Monetary Policy Identification and Transmission: A Narrative High-Frequency Approach

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Abstract

We identify four dimensions of monetary policy in the Euro Area using narrative restrictions applied to high-frequency data. By leveraging well-known historical episodes—such as Mario Draghi's "whatever it takes" speech—we can separately identify conventional policy, forward guidance, quantitative easing, and asymmetric country risk premia shocks using a single narrative restriction per shock. After controlling for predictability in high-frequency asset movements and state-dependent variance in a Bayesian factor model, we find limited evidence for the importance of information shocks. We use our shock measures to estimate the aggregate effects of monetary policy instruments. We implement a Bayesian VAR with distributed lags and stochastic volatility that allows for overidentifying restrictions on the impulse responses. We find that tightening along any monetary policy dimension causes declines in activity and inflation, though magnitudes vary considerably. Forward guidance has marginal effects on economic variables, while asset purchases induce larger impacts, but both remain less potent than conventional policy.

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1 Introduction

Following the Great Recession, central banks across Europe and North America have had to experiment with new unconventional monetary policy instruments to stimulate economic activity and achieve their inflation targets. Given the recency of these policies, there is only but limited direct empirical evidence on the impact these measures have had on economic aggregates.

In this paper, we identify four dimensions of monetary policy and their economic effects using narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018) and high-frequency data (Kuttner, 2001; Gürkaynak et al., 2005) for the Euro Area. We use the identified to shocks to trace out the aggregate dynamic causal effects of unconventional monetary policy. We find that all instruments induce persistent declines in economic activity and inflation, and the impulse-responses do not display puzzling behaviors frequently obtained using high-frequency data (Ricco et al., 2025).

Identification relies on well-known historical episodes during which one can primarily attribute to one specific monetary policy instrument. For instance, during the Governing Council (GC) meeting of the 22nd of January 2015, the ECB surprised markets by announcing a larger than expected asset purchase program, and long-dated yield fell sharply. We identify similar other episodes for conventional monetary policy, forward guidance, quantitative easing, and asymmetric country risk premia. A single narrative sign restriction per shock is sufficient to tightly identify each shock separately. We find that the identified shocks have persistent effects on financial variables extending 6 months and beyond.

We establish that for the Euro Area information shocks (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020) play a negligible role in the high-frequency movements of assets around policy events. After controlling for predictability in high-frequency movements (Bauer and Swanson, 2023), four types of monetary policy shocks, and state-dependent variance in both policy shocks and idiosyncratic errors, we find there is a very little residual variation left for information shocks to be meaningful. We show that, unlike the other monetary policy shocks we identify, the information shocks are noisy, do not display heavy-tails, and are very difficult to connect to the historical record.

At the aggregate level, we propose to estimate the effects of monetary policy using a Bayesian VAR model with distributed lags for the policy shocks. This specification carries several advantages. First, Baek and Lee (2022) and Montiel Olea et al. (2025) show that distributed lag models are equivalent to local projections in terms of bias. Second, VAR-DL models are straightforward to estimate in a Bayesian setting[1]. This setting allows one to place overidentifying sign and zero restrictions on the IRFs by either truncating posteriors and/or rejection sampling[2]. Third, the Bayesian paradigm allows to sample shocks from their high-frequency posterior in each MCMC iteration, thus naturally propagating estimation uncertainty from the high-frequency factor model to the impulse response estimates. This overcomes a major limitation of frequentist distributed lag models, which require either directly observable shocks or complex adjustments to account for estimation uncertainty in the shock series (Montiel Olea et al., 2025). Finally, we propose priors on the distributed lag coefficients which allow one to trade off bias for variance by either shrinking coefficients toward polynomials or penalizing the difference in adjacent IRF estimates.

Our estimates indicate that forward guidance has marginal effects on economic activity, while the effects of assets purchase are comparable in magnitude to those of conventional monetary policy. We find that a tightening along any of the monetary dimension we consider cause declines in economic activity and prices, rising exchange rates, falling stock prices, and large contractions in money supply. We do not report puzzling behaviors for the output and price responses. Finally, we show that overidentifying sign restrictions can substantially narrow confidence intervals for the responses to unconventional monetary policy shocks.

Related Literature

- **High-Frequency Identification of Monetary Policy Shocks**: Kuttner (2001), Gürkaynak et al. (2005), Ramey (2016), Nakamura and Steinsson (2018), Altavilla et al. (2019),

[1] On the other hand, local projections do not induce a proper likelihood and require Bayesian quasi-likelihood techniques, see Ferreira et al. (2025)

[2] If only imposing restrictions on the contemporaneous IRF, then one can directly truncate the posterior of the coefficient on the shock at time t. Otherwise, since IRFs are non-linear functions of autoregressive and distributed lag coefficients in a VAR-DL, one needs to implement an accept/reject algorithm

Jarociński and Karadi (2020), Swanson (2021), Bauer and Swanson (2023), Lewis (2023), Jarociński (2024).

- **Narrative Identification of Monetary Policy Shocks**: Romer and Romer (1989), Romer and Romer (2004), Coibion (2012), Cloyne and Hürtgen (2016).

- **Macroeconomic Effects of Monetary Policy**: Christiano et al. (1996), Christiano et al. (1999), Bernanke et al. (2005), Uhlig (2005), Gertler and Karadi (2015), Caldara and Herbst (2019), Miranda-Agrippino and Ricco (2021), Badinger and Schiman (2023), Barigozzi et al. (2024), Swanson (2024), Jarociński and Karadi (2025), Ricco et al. (2025).

2 High-Frequency Identification

In this section, we describe the Bayesian factor model we use to identify high-frequency monetary policy surprises. We discuss the econometric implementation of our identification strategy and the identifying assumptions we rely upon.

2.1 Data and High-Frequency Model

The high-frequency analysis leverages the Euro Area Communication Event-Study Database (EA-CED) collected by Istrefi et al. (2024). The dataset covers the period 1999-2024 and includes high-frequency movements for overnight interest swaps (OIS), sovereign yields, exchange rates, stock price indices, and inflation-linked swaps around over 300 scheduled Governing Council (GC) meetings and 4,400 intermeeting communication events. The latter include speeches and interviews given my members of the European Central Bank (ECB) president, members of the Executive Board of the ECB, and the governors of the national central banks of France, Germany, Italy, and Spain.

To ensure the intermeeting events only capture information about the path of Euro Area monetary policy, I apply the following filters. First, we retain only those events which induced abnormal returns, as calculated by Istrefi et al. (2024), in at least three of the assets we consider in the high-frequency model. Second, we discard observations which do not fall during market hours or which occur less than one hour after an FOMC policy decision or a macroeconomic data surprise. Third, we discard events prior to 2002 to avoid measurement error from the illiquid and underdeveloped OIS market that characterized the early years of the monetary union. The final sample includes 550 events.

The high-frequency model we consider is a Bayesian factor model with regime-dependent variances:

$$y_t = \boldsymbol{\Lambda}\epsilon_t + \boldsymbol{B}x_t + v_t \tag{1}$$

$$\epsilon_t \sim N(0, \boldsymbol{\Sigma}^{\boldsymbol{\epsilon}}_{\boldsymbol{s_\epsilon}}), \quad \mathbf{v}_t \sim N(0, \boldsymbol{\Sigma}^{\boldsymbol{v}}_{\boldsymbol{s_v}}), \quad s_\epsilon, s_v \in \{\text{low}, \text{high}\} \tag{2}$$

where y_t is a $N \times 1$ vector of high-frequency movements in asset prices, $\boldsymbol{\Lambda}$ is a $N \times K$ matrix of factor loadings, ϵ_t is a $K \times 1$ vector of monetary policy structural shocks, $\boldsymbol{B}$ is a $N \times M$ matrix of coefficients, x_t is a $M \times 1$ vector of financial and economic control variables, and finally v_t is a $N \times 1$ vector of idiosyncratic components. Both the structural shocks and the idiosyncratic components feature regime-switching volatility. This allows to control for heteroskedasticity and the empirical regularity that asset price volatility is higher during scheduled GC meetings than intermeeting events.

The model includes 15 variables: overnight interest swaps (1-month, 3-month, 6-month, 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year), Italian sovereign yields (2-year, 5-year, and 10-year), the EURO STOXX 50 stock price index, the Euro/Dollar exchange rate, and the 1-year inflation-linked swap (ILS).

The model also controls for predictability in the high-frequency movements of assets (Bauer and Swanson , 2023) by allowing for a vector of exogenous controls x_t. Specifically, we include the lagged 3-month changes for the following eight variables: the Composite Indicator of Systemic Stress (Hóllo et al., 2012), the Monetary Policy Uncertainty (Bauer et al., 2021) indicator for the Euro Area, the EURO STOXX 50 stock index, Brent crude, the yield curve slope (measured as the difference between the 10-year and 3-month OIS yields), the Germany-Italy 10-year sovereign spread, core HICP inflation, and unemployment.

