reveals that a standard-deviation monetary policy shock, which increases the short-term interest rate by roughly 5 basis points, leads to an immediate fall in the oil price by approximately 2%. To shed some light on the plausibility on the magnitudes we use a representative agent version of the HANK model of Bayer et al. (2023) to gauge the plausibility of out results through the lens of a state-of-the-art model that features an energy market along the lines sketched above.[29]

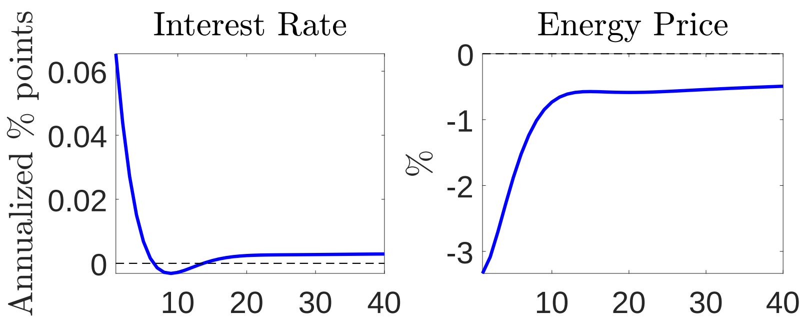
The model of Bayer et al. (2023) is an arguably standard model of a monetary union with two countries and nominal frictions in terms of price and wage setting. The crucial ingredient is that firms (households) in these countries use (consume) energy goods. Energy goods are assumed to be in fixed supply and, crucially, as the model does not feature a small open economy assumption, a change in the demand for energy from households and firms in the monetary union, will affect the price of energy. Therefore the model features a market for energy goods along the lines of the one that we sketch in Section F.1. To use the model for our purposes we add a monetary policy shock to the Taylor Rule of the monetary authority in the monetary union, while keeping the calibration and all other model features exactly as in Bayer et al. (2023).

Figure F.1 illustrates that in this state-of-the-art model, a monetary shock that leads to roughly the same interest rate response as in our empirical model, causes energy prices to fall by even more than what we find empirically. The intuition for the large volatility of energy prices is that energy goods are in fixed supply and the elasticity of energy- and non-energy goods is assumed to be non-zero but relatively low in line with Auclert et al. (2023) and Bachmann et al. (2022). Therefore, as the market for energy goods has to clear, the energy price has to move a lot to realign the demand with the supply of energy goods. Intuitively, all else equal, a monetary shock induces a fall in demand for all goods. Given the low elasticity of household demand to a change in the energy price, the price of these energy goods has to fall a lot to ensure that households ultimately buy the fixed amount

[29]We thank Fabian Seyrich for sharing the code with us.

of energy goods supplied.

Figure F.1: IRF of the energy price to a monetary shock in the model of Bayer et al. (2023)



F.3 Allowing for more elastic energy supply

If we relax the assumption of a sticky energy supply, we get

$$Y^S_{E,t} = \bar{E}\Big(\frac{P^E_t}{P^W_t}\Big)^{\varphi_s}, \qquad \varphi_s \approx 0. \tag{F.3}$$

Log-linearizing yields $\widehat{y}^s_t = \varphi_s \, \widehat{p}^E_{t,r}$. Demand in (F.1) log-linearizes to $\widehat{y}^d_t = \widehat{y}^W_t - \sigma \, \widehat{p}^E_{t,r}$. Imposing market clearing, $\widehat{y}^d_t = \widehat{y}^s_t$, implies

$$\widehat{p}^E_{t,r} = \frac{1}{\sigma + \varphi_s} \, \widehat{y}^W_t . \tag{F.4}$$

