

Monetary Policy, Information and Country Risk Shocks in the Euro Area

Giovanni Ricco¹, Emanuele Savini², and Anshumaan Tuteja³

¹*École Polytechnique CREST, University of Warwick, OFCE-SciencesPo, and CEPR*

²*University of Warwick*

³*Ashoka University*

This draft: February 26, 2026

First draft: November 14, 2024

Abstract

The high-frequency market responses to ECB policy announcements bundle four types of policy shocks – conventional, forward guidance, quantitative easing, and asymmetric country risk – together with information surprises. The latter create powerful confounding effects for the identification of policy shock through non-linear information effects, prominent during episodes of acute market stress in euro area crises. These effects explain the puzzles in the responses of macroeconomic variables reported in studies using instruments from high-frequency data. Information-robust IVs yield, in VAR models, dynamic responses to monetary tightening with standard contractionary effects on output and prices.

JEL classification: E32, E52, E58

Keywords: Monetary policy, euro area, information effects, unconventional monetary policy

We thank Refet Gürkaynak, Luca Fornaro, Carlo Altavilla, Burçin Kısacıkoglu, Peter Karadi, Paul Hubert, Lucrezia Reichlin, Evi Pappa, Julia Schmidt, Cristiano Cantore, Matthias Kredler, Carlo Galli, Felix Wellschmied, Roberto Pancrazi, and Sang Seok Lee for providing helpful suggestions. We also thank seminar participants to the Banco de España, Bilkent University, the Bank of Italy, Universidade do Porto, DIW Berlin, the ISI Delhi, the macroeconomic reading group of Universidad Carlos III de Madrid, the macroeconomic workshop of University of Warwick and the EEA conference for useful comments.

1 Introduction

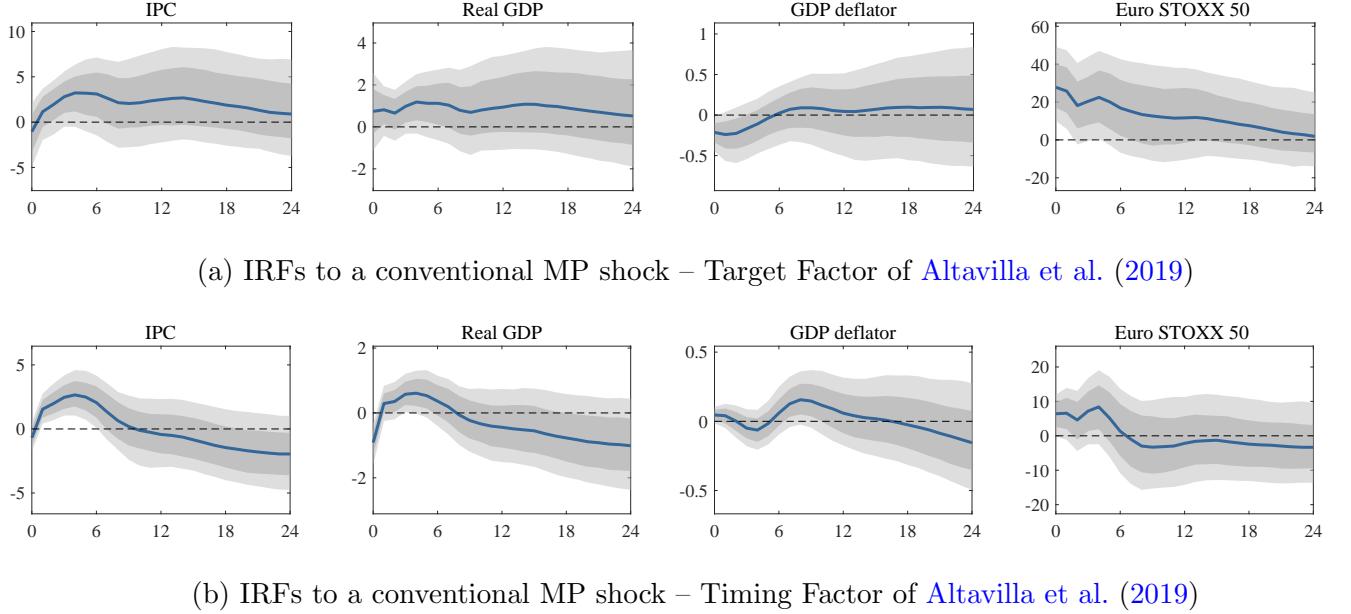
The study of high-frequency market reactions to monetary policy decisions, pioneered by [Gürkaynak et al. \(2005\)](#), has provided researchers with instrumental variables (IVs) for identifying policy shocks in reduced-form macro models without relying on assumptions about the sign or timing of macroeconomic responses, as proposed by [Gertler and Karadi \(2015\)](#). Initially limited to the United States, this approach has been extended to other economies, notably the euro area by [Altavilla et al. \(2019\)](#), who provided a comprehensive set of high-frequency responses of risk-free rates across different maturities and other assets to policy announcements of the European Central Bank (ECB).