2.2 Determining the Number of Factors

To determine the dimension K of the structural shocks, and therefore the number of monetary policy instruments, we apply Bayesian LASSO shrinkage with factor-specific hierarchical priors on the factor loadings:

$$\Lambda_{ij}|\lambda_j \sim \text{Laplace}(0, 1/\lambda_j), \quad \lambda_j \sim \text{Gamma}(a_\lambda, b_\lambda) \tag{3}$$

The Bayesian LASSO prior induces adaptive L_1 regularization on the factor loadings through its hierarchical structure. Each loading Λ_{ij} receives a Laplace prior centered at zero. The Laplace distribution is sharply peaked at zero, and allows for non-zero values only if supported by the data. Factors with weak explanatory power are assigned large λ_j values, thereby inducing aggressive shrinkage of the corresponding column of loadings $\Lambda_{\cdot,j}$ toward zero. The intensity of the shrinkage applied is governed by the hyperparameters (a_λ, b_λ). During the factor selection phase, we point-identify a rotation of the factors ϵ_t by imposing block-lower triangularity on $\mathbf{\Lambda}$ with positive diagonal elements (Lopes and West, 2004), and we allow for up to nine factors.

Figure 1 displays the posterior medians of the absolute factor loadings Λ. We allow for up to nine factors and set $a_\lambda = 0.25, b_\lambda = 0.25$ for moderate shrinkage [3]. The heatmap reveals four factors with substantial loadings. The first one primarily affects short-term rates, the second the middle- and long-end of the yield curve, the third sovereign yields, and the fourth the longer-end of the yield curve. A fifth factor loads weakly across longer-dated risk-free and sovereign yields. Based on this evidence, we set $K = 5$.

2.3 Identification Strategy

2.3.1 Econometric Framework

Identifying five distinct dimensions of monetary policy in the high-frequency poses substantially challenges. Relying only on zero restrictions (Altavilla et al., 2019; Swanson, 2021)

[3]We verify that the results are preserved when varying the values of the hyperparameters (a_λ, b_λ).

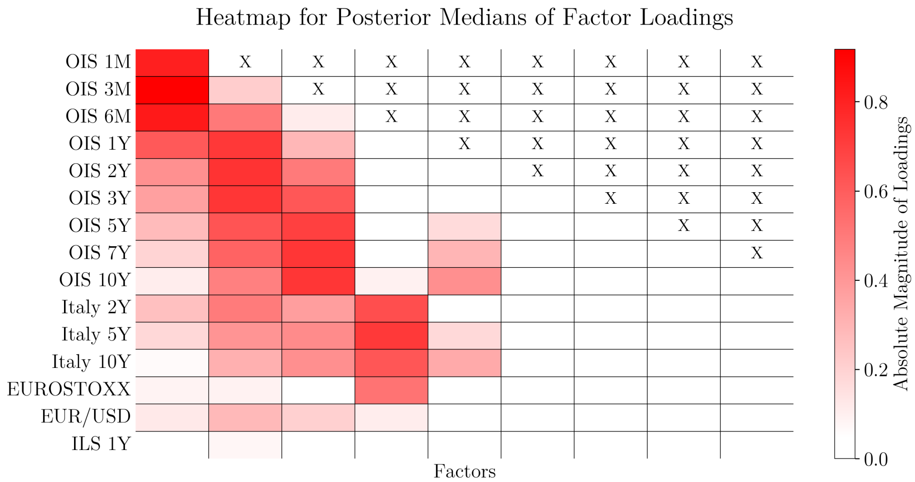

Figure 1: Heatmap for Posterior Medians of Factor Loadings

Note: The heatmap displays the absolute value of posterior median factor loadings $|\Lambda_{ij}|$ under strong Bayesian LASSO shrinkage ($a_\lambda = 0.25$, $b_\lambda = 0.25$). Darker red indicates larger loadings in absolute value. The X's denote zero restrictions imposed by the block-lower triangular identification scheme.

would require ten constraints to achieve point-identification, a demanding requirement. Sign restrictions require weaker assumptions but are not sufficient to disentangle multiple monetary policy instruments expected to have similar effects on variables. For instance, theory suggests that contractionary shocks operating through conventional policy, forward guidance, or asset purchases all raise yields and the exchange rate while depressing stock valuations and inflation expectations.

We overcome these identification challenges by augmenting sign restrictions with narrative restrictions (Antolín-Díaz and Rubio-Ramírez, 2018) based on well-documented historical episodes. We translate historical evidence into inequality constraints on the posterior of factor loadings by exploiting variations in the relative importance of different shocks across events.

For a narrative event at time τ, let shock j be the most important driver of the high-frequency movement of asset i:

$$|\boldsymbol{\Lambda_{ij}}\epsilon_{j\tau}| > \max_{k\neq j} |\boldsymbol{\Lambda_{ik}}\epsilon_{k\tau}| \tag{4}$$

We implement narrative restrictions on loadings $\mathbf{\Lambda}_{ij}$ using element-by-element Gibbs sampling (Korobilis, 2022), The unrestricted posterior for $\mathbf{\Lambda}_{ij}$ conditional on all other parameters follows from conjugate normal-normal updating:

$$p(\Lambda_{ij}|\cdot) \propto \mathcal{N}(\bar{\mu}_{ij}, \bar{\sigma}_{ij}^2) \tag{5}$$

$$\bar{\sigma}_{ij}^{-2} = \underline{\Omega}_{ij} + \sum_{t=1}^{T} \frac{\epsilon_{jt}^2}{\sigma_{i,s_v(t)}^v} \tag{6}$$

$$\bar{\mu}_{ij} = \bar{\sigma}_{ij}^2 \left[\underline{\Omega}_{ij}\underline{\mu}_{ij} + \sum_{t=1}^{T} \frac{\epsilon_{jt}\tilde{y}_{it}}{\sigma_{i,s_v(t)}^v} - \sum_{k\neq j} \Lambda_{ik} \sum_{t=1}^{T} \frac{\epsilon_{jt}\epsilon_{kt}}{\sigma_{i,s_v(t)}^v} \right] \tag{7}$$

where the notation $p(\mathbf{\Lambda}_{ij}|\cdot)$ denotes the conditional distribution given all other parameters, $\bar{\mu}_{ij}$ and $\bar{\sigma}_{ij}^2$ are the posterior mean and variance of $\mathbf{\Lambda}_{ij}$, $\underline{\Omega}_{ij}$ and $\underline{\mu}_{ij}$ are the prior precision and mean, $\tilde{y}_{it} = y_{it} - \sum_{m=1}^{M} B_{im}x_{mt}$ is the residualized asset price movement, and $\sigma_{i,s_v(t)}^v$ denotes the idiosyncratic variance for asset i in regime state $s_v(t)$.

Narrative restrictions truncate the posterior for Λ_{ij}. Let $\mathcal{T}_j$ denote the set of narrative events for shock j. The restricted posterior becomes:

$$p(\mathbf{\Lambda}_{ij}|\cdot, \mathcal{A}) \propto \mathcal{N}(\bar{\mu}_{ij}, \bar{\sigma}_{ij}^2) \times \prod_{\tau\in\mathcal{T}_j} \mathbb{I}\{\mathbf{\Lambda}_{ij} \in \mathcal{A}_{ij}(\tau)\} \tag{8}$$

where $\mathcal{A}_{ij}(\tau)$ is the admissible region defined by the narrative restriction:

$$\mathcal{A}_{ij}(\tau) = \left\{ \Lambda_{ij} : |\Lambda_{ij}| > \max_{k\neq j} \frac{|\Lambda_{ik}\epsilon_{k\tau}|}{|\epsilon_{j\tau}|} \right\} \tag{9}$$