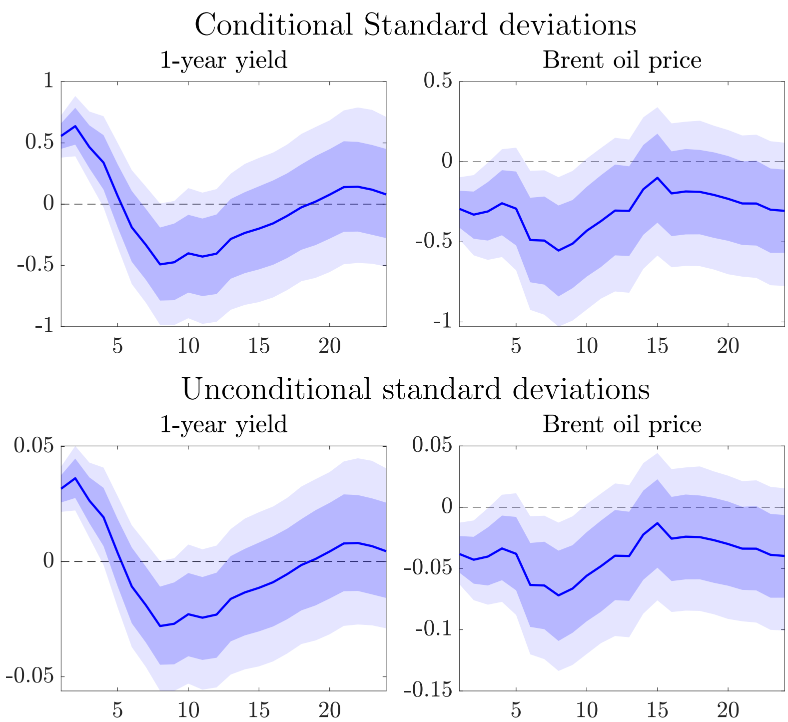
Hence, when both demand is inelastic (low σ) and supply is close to vertical (low φ_s), demand-driven fluctuations in $\widehat{y}^W_t$ translate into large movements in energy prices.

F.4 Relative volatilities of the interest rate and oil price

An arguably simpler argument for why the "elasticity" of oil prices to a monetary shock that we find empirically is not excessively large can be made by taking into account the relative volatilities of these variables. In line with the intuition sketched above, the oil price is very volatile compared to the short-term interest rate.

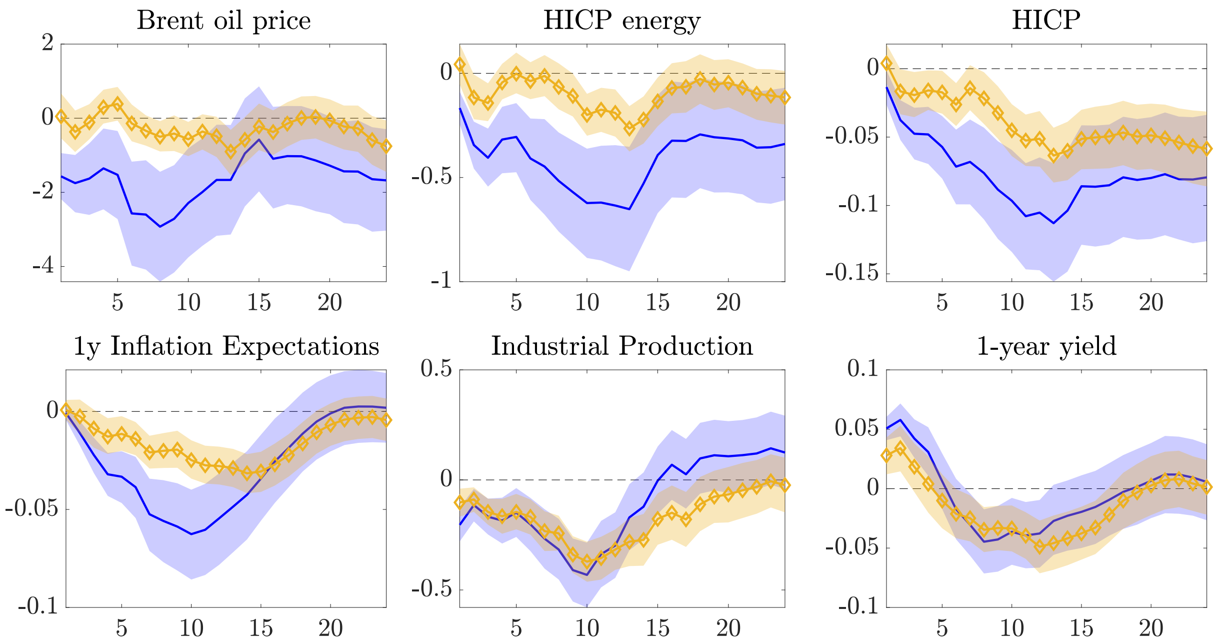
Figure F.2 illustrates this by plotting the impulse responses of the interest rate and the oil price in terms of their unconditional and conditional standard deviations (i.e. the standard deviation of their one-step ahead forecast error). It becomes apparent that, when measured in terms of the standard deviation of the respective forecast error, the average monetary policy shock causes the interest rate to increase by approximately half a standard deviation and the oil prices to fall by roughly a quarter of the standard deviation. Comparing this to the responses in levels of 5 basis points and 2% it becomes apparent that the 2% fall in the oil price is by no means excessively large. Thus, under the assumption that the forecast error is normally distributed around zero, an unexpected 5 basis point surprise in the interest rate is less likely than an unexpected 2% fall in the oil prices, as the latter only corresponds to a quarter of a standard deviation while the former corresponds to a surprise of half a standard deviation. The second row, which plots the IRFs in terms of their unconditional standard deviations, underscores the fact, that even unconditionally, the two magnitudes are more than comparable. In line with the intuition that we derived above, the oil price is just an arguably much more volatile object.