This detailed dataset is a valuable asset for studying the unique aspects of monetary policy in Europe and understanding the transmission of both the conventional and the unconventional tools in the ECB's toolkit. However, it is well known that puzzling results often emerge when monetary policy surprises for the euro area – i.e. the identified principal components of the high-frequency responses to policy decisions – are used as IVs for policy shocks.¹ For example, Figure 1 reports the impulse response functions (IRFs) to two monetary policy shocks, identified in a VAR model using the target (conventional monetary policy) and timing (next policy decision) factors of [Altavilla et al. \(2019\)](#). Following a policy tightening, output expands, the stock market surges, and prices show no deflationary pressure.

Similar puzzling responses – albeit less pronounced – have been reported in studies using U.S. monetary policy surprises as instruments to identify policy shocks in a VAR or local projection (LP) approach (see the excellent review by [Ramey, 2016](#)). Recent literature has pointed to the information effects of policy communication as the likely source of these puzzles in the United States (see, among others, [Campbell et al., 2012](#), [Nakamura and Steinsson, 2018](#),

¹From an econometric point of view, the use of monetary surprises in event studies is uncontroversial, as surprises in these studies are only intended to reflect news with respect to market participants' information sets. Conversely, VARs and LPs can identify the causal effect of monetary policy shocks only if the IV captures innovations that are (i) news to market participants, and (ii) orthogonal to the economic state. This assumption is violated when policymakers' and agents' information sets diverge, as in the presence of informational frictions (see [Miranda-Agrippino and Ricco, 2021](#) and [Gürkaynak et al., 2021](#) for a discussion).

Figure 1: MONETARY POLICY SHOCKS IDENTIFIED WITH [ALTAVILLA ET AL. \(2019\)](#)'s IVs



Notes: The figure reports IRFs to two monetary policy shocks identified using (1a) the target, and (1b) the timing factors of [Altavilla et al. \(2019\)](#) as external instruments. The target shock is normalised to induce a 100 basis points increase in the 1m-OIS rate, while the timing shock is normalised to have a 100 basis points increase in the 2y-OIS rate. The plotted variables are industrial production (including construction), real GDP, the GDP deflator, and the Euro STOXX 50 market index. The shocks are identified in a VAR(12) model with monthly variables and Minnesota priors, using the factors as an external instrument. The grey shaded areas are 90% coverage bands. The sample considered is 2002m1-2018m8.

[Jarociński and Karadi, 2020](#), and [Miranda-Agrrippino and Ricco, 2021](#)). Information effects in monetary policy refer broadly to the hypothesis that, not being able to perfectly observe the economic fundamentals, market participants can infer information about the economic outlook from central bank actions (and possibly communication). When a central bank takes policy decisions such as changing interest rates or implementing quantitative easing, market participants interpret these actions as signals about the central bank's view of the economy and update their own projections accordingly (see [Melosi, 2017](#)). For instance, an unexpected interest rate hike may signal that the central bank anticipates inflationary pressure exceeding market forecasts, rather than simply indicating a policy shock.