In practice, we impose sign and narrative restrictions on the loadings $\mathbf{\Lambda}_{ij}$ by sampling from the following truncated normal distribution:

$$\mathbf{\Lambda}_{ij}|\cdot \sim \mathcal{TN}(\bar{\mu}_{ij}, \bar{\sigma}_{ij}^2, a_{ij}, b_{ij}) \tag{10}$$

$$\begin{cases} a_{ij} = \max\left\{0,\ \max_{\tau\in\mathcal{T}_j,\,k\neq j} \frac{|\mathbf{\Lambda}_{ik}\epsilon_{k\tau}|}{|\epsilon_{j\tau}|}\right\}, \quad b_{ij} = \infty & \text{if } \mathbf{\Lambda}_{ij} > 0 \\ a_{ij} = -\infty, \quad b_{ij} = \min\left\{0,\ -\max_{\tau\in\mathcal{T}_j,\,k\neq j} \frac{|\mathbf{\Lambda}_{ik}\epsilon_{k\tau}|}{|\epsilon_{j\tau}|}\right\} & \text{if } \mathbf{\Lambda}_{ij} < 0 \end{cases} \tag{11}$$

where $\mathcal{TN}(\mu, \sigma^2, a, b)$ denotes the Normal distribution with mean μ and variance σ^2 truncated to the interval $[a, b]$. The bounds ensure that shock j is the largest contributor to the movement in asset i for each narrative event $\tau \in \mathcal{T}_j$ while respecting the sign restrictions imposed on $\mathbf{\Lambda}_{ij}$. This element-by-element[4] sampling strategy[5] automatically satisfies both sign and narrative restrictions without having to implement computationally demanding accept/reject algorithms[6]

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2.3.2 Identifying Assumptions

We implement a set of sign and narrative restrictions to set-identify conventional monetary policy, forward guidance, asset purchases, asymmetric country risk premia, and information shocks. The first three are the standard policy instruments documented in the literature (Altavilla et al., 2019; Swanson, 2021). The fourth is specific to the Euro Area currency union and captures diverging sovereign risk premia dynamics between core and peripheral countries (Motto and Özen, 2022; Ricco et al., 2025). Finally, the fifth factor captures unexpected shifts in the ECB's assessment of the economy outlook (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020).

Sign Restrictions. The sign restrictions impose theory-consistent patterns for contractionary shocks:

1. Conventional monetary policy, forward guidance, and asset purchases raise yields and the exchange rate, depress stocks and ILS.

[4]Element-by-element Gibbs sampling induces serial correlation in the MCMC draws. To mitigate autocorrelation in posterior samples, we thin the chain by retaining every 5-th draw after the burn-in phase.

[5]Korobilis (2022) implements a similar algorithm in a Bayesian factor model for sign restrictions only.

[6]It should be mentioned, however, that this does not imply one can impose any identifying restriction on the model either. If the restriction is rejected by the data, then the truncated interval $[a, b]$ might be empty or contain negligible posterior probability mass.

2. Asymmetric country risk premia shocks raise peripheral yields and inflation expectations, lead to declines in risk-free yields (OIS), stocks, and exchange rates.

3. The information shock induces a positive comovement between all assets (Jarociński and Karadi, 2020).

Narrative restriction for conventional policy (10 May 2001). Amid a deteriorating economic outlook, the ECB cut interest rates by 25bps to 4.5% for the second time only since its inception in 1998. In doing so, the ECB reversed prior expectations set earlier in public statements emphasizing the central bank's mandate to maintain price stability.

CNN covered the event with an article headlined "ECB surprises with rate cut" and notes "Only three economists out of 50 polled by Reuters expected a rate cut." The article reported comments by David Brown, then chief economist at Bear Stearns, who stated "That's got to be the biggest monetary shock of the new millennium [...] They've completely pulled the wool over the market's eyes." Similarly, Forbes reported "A very surprising European Central Bank interest rate cut propelled stock markets in Europe higher [...] The move [...] came as a surprise to most observers [...]". This restriction is imposed on 1-, 3-, and 6-month OIS yields, the stock index, the EUR/USD exchange rate, and the 1-year ILS.

Narrative restriction for forward guidance (15 December 2022). During the post-pandemic inflation surge, the ECB issued hawkish forward guidance stating that "based on the substantial upward revision to the inflation outlook, expects to raise them [interest rates] further. In particular, the Governing Council judges that interest rates will still have to rise significantly at a steady pace". The press release reiterates again, in a new passage compared to the previous press release, that "The Governing Council decided to raise interest rates today, and expects to raise them significantly further" and changed "Inflation [...] will stay above the target for an extended period" to "inflation [...] is projected to stay above the target for too long." It also adds the following new passage "underlying price pressures across the economy have strengthened and will persist for some time".

The next day, the Financial Times covered the event with the headline "Lagarde admits ECB 'in for the long game' on rate rises". Similarly, the New York Times reports "Europe's

Central Banks Raise Rates, and Prepare for More". This is the largest contractionary forward guidance shock in the entire sample. This restriction is imposed on 1-, 2-, and 3-year OIS yields, the stock index, the EUR/USD exchange rate, and the 1-year ILS.

Narrative restriction for quantitative easing (22 January 2015). Mario Draghi confirmed circulating rumours of further monetary stimulus beyond an interest rate cut with the announcement of the asset purchase programme (APP) starting in March 2015 and with monthly purchases of €60 billion per month. The decision was partially leaked the previous evening and anticipated by markets, but the scale of purchases exceeded expectations.

The main headline on the Financial Times Europe edition cover page on 23 January 2015 reads "Markets rally as ECB bond-buying plan exceeds investor expectations." Similarly, the New York Times writes "Mario Draghi, said [...] would begin buying bonds worth 60 billion euros, [...] a month. That is more spending than the €50 billion a month that many analysts had been expecting." One of the largest QE shocks identified by Altavilla et al. (2019). This restriction is imposed on 5-, 7-, and 10-year OIS yields, the 5- and 10-year Italian sovereign yield, the stock index, the EUR/USD exchange rate, and the 1-year ILS.

Narrative restriction for asymmetric country risk (26 July 2012). Famous "Whatever it takes" speech by Mario Draghi in London during which he pledged an unlimited commitment towards the Euro, stating "Within our mandate, the E.C.B. is ready to do whatever it takes to preserve the euro. And believe me, it will be enough [...] the euro is irreversible."

The New York Times reported on the speech with an article titled "Assurances on Euro by Central Bank Chief Lift Stocks". Similarly, CNN titles an article "Draghi to the rescue". One of the largest expansionary shocks leading to a negative comovement between OIS and peripheral yields. This restriction is imposed on 2-, 5-, and 10-year Italian sovereign yields, the stock index, the EUR/USD exchange rate, and the 1-year ILS.

3 Euro Area Monetary Policy Shocks

In this section, we present the identified high-frequency monetary policy shocks for the Euro Area. We connect these to the narrative record and discuss the existence of information shocks. We then relate our identified shock series with the literature.

3.1 Identified Shocks

Though the restrictions we impose are set-identifying only, the monetary policy factors we recover are tightly identified. Figure 2 displays the columns of the loadings matrix $\mathbf{\Lambda}$ along with 95% highest posterior together with the identified time series of shocks. Figure 3 presents the plots for information shocks.

Conventional monetary policy predominantly affects short-term interest rates, with impacts declining smoothly along the yield curve. Forward guidance operates through the middle and long end of the yield curve while leaving short-term rates largely unchanged, and generates substantial exchange rate movements. Quantitative easing shocks influence only maturities exceeding five years. The asymmetric country risk shock triggers flight-to-safety dynamics: it moderately depresses long-dated risk-free yields while sharply elevating peripheral sovereign spreads, and simultaneously generates strong reactions in both equity markets and the exchange rate. Finally, the information shock closely resembles forward guidance in its term structure effects but induces positive comovements between yields and stock prices.

The identified shocks align closely with the historical narrative record. The largest expansionary target shock identified captures the coordinated response to the 9/11 attacks, when on 17 September 2001 the ECB cut rates by 50 basis points in conjunction with the Federal Reserve and other major central banks. The largest contractionary forward guidance shock occured on June 5, 2008, when amid rising inflationary pressures the ECB held rates at 4% while Trichet issued hawkish guidance. The New York Times noted the ECB "warned unexpectedly that it might raise interest rates next month," though markets had expected rates to remain steady. Lehman Brothers would collapse just two months later.