Figure F.2: IRF of the oil price to a monetary policy shock in standard deviation units



G Additional material on the OPEC counterfactual

Figure G.1: What if EA monetary policy shocks do not affect oil prices (including credible sets)



Notes: Impulse response functions to a one standard deviation monetary policy shock showing the point-wise posterior means along with 68% point-wise credible sets in blue. Horizon in months. The golden line with diamonds shows the point-wise posterior means of the counterfactual where EA monetary policy does not affect the oil price 68% point-wise credible sets. We approximate the solution to the counterfactual using the "best Lucas-Critique-robust approximation" of McKay and Wolf (2023), where we follow McKay and Wolf (2023) and condition on the point estimate to the monetary policy shock depicted in Figure 2. We also plot the 68% point-wise credible sets of this approximation in yellow.

G.1 Quantifying the role of global energy price for monetary policy trade-offs

Our framework not only allows us to quantify how the ability of the central bank to influence energy prices shapes the transmission of monetary policy to domestic inflation and inflation expectations but also enables us to speak to the role that this ability plays in the inflation-unemployment/inflation-output trade-off that central banks typically face. We follow Mankiw (2001) and Barnichon and Mesters (2021) and aim to measure the central banks's average trade-off, meaning we aim to measure the average fall in inflation caused by a change in policy that increases the unemployment rate by 1ppt or decreases output by 1%.

As shown by Barnichon and Mesters (2021) the inflation-unemployment trade-off can be quantified using standard semi-structural methods such as our BPSVAR and can be estimated by a statistic that the authors coin "Phillips-Multiplier". We next lay out their approach, which we then adapt to our goal of measuring the output-inflation trade-off. The authors suggest to compute the sequence of "Phillips-Multipliers" ($\mathcal{P}_{\mathcal{A}}$) as

$$\mathcal{P}^h_{\mathcal{A}} = \frac{\Theta^h_{\bar{\pi},\nu^{mp},\mathcal{A}}}{\Theta^h_{\bar{U},\nu^{mp},\mathcal{A}}}. \tag{G.1}$$