The key contribution of this work is to show that the particularly strong and non-linear information frictions that arise during periods of market stress and dislocation, which have

marked the history of the euro area, explain the puzzles in the ECB’s monetary policy factors (see [Fornaro and Grosse-Steffen, 2025](#) for a model of financial fragmentation in monetary unions). The intuition is straightforward: when financial markets are under stress and transactions are dominated by high volatility, market participants find it harder to extract clear signals about economic developments from market prices and news. In contrast, the central bank has a more direct gauge of the economy due to its access to primary data sources and its ability to directly survey financial and economic institutions. During these events, market participants rely more heavily on information conveyed by policy decisions and communication, thus amplifying the central bank’s information effects.

It is important to observe that our results provide a rationale for practical approaches commonly adopted in empirical and policy work to address the puzzles discussed above – typically a combination of excluding specific events, imposing sign restrictions, or winsorising the surprises. Indeed, during episodes of heightened market stress, information effects are amplified and generate unusually large price revisions around announcements, contaminating measured surprises as instruments for exogenous policy shocks. By excluding some of the largest surprises and implementing information corrections, an empirical researcher can obtain reliable inference on the effects of monetary policy in the euro area.

In Section 2, we formalise the intuition underpinning our approach within a model of dispersed information, where agents are rational but have imperfect information (see [Coibion and Gorodnichenko, 2012, 2015](#)). They receive private, noisy signals about the state of the economy. The noise in these signals can alternate between low-variance and high-variance states. The central bank, however, receives a signal with constant noise and sets interest rates based on it. Agents observe these interest rates and, given their forecast errors, use a Kalman filter to update their beliefs about the economy, interpreting the central bank’s decision as a public signal.² A key prediction of the model is that, when the economy enters a high-noise

²The model serves as a stylised representation of an economy where agents with information constraints independently sample noisy signals from a pool of public information about the economy. It is important to note that the model’s predictions do not depend on the central bank possessing a superior information set, as is sometimes suggested. The precision of the central bank’s signal only influences the strength of information

state – interpreted as a phase of market stress – the private sector’s forecasts become less precise, and agents rely more heavily on the central bank’s signal, leading to a sharp increase in information effects distorting market price surprises.

Before presenting our empirical strategy to test for information effects, we briefly discuss some key characteristics of monetary policy in the euro area (see [Rostagno et al., 2021](#), for a comprehensive discussion). The euro area is characterised by a single central bank responsible for monetary policy and, currently, 21 national governments responsible for fiscal policy, each issuing debt at varying maturities and facing country-specific default risk. This makes the ECB’s policy problem particularly complex, since monetary tools that affect the common risk-free yield curve (typically proxied by the Overnight Index Swap (OIS) curve) can also differentially affect the risk premia associated with country-specific yield curves. Crucially, the incomplete federal architecture of the euro area makes it intrinsically exposed to episodes of severe market stress.

Indeed, during periods of macroeconomic and financial stress, the lack of a federal fiscal authority and the presence of large fiscal imbalances in the euro area periphery, coupled with the absence of a central bank able to act as a lender of last resort, can generate market stress and dislocation. These are precisely the high-stress episodes that our model seeks to capture in order to account for information effects.

In cases in which stress is not promptly contained by policymakers, the incomplete institutional architecture of the monetary union provides scope for flight-to-safety dynamics – i.e. investors reallocating capital from peripheral countries such as Italy or Greece to German Bunds and other core-country sovereign bonds – market fragmentation along geographical lines, and ultimately, if not countered by policy actions, break-up risks. This, in turn, has produced large asymmetric movements in country yields in response to perceived sovereign risk, with the potential for self-fulfilling debt crises, as was evident during the European sovereign debt crisis (see, for example, [Corsetti and Dedola, 2016](#), [Bocola and Dovis, 2019](#),

effects.