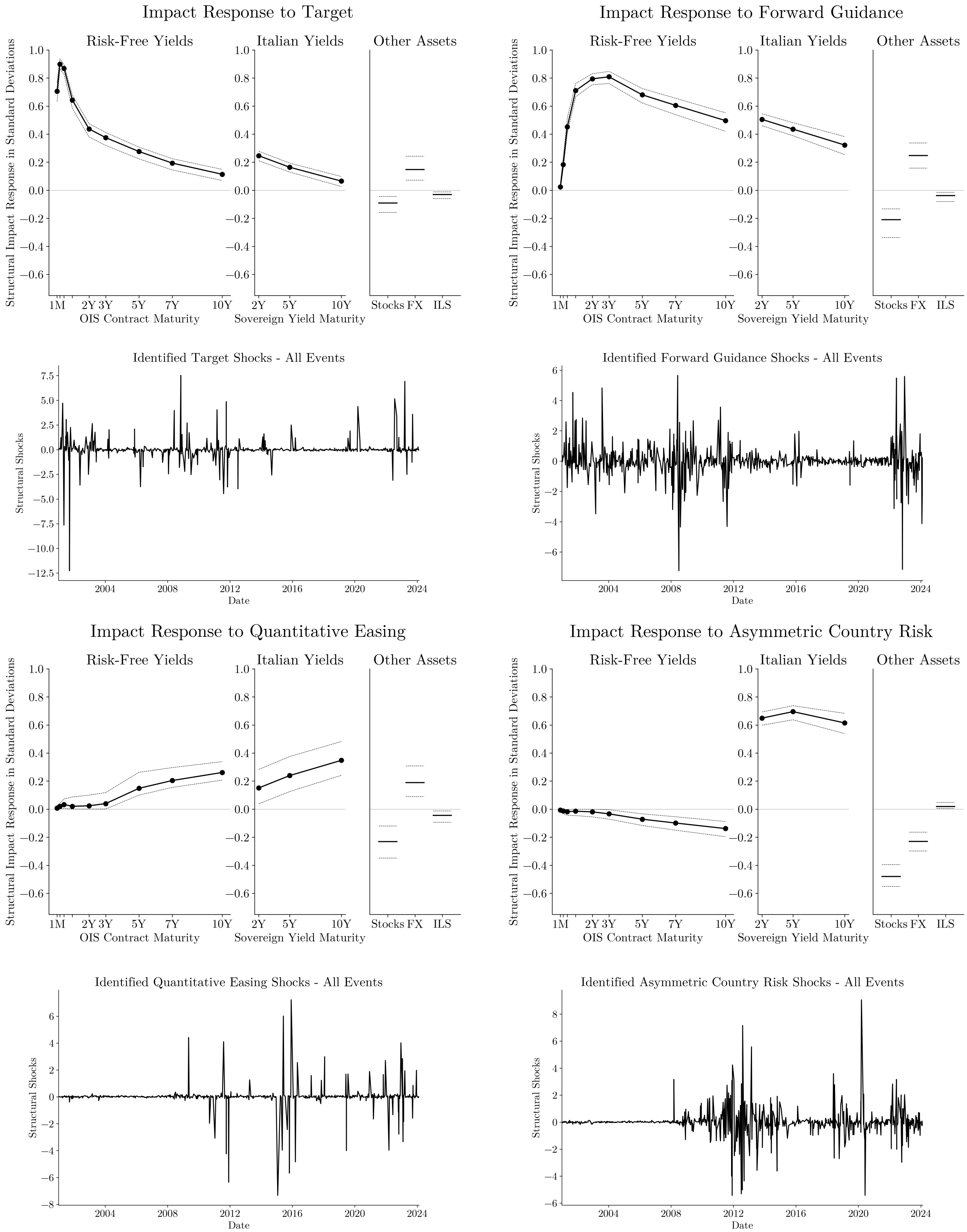


Figure 2: Identified Monetary Policy Shocks: Impact Matrix $\mathbf{\Lambda}$ and Time Series

Notes: The first and third rows display posterior medians of factor loadings $\mathbf{\Lambda}_{\cdot,j}$ for each shock, showing the structural impact of a one-standard-deviation shock on each asset. The second and fourth rows show the identified shock time series ϵ_{jt} over the sample period.

The largest contractionary quantitative easing shock happened on December 3, 2015, when the ECB maintained the prevailing monthly rate of asset purchases under the APP, disappointing market expectations of further expansion. The Financial Times headlined "Market sell-off as fresh Draghi bid to boost growth disappoints,". The largest contractionary sovereign risk shock happened on 12 March 2020 when ECB President Christine Lagarde stated the bank was "not here to close spreads," triggering a widening in peripheral sovereign spreads[7].

The time series also reflect the evolving nature of Euro Area monetary policy. Prior to the financial crisis, policy was conducted exclusively through conventional interest rate adjustments and forward guidance. During the sovereign debt crisis, asymmetric country risk premia shocks became the most important drivers of high-frequency movements in asset prices around policy events. As the ECB reached the zero lower bound, asset purchases became the primary policy instrument in the mid-2010s. Finally, all policy tools were simultaneously used during the post-pandemic inflation surge.

3.2 The Role of Information Shocks

The time series plots reveal substantial time-varying heteroskedasticity and heavy tails[8] in the monetary policy shocks. The information shock, however, exhibits markedly different behavior. Unlike the four policy shocks, which align closely with documented ECB communications and market commentary, the information shock series appears extremely noisy and fails to map onto identifiable historical episodes. The largest contractionary information shock identified corresponds to a speech on payment systems which did not reveal any material information about the economic outlook[9]. Most large information shocks are identified during intermeeting events, in contrast to large policy shocks which occur predominantly

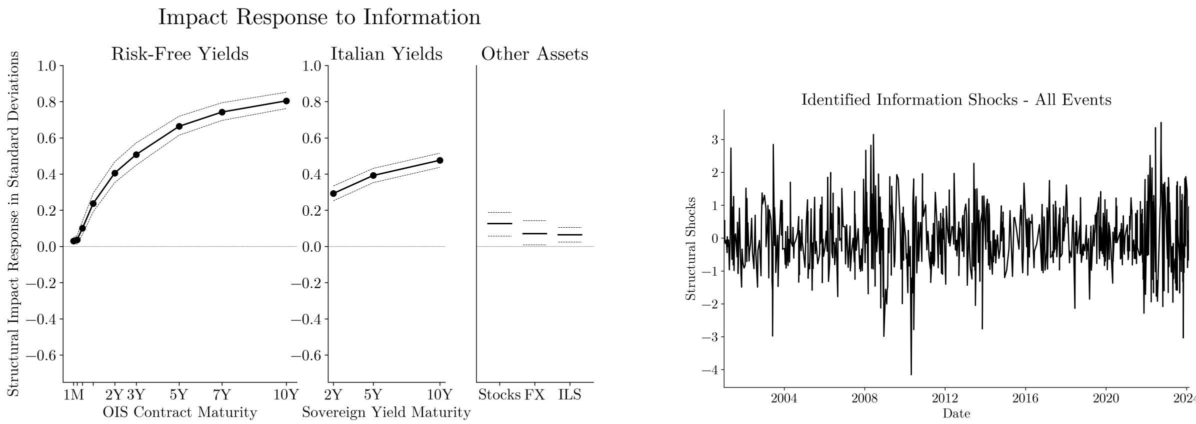
[7] In a CNBC interview later that day, she reversed course, stating "I am fully committed to avoid any fragmentation in a difficult moment for the euro area"

[8] We find negligible cross-correlation among squared monetary policy shocks. This finding, together with the high kurtosis of the identified shocks, provides support for identification strategies that exploit non-Gaussianity and shock independence (Jarociński, 2024)

[9] The transcript for the speech can be accessed here: https://www.ecb.europa.eu/press/key/date/2022/html/ecb.sp220616~9f8d1e277b.en.html

during GC meetings.

Figure 4 reveals substantial tail deviations from normality for all policy shocks, while information shocks are concentrated around the mean and close to being Normal. Across posterior draws, the ratio of high-state to low-state variance ranges from 30 to 350 for monetary policy shocks, but stands at just 2.7 for information shocks.



(a) Information Shock Impact ($\mathbf{\Lambda}_{\cdot,5}$) (b) Information Shock Time Series

Figure 3: Information Shock: Structural Impact and Time Series

Note: Panel (a) displays posterior medians of factor loadings $\mathbf{\Lambda}_{\cdot,5}$ for the information shock, showing the structural impact of a one-standard-deviation shock on each asset. Panel (b) shows the identified shock time series ϵ_{5t} over the sample period.

Further, Table 1 shows that monetary policy uncertainty (Bauer et al., 2021) and the CISS (Hóllo et al., 2012) are significant predictors of high-frequency movements in several risk-free and sovereign yields at maturities of 2 years and beyond, segments of the yield curve generally associated with information effects. This confirms findings by Bauer and Swanson (2023) and Ricco et al. (2025) that high-frequency surprises are partially predictable. The estimates in Table 1 imply that, when systemic stress is high, the ECB provides less accommodation than expected by markets, and vice versa when there is uncertainty regarding the stance of monetary policy.