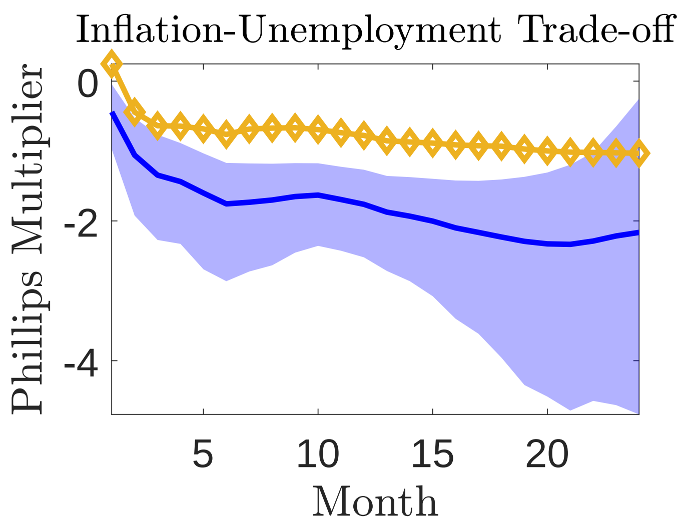
where $\Theta^h_{\bar{x},\nu^{mp},\mathcal{A}}$ measures the horizon h impulse response of the average of variable x to a unit monetary policy shock ν^{mp} under the OPEC policy rule described by $\mathcal{A}$. For each variable x and horizon h this quantity can be computed by the average of the running cumulative sum of impulse responses $\Theta^h_{\bar{x},\nu^{mp},\mathcal{A}} = \frac{1}{h}\sum_{j=0}^{h-1}\Theta^j_{x,\nu^{mp},\mathcal{A}}$. The "Phillips-Multiplier" at period h measures how the average rate of inflation changes if monetary policy were to engineer a 1ppt increase in the unemployment rate over the next h periods. In other words, this statistic measures how the expectation (forecast) of inflation changes if monetary policy announces at period t that it will engineer an average increase of unemployment by 1ppt. over the next h horizon. Intuitively, in the textbook three equation New Keynesian model of Galí (2015), the "Phillips-Multiplier" is constant across periods and recovers the slope of the Phillips-curve with respect to unemployment (see Barnichon and Mesters (2021))

Given that this statistic can be computed solely based on impulse responses, we can also ask how this measure of the inflation-unemployment trade-off would change if the ECB would not affect global energy prices as in Section 5. In particular, as in Section 5 we assume that OPEC follows a counterfactual policy rule $\widetilde{\mathcal{A}}$ aims to stabilize the oil price and calculate

$$\mathcal{P}^h_{\widetilde{\mathcal{A}}} = \frac{\Theta^h_{\bar{\pi},\nu^{mp},\widetilde{\mathcal{A}}}}{\Theta^h_{\bar{U},\nu^{mp},\widetilde{\mathcal{A}}}}. \tag{G.2}$$

Our baseline VAR does not feature unemployment. Therefore, to calculate this statistic, we transform IRFs of industrial production to IRFs of unemployment by (i) transforming IRFs of industrial production to its GDP counterpart by taking into account the relative variances (3.3) and then computing the implied IRF of unemployment using Okun's law with a Coefficient of 2. Figure G.2 compares the baseline sequence of the Phillips-Multipliers as depicted by the blue lines and the counterfactual sequence of Phillips-Multipliers depicted in gold. By comparing the blue and the golden line in Figure G.2 it becomes apparent that the ability to affect global energy prices plays a crucial role in the inflation output trade-off that the ECB faces. For instance, if the ECB were to engineer an increase in unemployment by 1ppt over the next year ($\mathcal{P}^{12}_{\mathcal{A}}$), this is estimated to yield a fall of average inflation of roughly 1.8% in the case where the ECB can affect energy prices. This value lies in the ballpark of the estimates of Barnichon and Mesters (2021). But this statistic changes dramatically in the counterfactual scenario, where this only brings about a fall in average inflation of about 0.8%. Thus, the ability of the ECB to affect global energy prices alleviates the unemployment-inflation trade-off by approximately 55% ((1.8-0.8)/1.8). When viewed through the lens of the textbook New-Keynesian model, this implies that the slope of the Phillips curve is steeper when monetary policy can affect fast-moving energy prices.