Lorenzoni and Werning, 2019, and the empirical work of Leombroni et al., 2021). We account for episodes of asymmetric movements in country yields in our empirical strategy for shock identification, as detailed below.

Let us now discuss our empirical approach. In Section 3, we extract common factors from the updated dataset of high-frequency reactions of asset prices to monetary policy announcements compiled by Altavilla et al. (2025).³ Our approach follows Altavilla et al. (2019), but with some important differences. Specifically, we consider the total effect of policy announcements by summing the market responses to the ECB’s press release on the policy decision and the details provided in the ECB President’s press conference. Alongside the risk-free yield curve price revisions, we also consider changes in (i) the stock market, (ii) exchange rates, and (iii) sovereign bond yield spreads between Germany and Italy. Our empirical results confirm the existence of four significant principal components, i.e. four independent dimensions of monetary policy in the euro area, one more than typically identified for the United States (as also reported by Motto and Özen, 2022 and Jouvanceau and Mikaliunaite-Jouvanceau, 2023).

Following Gürkaynak et al. (2005), in Section 3, we impose restrictions on the responses of various assets to map these four principal components into factors representing different dimensions of the ECB’s policy decisions: (i) a target factor associated with conventional monetary policy; (ii) a forward guidance factor capturing communication about medium-term policy developments; (iii) a QE/QT factor representing unconventional monetary policy in the form of quantitative easing or tightening and potential changes to risk premia triggered by policy communication (as in Swanson, 2021); and (iv) an asymmetric country risk factor capturing opposite risk premia dynamics between sovereign bonds in core and peripheral euro area countries. While the first three factors are similar to those identified by Altavilla et al. (2019), the last one is akin to the market stabilisation factor of Motto and Özen

³The Euro Area Extended Monetary Policy Event-Study Database (EA-EMPD) is an updated version of the Euro Area Monetary Policy Database (EA-MPD) and both are maintained and updated on the ECB’s website. In previous versions of this work, which are online, we employed the EA-MPD. Results with the older dataset are very similar to the ones we report in this version.

(2022), though obtained under different assumptions that do not restrict the spreads' response. Empirically, the target factor lifts the short-end of the yield curve, with diminishing effects on longer maturities and almost no effect at the 10-year horizon. It strengthens the euro and negatively affects the stock market. The forward guidance factor has its largest impact on the medium-segment of the risk-free yield curve and a positive impact on the stock market – this possibly indicating a dominant information component, as argued by [Jarociński and Karadi \(2020\)](#). The QE/QT factor lifts the long end of the yield curve, with a strong positive exchange rate effect and a negative impact on the stock market. The last factor, capturing asymmetric country risk, leaves the risk-free yield curve almost unchanged while producing a significant increase in the spread between Italian and German sovereign bonds.

In Section 4, we test for the non-linear information effects predicted by the model. We do this by projecting the market price revisions triggered by policy announcements onto (i) a set of ECB and professional forecasts, and (ii) their interaction with a market stress index that equals one when market volatility (the Euro STOXX Volatility index) is one standard deviation above its average, using a threshold regression model. Following [Miranda-Agrippino and Ricco \(2021\)](#), we employ the residuals from these non-linear information regressions to construct instrumental variables to identify four exogenous monetary policy shocks: conventional monetary policy, forward guidance, quantitative easing/tightening, and asymmetric country risk shocks. An additional IV for information in monetary surprises is obtained as the common factor of the fitted component in the non-linear information regressions.

The empirical results from the information regressions align with the model's predictions. Monetary policy surprises in the euro area are predictable by the pre-decision forecasts of the ECB and private forecasts. In a linear information regression specification, predictability arises from both short-term and long-term forecasts, with an R^2 of around 9% for longer maturities. This result parallels findings from the U.S. (see [Miranda-Agrippino and Ricco, 2021](#)) and validates the existence of an information channel of monetary policy in the euro area.