These observations suggest that the identified information shocks may in fact capture residual positive comovements across assets—fluctuations that, by construction, cannot be attributed to the other four shocks given the sign restrictions we impose. We also note that

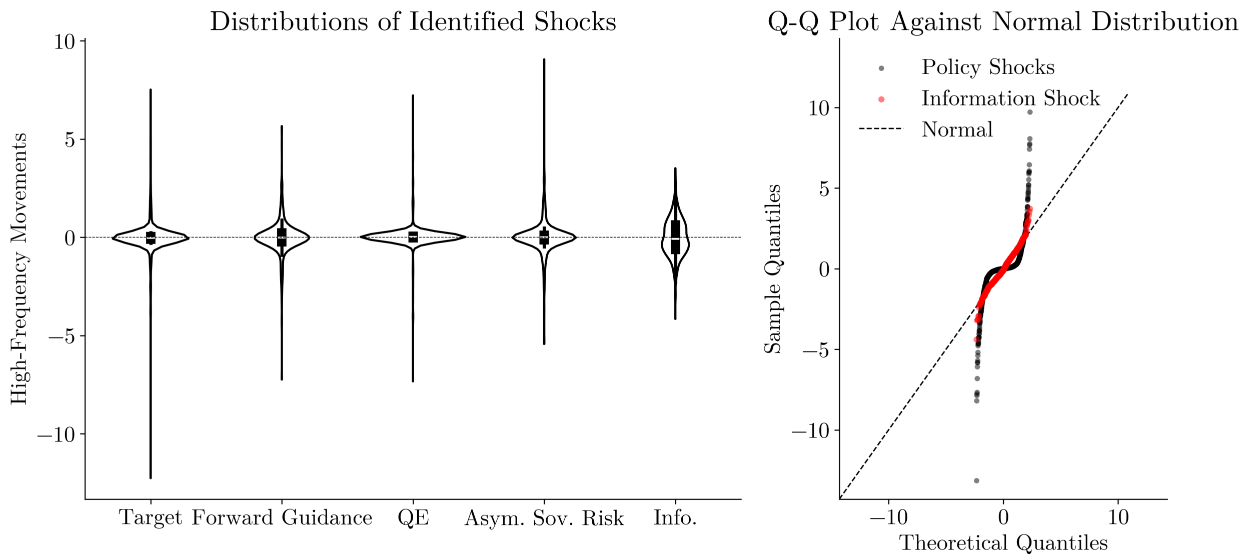


Figure 4: Distributions of Identified Structural Shocks

Note: The left panel shows violin plots of the identified structural shocks. The right panel displays Q-Q plots against the normal distribution, with policy shocks (target, forward guidance, quantitative easing, and asymmetric country risk premia) pooled together in black and the information shock shown separately in red. Deviations from the 45-degree line indicate departures from normality.

the first four principal components already explain over 91% of the variations in the time series we consider, thus leaving little residual variation for a potential fifth factor.

3.3 Comparison with the Literature

We also verify that the shocks we identify correlate with those previously identified. In Table 2, we compute the Pearson and rank correlations between our identified shocks and the ones derived by Altavilla et al. (2019). They consider seven OIS yields in their specification. Our target and forward guidance shocks correlate strongly with theirs, though they also correlate with the additional near-term forward guidance (Timing) they recover. On the other hand, their quantitative easing shock is positively correlated with our residual information shock. This may reflect the fact they do not impose restrictions inducing negative comovements between yields and stock prices, such that their quantitative easing shock may incorrectly capture positive comovements between these assets.

The shocks we identify also align with the narrative restrictions used by Badinger and

Table 1: Predictability of High-Frequency Surprises in Financial Assets

	CISS	**MP Uncer.**	**STOXX50**	**Oil Price**	**Yield Slope**	**DE-IT Spread**	**Core HICP**	**Unemp.**
OIS 1M	0.01	−0.01	−0.02*	−0.01	0.00	−0.02	0.00	0.00
OIS 3M	−0.02	−0.01	−0.03*	−0.01	0.01	0.01	0.01	0.01
OIS 6M	0.02	−0.03	−0.01	−0.03	0.03	0.01	0.01	0.01
OIS 1Y	0.04	−0.05*	0.01	−0.02	0.02	0.02	0.00	0.00
OIS 2Y	0.11***	−0.08***	0.03	−0.04	0.02	0.02	−0.03	0.02
OIS 3Y	0.12***	−0.09***	−0.01	−0.06	0.03	0.02	−0.03	0.02
OIS 5Y	0.10**	−0.07**	0.00	−0.08	0.03	0.01	−0.04	0.02
OIS 7Y	0.11**	−0.06*	−0.01	−0.11	0.02	0.02	−0.05	0.02
OIS 10Y	0.11**	−0.05	−0.02	−0.11	0.02	0.02	−0.05	0.03
IT 2Y	0.07**	−0.06***	−0.02	−0.03	0.02	0.01	−0.04	0.01
IT 5Y	0.06**	−0.06***	−0.01	−0.00	0.02	0.00	−0.05	0.01
IT 10Y	0.08**	−0.05**	−0.02	−0.01	0.02	−0.01	−0.02	0.02
EUROSTOXX	−0.01	0.01	−0.00	−0.04	0.07	0.01	−0.04	−0.05*
EUR/USD	0.05	−0.03	−0.01	−0.01	0.04	0.01	−0.05	0.01
ILS 1Y	−0.00	0.07**	0.02	−0.01	0.08	−0.02	0.01	0.01

Notes: This table reports the predictability of high-frequency surprises in financial assets to financial and economic variables following Bauer and Swanson (2023). *, **, and *** denote that zero is not contained in the 90%, 95%, and 99% HPD intervals, respectively.

Schiman (2023), who impose narrative sign restrictions at monthly frequency to estimate the effects of conventional Euro area monetary policy on macroeconomic aggregates. One of the event they use in their narrative analysis is the GC meeting on November 6, 2008, when the ECB cut rates by 50 basis points, disappointing markets after the Bank of England had slashed its policy rate by 150 basis points less than two hours earlier. We identify this as the largest contractionary target shock. They also use the October 6, 2011, GC meeting when Trichet held rates constant but emphasized inflation risks on the upside, while most market participants had either expected rates to remain unchanged or cut. We identify this episode as the fourth largest contractionary shock in our sample. This was followed by the surprise 25 basis point rate cut by Mario Draghi on November 3, 2011. The cut, which occurred during Draghi's first GC meeting, was perceived as a shift toward a more dovish policy stance and reversed expectations that Trichet had set in motion at his final meeting. This is the fifth largest expansionary target shock we identify.

Table 2: Correlation of Identified Shocks with Altavilla et al. (2019)

ABGMR 2019	Target	Forward Guidance	Quantitative Easing	Asymmetric Country Risk	Information
Target	0.73 (0.59)	−0.15 (−0.03)	0.10 (0.15)	0.05 (−0.04)	0.09 (0.17)
Timing	0.52 (0.58)	0.29 (0.21)	0.23 (0.26)	−0.12 (−0.13)	−0.07 (−0.06)
Forward Guidance	0.23 (0.16)	0.72 (0.71)	0.15 (0.02)	−0.01 (−0.10)	0.22 (0.24)
Quantitative Easing	−0.04 (−0.08)	0.04 (0.01)	0.48 (0.36)	−0.29 (−0.19)	0.63 (0.69)

Notes: This table reports Pearson correlations between shocks identified in this paper and those from Altavilla et al. (2019) over the common sample of ECB Governing Council meetings. Spearman rank correlations are shown in parentheses.

4 The Macroeconomic Effects of Monetary Policy

In this section, we present the macroeconometric model used to trace out the impact of monetary policy shocks on the economy. We then present our results and discuss sensitivity to the identifying assumption we impose.

4.1 Model Specification

We study the aggregate dynamic causal effects of monetary policy instruments using a Bayesian VAR with distributed lags (VAR-DL):

$$\mathbf{y}_t = \sum_{l=1}^{p} \Phi_l \mathbf{y}_{t-l} + \sum_{j=0}^{q} \Psi_j \mathbf{m}_{t-j} + \mathbf{v}_t \tag{12}$$

$$\mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_t) \tag{13}$$

$$\mathbf{\Sigma}_t = e^{h_t}\mathbf{\Sigma} \tag{14}$$

$$h_t = \phi h_{t-1} + u_t^h, \quad u_t^h \sim \mathcal{N}(0, \sigma^2) \tag{15}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, Φ_l are $n \times n$ autoregressive coefficient matrices, p is the number of autoregressive lags, $\mathbf{m}_t$ denotes the aggregated high-frequency monetary policy shocks, Ψ_j are $n \times 1$ distributed lag coefficient vectors, and q is the number of distributed lags of the shock. Following Carriero et al. (2016), we model time-varying volatility with a single common factor that proportionally scales all covariances. This parsimonious specification controls for heteroskedasticity, which is particularly important when including the pandemic era in the sample.