Figure G.2: Inflation-Unemployment trade-off under Baseline and Counterfactual OPEC rule



Notes: Point-wise median of the Phillips-Multiplier under the baseline policy rule alongside 50% credible sets in blue. Phillips-Multiplier estimated using the point-estimate of the Least-squares approximation of the counterfactual impulse responses depicted in gold. To calculate this statistic, we transform IRFs of industrial production to IRFs of unemployment by (i) transforming IRFs of industrial production to its GDP counterpart by taking into account the relative variances (3.3), and then computing the implied IRF of unemployment using Okun's law with a Coefficient of 2. We compute the IRFs of (y-o-y) inflation by transforming the impulse responses of the HICP accordingly. We plot 68% credible sets to not distort the scale of the figure, as the posterior is very much skewed to the left.

To calculate the Phillips-Multiplier of Barnichon and Mesters (2021), we had to take a stand on how a monetary policy-induced change in industrial production translates into a change in unemployment. To avoid this ambiguity, we therefore instead report the same statistic for the inflation-output trade-off. In particular, we use the same approach as outlined above but replace the (constructed) impulse response of average unemployment with the (actual) response of average industrial production. This yields the statistic that we report in the main text. To be more precise, we define the "Output-Phillips-Multiplier" as

$$\mathcal{P}^h_{\widetilde{\mathcal{A}}} = -\frac{\Theta^h_{\bar{\pi},\nu^{mp},\widetilde{\mathcal{A}}}}{\Theta^h_{\bar{Y},\nu^{mp},\widetilde{\mathcal{A}}}}, \tag{G.3}$$

where $\Theta^h_{\bar{Y},\nu^{mp},\widetilde{\mathcal{A}}}$ measures the response of average industrial production to a monetary policy shock. At each horizon, the statistic measures how the average rate of disinflation if monetary policy were to engineer a 1% fall in the industrial production over the next h periods. The results are shown in Figure 6 in the main text.

H Further material for the optimal policy counterfactuals

H.1 Deriving the optimal policy rule

Focusing on a single variable $\boldsymbol{x}_i$, Equation (19) implies that the space of possible allocations that the policymaker can achieve for this variable is given by

$$\boldsymbol{x}_i = \sum_{j=1}^{n_\nu} \Theta_{x_i,\nu_j,\mathcal{A}} \times \nu_j. \tag{H.1}$$

Plugging this expression into Equation (18) and taking the first-order conditions with respect to each ν_j, one arrives at the condition

$$\sum_{i=1}^{n_x} \lambda_i \Theta'_{x_i,\nu,\mathcal{A}} W \times \boldsymbol{x_i} = \mathbf{0}. \tag{H.2}$$

For each $\boldsymbol{x}_i$ the term in front of the sum describes how a change in the policy instruments $\boldsymbol{\nu}$ would translate into a change in the endogenous variable $\boldsymbol{x}_i$ and weights these changes over time using the time discount matrix W. All the implied changes are then summed over all variables x_i using the policy weight λ_i, which translates them into changes in the loss function of Equation (18). This rule then implies that the (weighted) sum of changes in the objective function resulting from a change in the policy instruments $\boldsymbol{\nu}$ has to equal zero. In other words, the gradient of the loss function with respect to the policy instruments has to be set to zero at the optimum.

This condition can be encapsulated into the matrices $\boldsymbol{\mathcal{A}_x}, \boldsymbol{\mathcal{A}_z}$ of the sequence-space representation of the model in Equation (11) by noting that the optimality condition in

Equation (H.2) can be written as

$$\sum_{i=1}^{n_x} \lambda_i \Theta'_{x_i,\nu,\mathcal{A}} W \boldsymbol{x_i} = \mathcal{A}^*_{\boldsymbol{x}} \boldsymbol{x} = \mathbf{0}. \tag{H.3}$$

H.2 Estimating the impulse responses under counterfactual optimal policy

The procedure for the counterfactual optimal policy is very similar to the one sketched in the main text for the baseline optimal policy exercise but involves two additional steps.

First, we estimate impulse responses to a generic identified oil supply shock. We use the same endogenous variables as in our baseline BPSVAR model. All variables enter the estimation in log levels if they are not already expressed in percentage terms.

Second, we identify the euro area conventional monetary policy and forward guidance shocks by combining the high-frequency proxies with the magnitude and sign restrictions described in the text. Again we use the same variables and transformations as in step 1.

Third, we use the same endogenous variables and sample as in the first step to estimate the impulse responses to a short- and medium-run oil supply news shock in line with the description in Section 5.3.