Moreover, the model’s key prediction – that information effects of central bank announcements strengthen during periods of heightened volatility, as market participants place greater weight on the central bank’s information – is supported by the data. Non-linear information effects are particularly strong yet concentrated in a limited number of high-volatility events, explaining up to around 30% of the price revisions at short maturities. This is a novel and key result for understanding both policy communication transmission and the role of imperfect information in the economy.

Finally, in Section 5, we examine the transmission of monetary policy shocks and information ‘shocks’ using a medium-scale Bayesian VAR model with standard macroeconomic priors and a rich set of macroeconomic variables. The shocks are identified using the four information-robust IVs and the proxy for the information component as external instruments.⁴ A few results are worth noting. First, the transmission of monetary policy shocks, identified with IVs that control for non-linear information effects, shows that exogenous tightenings from both conventional and unconventional monetary policy have contractionary effects on production, prices, and the stock market. Almost no puzzling response appears, with the exception of the response of inflation and the impact response of industrial production to a forward guidance shock. Asymmetric country risk shocks, meanwhile, widen the spreads and affect prices and production differently in the euro area core and periphery. Second, a detailed analysis of the impact of the various empirical choices indicates that non-linear information effects are crucial for addressing the puzzles reported in the literature; linear information corrections are insufficient to eliminate these puzzles and provide only marginal improvements. These findings further supports our model’s predictions. Third, IRFs for the information component of monetary surprises suggest that the set of shocks to which the central bank responds are akin to the aggregate effects of demand shocks, increasing prices and production. Finally, results obtained with these IVs are robust across subsamples.

⁴This methodology was introduced by Stock and Watson (2012) and Mertens and Ravn (2013). See Stock and Watson (2018) and Miranda-Agricoppino and Ricco (2023) for a discussion on the conditions under which IV methods enable successful identification in VARs and LPs.

A number of robustness exercises and additional results are presented in Section 6 and the Online Appendix, while Section 7 concludes the paper. The remainder of this introduction provides a non-exhaustive review of related works.

Related Literature. A comprehensive survey of the literature on monetary policy shocks far exceeds the scope of this paper. Here, we mention only a few studies closely related to our work. In constructing monetary policy surprises from high-frequency shocks, our study follows the pioneering work of [Kuttner \(2001\)](#) and [Gürkaynak et al. \(2005\)](#). Specifically, [Gürkaynak et al. \(2005\)](#) were the first to observe the existence of multiple common components in the responses of forward contracts on the U.S. yield curve to policy surprises – labelled by them as a target and a path factor. [Swanson \(2020\)](#) extended this approach to capture unconventional monetary policy in the U.S., including forward guidance and LSAP (i.e. QE) factors. This method has been applied to the euro area by [Altavilla et al. \(2019\)](#) and [Altavilla et al. \(2025\)](#), who employed risk-free OIS rates. [Wright \(2019\)](#) and [Leombroni et al. \(2021\)](#) were among the first to highlight the potentially important role of sovereign spread surprises in the euro area. More recently [Fornaro and Grosse-Steffen \(2025\)](#) have provided a theory of fragmentation risk in the euro area, that can provide a rationale for the asymmetric country risk shock.⁵ Different approaches to understanding the role of spreads in the transmission of shocks identified with high-frequency surprises have been proposed in [Reichlin et al. \(2022\)](#), [Jouvanceau and Mikaliunaite-Jouvanceau \(2023\)](#), and [Motto and Özen \(2022\)](#). The latter were the first to isolate an additional factor in policy surprises related to diverging dynamics in core and periphery country spreads, which they labelled the ‘market stabilisation factor’. To the best of our knowledge, our work is among the first to propose a comprehensive study of all the different policy dimensions and information surprises, in the euro area.