The Bayesian VAR-DL framework offers several advantages in our setting. First, as shown by Baek and Lee (2022), impulse-response coefficients are asymptotically unbiased up to horizon $H \leq q$. In fact, autoregressive distributed lags models are equivalent to local projections with additional controls for the future realizations of the shocks, thus improving efficiency (Montiel Olea et al., 2025). Second, the Bayesian implementation allows us to propagate the uncertainty surrounding the high-frequency estimates of the monetary policy shocks by directly sampling $\mathbf{m}_t$ at each MCMC iteration from the posterior draws obtained from the high-frequency Bayesian factor model[10]. As such, Bayesian methods allow us to overcome a major difficulty in using such models in frequentist settings where the shock series $\mathbf{m}_t$ either needs to be observed or estimates need to be adjusted for generated regressors.

In addition, this framework allows us to impose overidentifying zero, sign, or magnitude restrictions on the impulse-responses to sharpen identification[11]. Moreover, Bayesian shrinkage can be applied to the autoregressive matrices Φ_l to facilitate the choice of lags p. Finally, it is also possible to trade off higher bias for lower variance in the impulse-response estimates by either (i) shrinking impulse-responses toward low-order polynomials or (ii) penalizing the differences in consecutive IRF coefficients. In our application, shrinking IRFs toward a second-order polynomial markedly smoothes the IRF estimates at the cost of minimal bias.

The specification we consider includes six variables at monthly frequency: the main policy rate, which is either the OIS 3-month yield for target shocks, the OIS 2-year yield for forward guidance shocks, or the 10-year German sovereign yield for quantitative easing shocks; industrial production, HICP inflation, real GDP[12], the real effective exchange rate

[10] In contrast, most studies treat identified high-frequency surprises as data. A notable exception is Jarociński and Karadi (2025) who employ a similar strategy to ours to account for uncertainty in the proxy measures $\mathbf{m}_t$.

[11] For impact restrictions, one can directly truncate the posterior for Ψ_j. For restrictions at longer horizons, one can use an accept/reject procedure instead.

[12] We linearly interpolate monthly real GDP.

based on a trade-weighted basket of 42 currencies, and M2 money supply. All the time series were downloaded from the ECB data portal. All variables enter in logarithms except for the policy rate, which enters in levels, and HICP inflation, which is computed as the logarithmic difference of the HICP index.

Given prior evidence that the effects of monetary policy take up to between 12 to 18 months to fully materialize themselves, we conservatively set $q = 24$ and consider a similar forecast horizon. We set $p = 3$ and impose standard Minnesota priors[13] on the matrices Φ_l. The sample covers 2001M1-2024M2, and for quantitative easing shocks we start the analysis in January 2008 instead.

Identifying the effects of unconventional monetary policy instruments is challenging without additional restrictions given the small sample sizes and the relatively sparse set of large monetary policy shocks identified (see Figure 2). Therefore, we impose the following overidentifying sign restrictions for two quarters following impact: contractionary policy must raise the relevant policy rate and real exchange rate while depressing industrial production, GDP, inflation, and money supply. We discuss the implications of these restrictions below.

All the figures we present depict the impulse-responses to a monetary policy shock rescaled to induce a 25bps peak response in the corresponding policy rate. We report the posterior medians of the impulse-responses along with 16^{th} and 84^{th} percentile HPD bands.

4.2 Results

- No puzzles with sign + proxy

- Conventional policy > asset purchases > forward guidance in terms of effectiveness

- Sign restrictions help to identify, in particular for unconventional tools (add comparisons with/without)

- Puzzling responses for forward guidance without sign restrictions, relate to literature encountering similar issues (Swanson, Miranda-Aggripino, Ricco, etc.) (show comparison

[13] We use standard values and set the overall tightness parameter to 0.2, the cross-lag shrinkage multiplier to 0.5, and the lag decay exponent to 1.

graphs)

- Shrinkage very good at ”ironing out wrinkles” in IRFs, but the point-estimate is very similar to the original IRF (show comparison graphs)

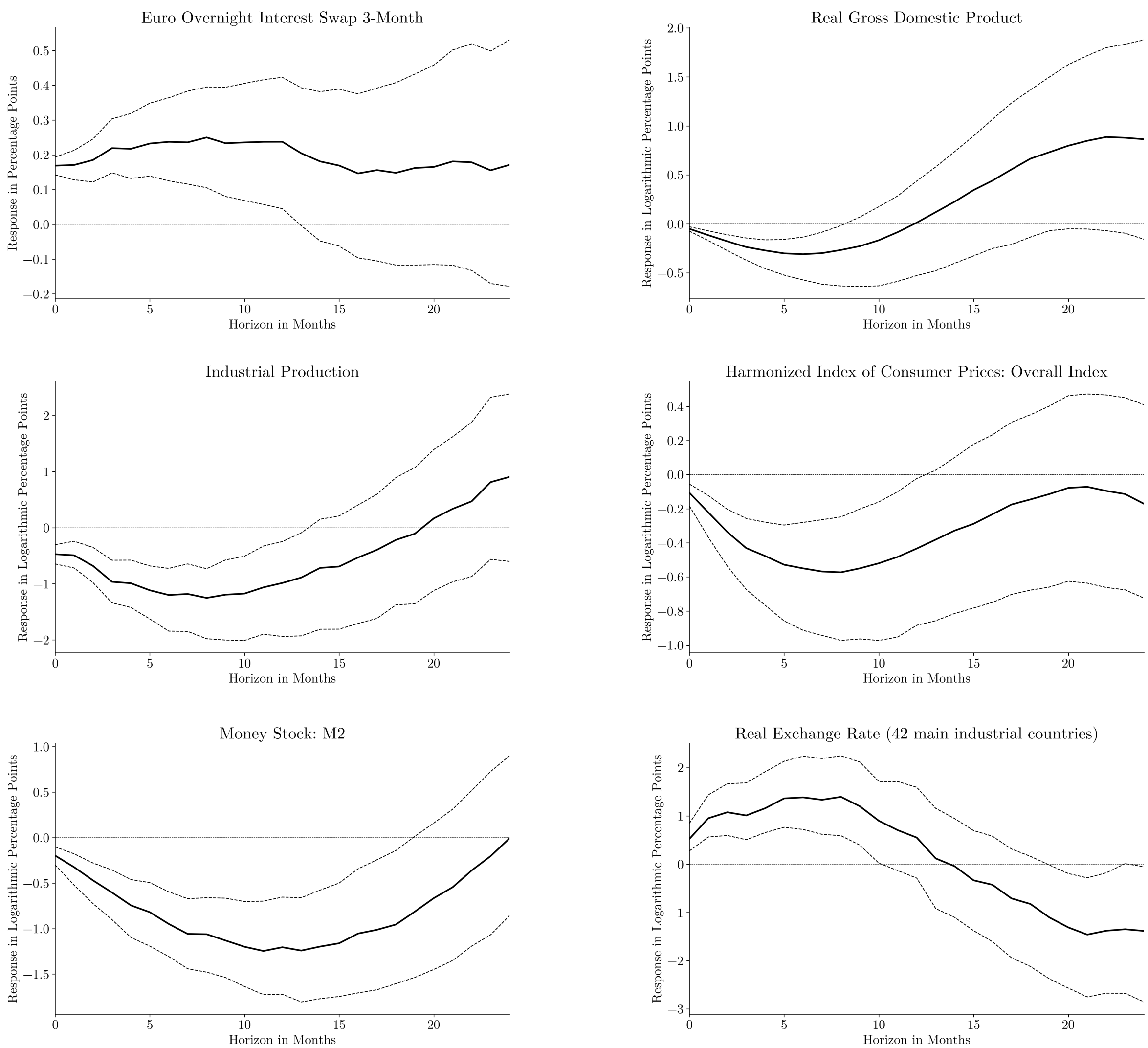


Figure 5: Impulse Responses to Conventional Monetary Policy Shocks
Notes: Impulse responses to a contractionary conventional monetary policy shock inducing a peak response of 25bps in the OIS 3-month yield. The solid black line shows the posterior median response, while the bands correspond to the 16^{th} and 84^{th} percentiles of the posterior samples. See text for a description of the model and identifying assumptions.