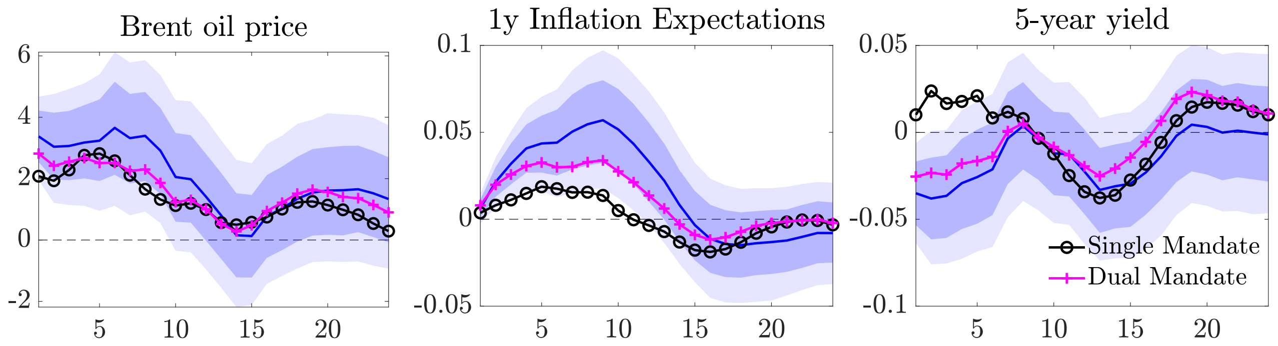
Fourth, we compute the posterior distribution for each counterfactual impulse response from the second step, assuming that the euro area monetary policy shocks from the second step do not affect energy prices. We do so by applying the procedure of McKay and Wolf (2023) to each draw from the posterior distribution of the second and third step.

Fifth, we condition the impulse responses from the first step and compute the optimal policy counterfactual for each draw from the posterior distribution of the fourth step.

Lastly, we plot the point-wise mean which can be interpreted as summarizing the posterior distribution of impulse responses under the optimal (counterfactual) policy response conditional on the data and the impulse responses from step 1.

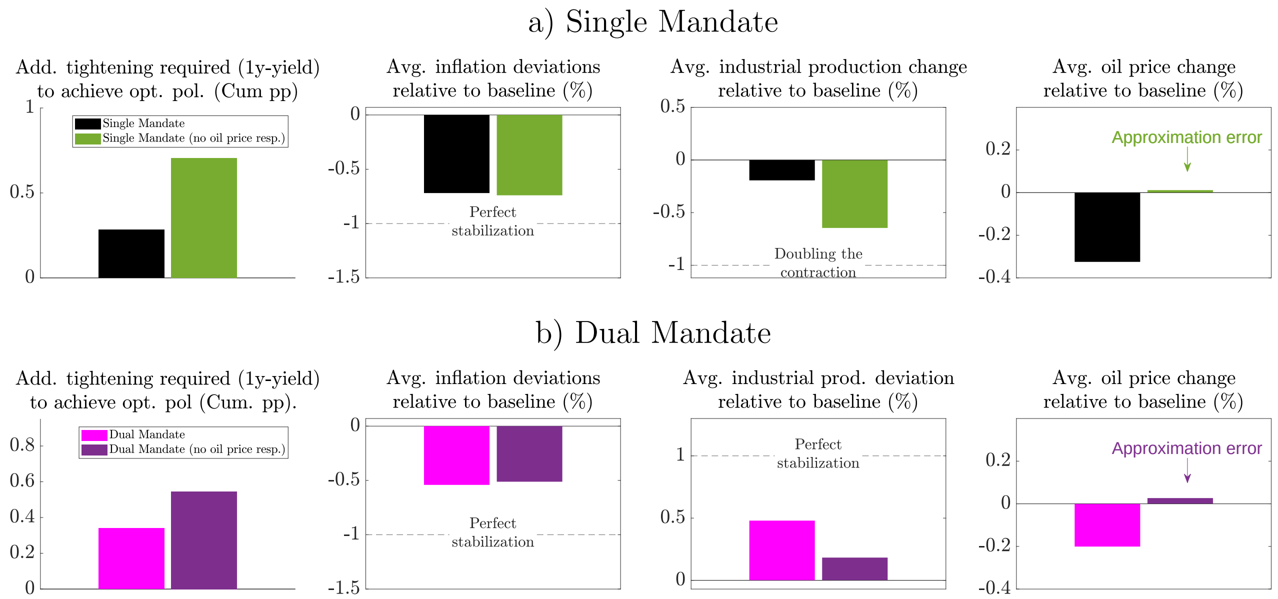
H.3 Additional figures for the optimal policy exercise