5 Conclusion

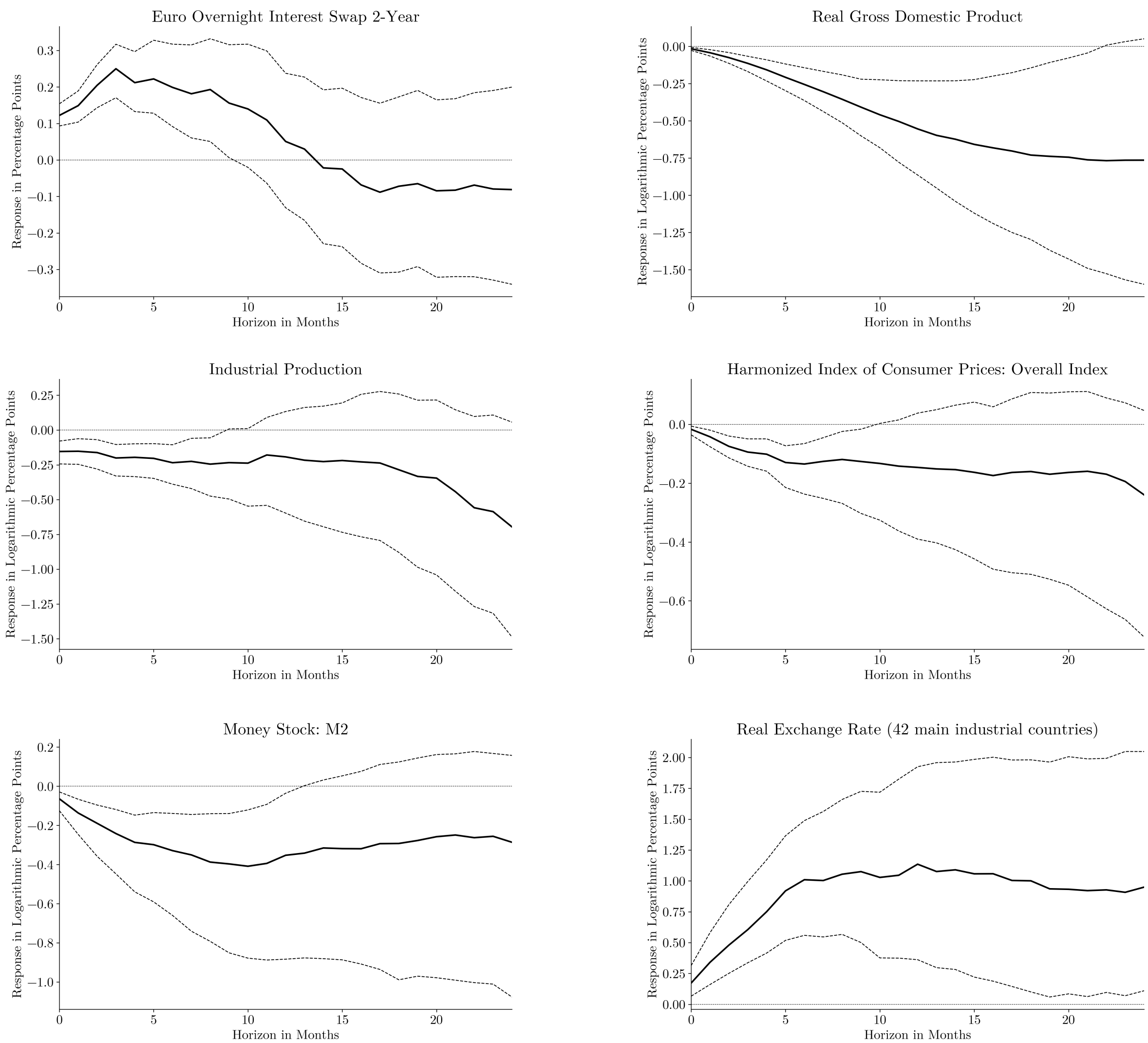


Figure 6: Impulse Responses to Forward Guidance Shocks

Notes: Impulse responses to a contractionary forward guidance shock inducing a peak response of 25bps in the OIS 2-year yield. The solid black line shows the posterior median response, while the bands correspond to the 16^{th} and 84^{th} percentiles of the posterior samples. See text for a description of the model and identifying assumptions.

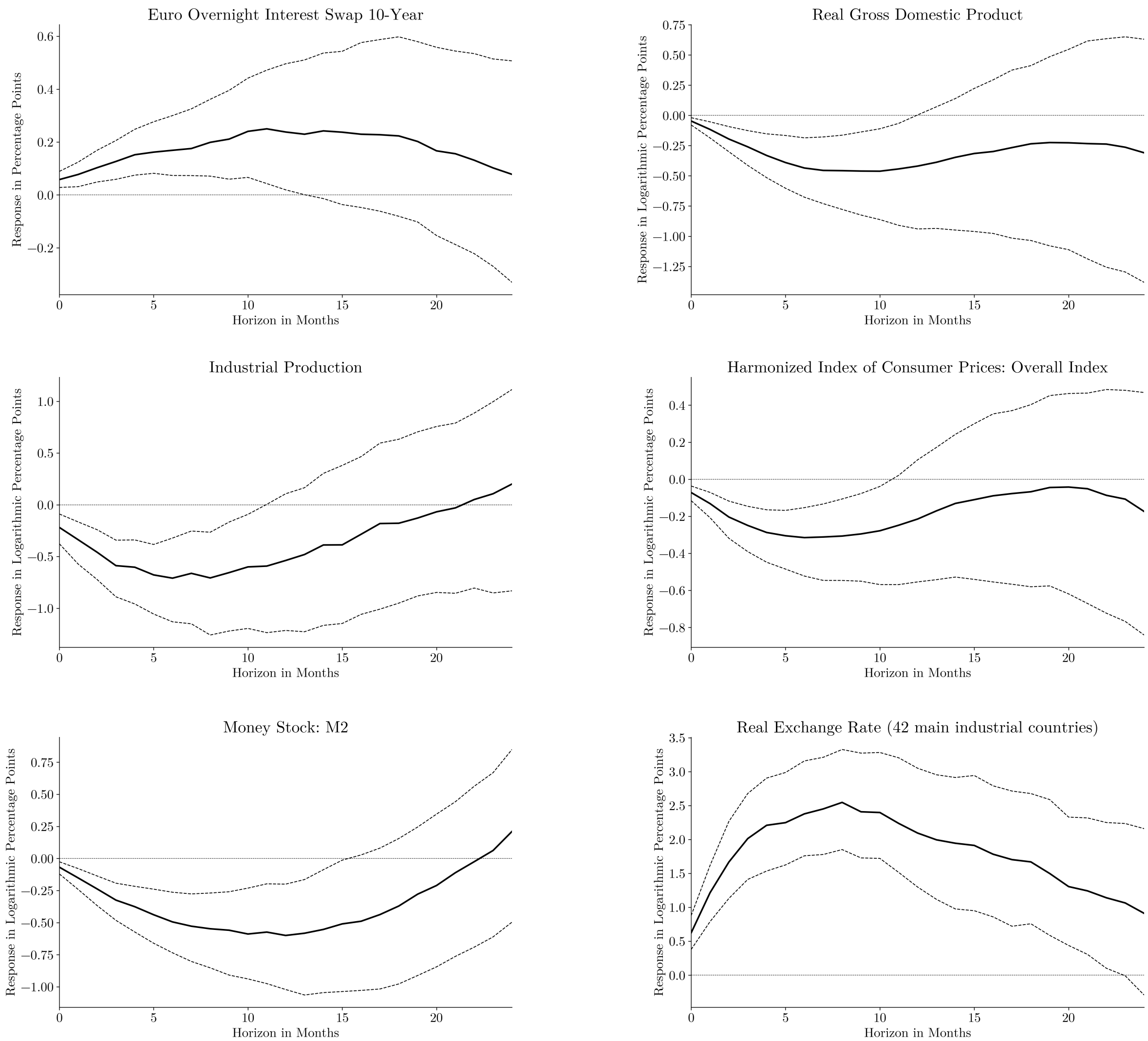


Figure 7: Impulse Responses to Quantitative Easing Shocks

Notes: Impulse responses to a contractionary quantitative easing shock inducing a peak response of 25bps in the German 10-year sovereign yield. The solid black line shows the posterior median response, while the bands correspond to the 16^{th} and 84^{th} percentiles of the posterior samples. See text for a description of the model and identifying assumptions.

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A Posterior Distributions

A.1 High-Frequency Model Posteriors

The Bayesian factor model uses Gibbs sampling to draw from posterior distributions. We describe the key posteriors below.

Factor Loadings Λ. Each element Λ_{ij} is sampled conditional on all other parameters. The unrestricted posterior combines a normal (or shrinkage) prior with the normal likelihood:

$$\Lambda_{ij}|\cdot \sim N(\mu_{ij}^{post}, \sigma_{ij}^{post}) \tag{16}$$

$$\mu_{ij}^{post} = (\Omega_{prior}^{ij})^{-1}(\Omega_{prior}^{ij}\mu_{prior}^{ij} + \mathbf{f}' R_i^{-1}\tilde{y}_i) \tag{17}$$

$$(\sigma_{ij}^{post})^{-1} = \Omega_{prior}^{ij} + \mathbf{f}' R_i^{-1}\mathbf{f} \tag{18}$$

where $\mathbf{f}$ denotes the factor matrix, R_i is the idiosyncratic variance for asset i, and $\tilde{y}_i$ represents asset i residualized with respect to control variables.

Sign and narrative restrictions truncate this distribution. For element (i, j) with lower bound a_{ij} and upper bound b_{ij}:

$$\Lambda_{ij}|\cdot \sim \text{TruncatedNormal}(\mu_{ij}^{post}, \sigma_{ij}^{post}, a_{ij}, b_{ij}) \tag{19}$$

Structural Factors $\boldsymbol{\epsilon}_t$. The factors follow a conditional normal distribution given loadings and data:

$$\boldsymbol{\epsilon}_t|\cdot \sim N(\boldsymbol{\mu}_t^{post}, \Sigma_t^{post}) \tag{20}$$

$$\Sigma_t^{post} = (\Sigma_{\epsilon,s_t}^{-1} + \Lambda' R^{-1}\Lambda)^{-1} \tag{21}$$

$$\boldsymbol{\mu}_t^{post} = \Sigma_t^{post}\Lambda' R^{-1}\tilde{\mathbf{y}}_t \tag{22}$$

where Σ_{ϵ,s_t} denotes the regime-specific factor variance and R is the diagonal matrix of idiosyncratic variances.

Regime-Switching Variances. For each factor k and regime $s \in \{1, 2\}$:

$$\sigma_{k,s}^2|\cdot \sim \text{InverseGamma}(a_s^{post}, b_s^{post}) \tag{23}$$

$$a_s^{post} = a_0 + \frac{n_s}{2} \tag{24}$$

$$b_s^{post} = b_0 + \frac{1}{2}\sum_{t:S_t=s} \epsilon_{kt}^2 \tag{25}$$

where n_s counts observations in regime s, and the regime indicators S_t are sampled from their posterior probabilities computed via the forward-backward algorithm.

Shrinkage Hyperparameters. Under the horseshoe prior:

$$\lambda_{ij}^2|\cdot \sim \text{InverseGamma}(1, \nu_{ij} + \Lambda_{ij}^2/(2\tau_j^2)) \tag{26}$$

$$\tau_j^2|\cdot \sim \text{InverseGamma}(1, \xi_j + \sum_i \Lambda_{ij}^2/(2\lambda_{ij}^2)) \tag{27}$$

The auxiliary variables ν_{ij} and ξ_j are sampled from inverse gamma distributions with shape and scale parameters equal to one.

A.2 Bayesian VAR-DL Posteriors

The VAR-DL model estimates impulse responses using distributed lags of the high-frequency shocks.

Autoregressive Coefficients Φ_l. Under a Minnesota prior with stochastic volatility weighting, each equation i has posterior:

$$\boldsymbol{\phi}_i|\cdot \sim N(\boldsymbol{\mu}_i^{post}, \Sigma_i^{post}) \tag{28}$$

$$\Sigma_i^{post} = (\Omega_{prior,i} + \mathbf{Y}_w'\mathbf{Y}_w \otimes \Omega)^{-1} \tag{29}$$

$$\boldsymbol{\mu}_i^{post} = \Sigma_i^{post}(\Omega_{prior,i}\boldsymbol{\mu}_{prior,i} + (\mathbf{Y}_w' \otimes \Omega)\mathbf{y}_{w,i}) \tag{30}$$

where $\mathbf{Y}_w = \mathbf{Y} \odot \exp(-\mathbf{h}/2)$ contains volatility-weighted lagged endogenous variables, $\mathbf{h}$ is the vector of log-volatilities, $\Omega = \Sigma^{-1}$ is the precision matrix, and $\Omega_{prior,i}$ implements Minnesota prior shrinkage with hyperparameters controlling own-lag, cross-lag, and lag decay.

Distributed Lag Coefficients Ψ_j. These coefficients relate monetary policy shocks to macroeconomic variables. We employ two alternative shrinkage specifications:

Polynomial Shrinkage: Constrains coefficients to follow a polynomial trend via the transformation $\boldsymbol{\psi}_i = Z\boldsymbol{\gamma}_i$ where Z is the $(q+1)\times(d+1)$ polynomial basis matrix with $Z_{j,k} = j^k$ for lag j and polynomial order $k \le d$. The polynomial coefficients $\boldsymbol{\gamma}_i$ have posterior:

$$\boldsymbol{\gamma}_i|\cdot \sim N(\boldsymbol{\mu}^{post}_{\gamma,i}, \Sigma^{post}_{\gamma,i}) \tag{31}$$

$$\Sigma^{post}_{\gamma,i} = (\Omega_{\gamma,prior,i} + \frac{\lambda_{poly,i}}{\sigma_{ii}} Z'Z)^{-1} \tag{32}$$

$$\boldsymbol{\mu}^{post}_{\gamma,i} = \Sigma^{post}_{\gamma,i} \frac{\lambda_{poly,i}}{\sigma_{ii}} Z'\boldsymbol{\psi}_i \tag{33}$$

where $\lambda_{poly,i}$ controls shrinkage intensity and follows a gamma prior: $\lambda_{poly,i} \sim \text{Gamma}(\alpha_{poly}, \beta_{poly})$.

Difference Penalty Shrinkage: Penalizes consecutive differences through the prior precision $\Omega_{\psi,prior,i} = I + \lambda_{diff,i}P$ where P is the penalty matrix for d-order differences. For second-order differences ($d = 2$), $P = D'D$ with difference operator:

$$D = \begin{pmatrix} 1 & -2 & 1 & 0 & \cdots & 0 \\ 0 & 1 & -2 & 1 & \cdots & 0 \\ \vdots & & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & -2 & 1 \end{pmatrix} \tag{34}$$

The distributed lag coefficients have posterior:

$$\boldsymbol{\psi}_i|\cdot \sim N(\boldsymbol{\mu}^{post}_{\psi,i}, \Sigma^{post}_{\psi,i}) \tag{35}$$

$$\Sigma^{post}_{\psi,i} = (I + \lambda_{diff,i}P + \frac{1}{\sigma_{ii}}\mathbf{M}'_w\mathbf{M}_w)^{-1} \tag{36}$$

$$\boldsymbol{\mu}^{post}_{\psi,i} = \Sigma^{post}_{\psi,i} \frac{1}{\sigma_{ii}} \mathbf{M}'_w \tilde{\mathbf{y}}_{w,i} \tag{37}$$

where $\mathbf{M}_w$ contains volatility-weighted shocks. The penalty parameter $\lambda_{diff,i}$ is sampled via random-walk Metropolis-Hastings in log-space with log-posterior:

$$\log p(\lambda_{diff,i}|\cdot) = (\alpha_{diff} - 1)\log \lambda_{diff,i} - \beta_{diff}\lambda_{diff,i} + \frac{1}{2}\log|I + \lambda_{diff,i}P| - \frac{1}{2}\boldsymbol{\psi}_i'(I + \lambda_{diff,i}P)\boldsymbol{\psi}_i \tag{38}$$

Stochastic Volatility Process. Time-varying volatility accommodates heteroskedasticity in macroeconomic data. The log-volatility h_t follows an AR(1) process:

$$h_t = \rho_h h_{t-1} + \eta_t, \quad \eta_t \sim N(0, \sigma_h^2) \tag{39}$$

with initial condition $h_1 \sim N(0, \sigma_h^2/(1-\rho_h^2))$ ensuring stationarity. We sample $\mathbf{h} = (h_1, \ldots, h_T)'$ using a precision-based sampler that constructs a Gaussian approximation to the conditional posterior via mode-finding, then applies accept-reject to account for the exact likelihood. The persistence parameter ρ_h has a truncated normal prior centered at 0.9, and the innovation variance σ_h^2 follows an inverse-gamma prior:

$$\sigma_h^2|\cdot \sim \text{InverseGamma}(\alpha_h + T/2, \beta_h + \frac{1}{2}\sum_{t=1}^{T}\tilde{\eta}_t^2) \tag{40}$$

$$\tilde{\eta}_1 = h_1\sqrt{1-\rho_h^2}, \quad \tilde{\eta}_t = h_t - \rho_h h_{t-1} \text{ for } t \geq 2 \tag{41}$$

Residual Covariance Σ. Conditional on volatility states, the covariance matrix posterior follows an inverse Wishart:

$$\Sigma|\cdot \sim \text{InverseWishart}(\nu_0 + T, S_0 + \sum_t \exp(h_t)\mathbf{u}_t\mathbf{u}_t') \tag{42}$$

where the scale matrix accumulates volatility-scaled squared residuals and ν_0, S_0 are prior hyperparameters.

Latent Structural Shocks ϵ_t. The model treats high-frequency shocks as observed with uncertainty. In each MCMC iteration, we sample shocks from their high-frequency model posterior, propagating estimation uncertainty to the VAR-DL impulse responses.