Figure H.1: Additional impulse responses under (couterfactual) optimal policy



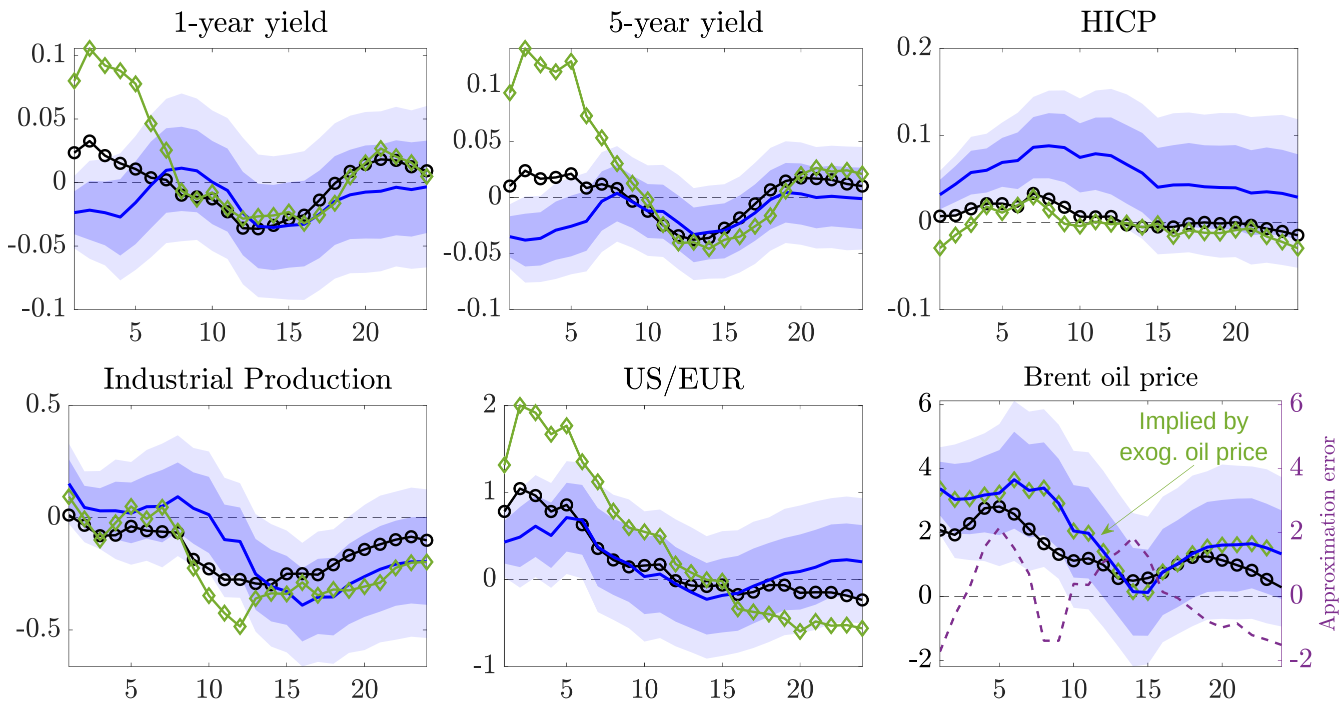
Notes: See notes to Figure 8.

Figure H.2: The role of energy prices for mandate-optimal monetary policy (approximation error)



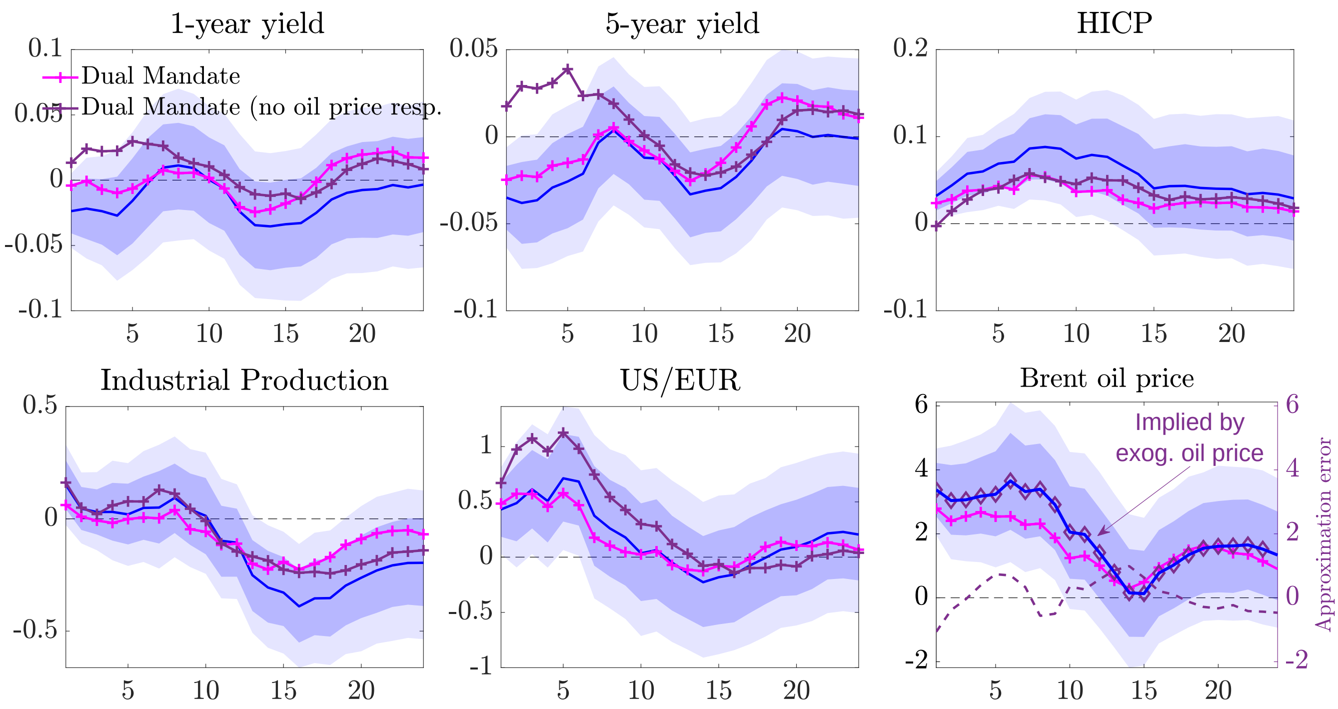
Notes: See notes to Figure 8. Note that, if the central bank cannot affect oil prices, the oil price response should be independent of the policy change, implying that the policy-induced change in the oil price should be zero relative to the baseline. As we approximate the solution, this is not exactly the case, but the average approximation error is small, as shown in the last row.

Figure H.3: Impulse responses to an oil supply shock (blue) under Single-Mandate optimal monetary policy when euro area monetary policy can (black) and cannot (green) affect the Brent oil price



Notes: See notes to Figure 8.

Figure H.4: Impulse responses to an oil supply shock (blue) under Dual-Mandate optimal monetary policy when euro area monetary policy can (magenta) and cannot (purple) affect the Brent oil price



Notes: See notes to Figure 8. Under a dual mandate, we specify a loss function that gives a weight of $\lambda = 1$ to y-o-y inflation and deviations of GDP from the steady state. To map industrial production deviations into GDP deviations, we scale the hypothetical equal weight of 1 that we want to give to GDP by the relative variance of GDP and industrial production ($\approx 1/3.3$).