The use of high-frequency surprises as instrumental variables to identify monetary policy shocks was pioneered by [Gertler and Karadi \(2015\)](#) and has quickly become the standard approach in the literature on monetary policy shocks. The literature has developed two

⁵In the context of emerging markets, [Pirozhkova et al. \(2024\)](#) has shown the role of monetary policy in modulating country risk, using a high-frequency identification of monetary policy.

strategies to control for information effects in these surprises: a ‘forecast-based’ approach and a ‘market-based’ approach. The first approach involves regressing high-frequency market surprises on the central bank’s internal forecasts, which serve as a direct measure of the policymaker’s information set, as in [Miranda-Agrippino and Ricco \(2021\)](#).⁶ The market-based approach, as in [Jarociński and Karadi \(2020\)](#), [Cieslak and Schrimpf \(2019\)](#), and [Cieslak and Pang \(2020\)](#), uses the stock market response to separate a component of surprises that moves interest rates and asset prices in the same direction (macroeconomic news) from a component that raises interest rates but depresses asset prices, or vice versa (policy shocks).⁷

For the euro area, [Jarociński and Karadi \(2020\)](#) pioneered the market-based approach, demonstrating a marked attenuation of the puzzles.⁸ More recently, [Kerssenfischer \(2022\)](#) has provided evidence that this methodology may help reduce puzzles in monetary policy surprises derived from one-year maturity futures.⁹ [Badinger and Schiman \(2023\)](#)’s approach combines high-frequency surprises with a narrative approach, using sign restrictions on structural residuals to address information effects. To our knowledge, our paper is the first to apply the survey-based methodology to the euro area and to demonstrate the significance of non-linear information effects in the dynamics of attention to policy signals. This contribution has potential implications beyond the policy dimension considered here.

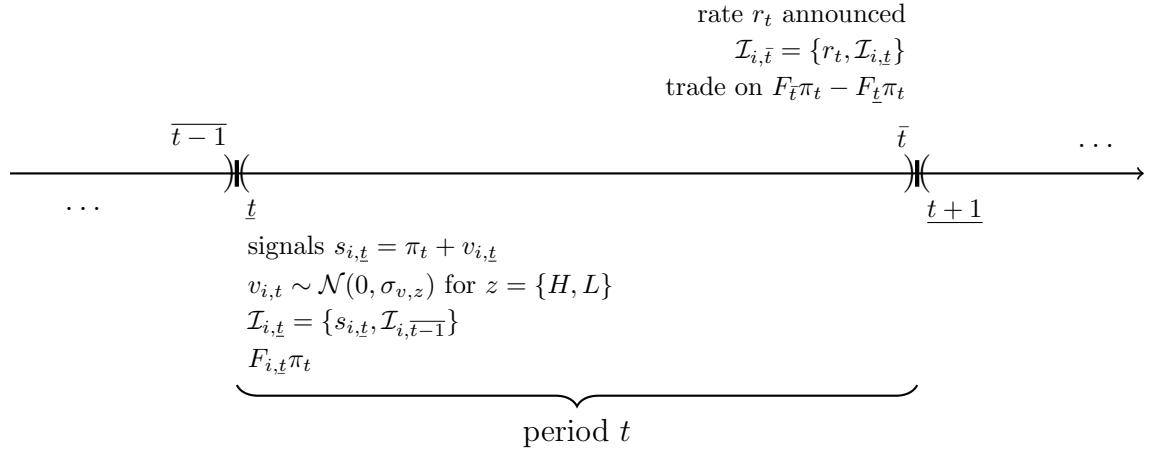
⁶This approach was introduced by [Campbell et al. \(2012\)](#), who used survey data from professional forecasters (SPF). While central banks’ forecasts provide a more direct measure of policymakers’ expectations, the mean SPF forecast is likely a good proxy for the bank’s forecast given private signals and dispersed information.

⁷[Bauer and Swanson \(2023\)](#)’s alternative explanation of the empirical evidence on information effects involves private agents using a misspecified Taylor rule that underestimate the hawkishness of the central bank, as discussed in [Coibion and Gorodnichenko \(2012, 2015\)](#). To address the predictability of monetary surprises, they suggest regressing these surprises on a set of past financial indicators. Their approach and the implications of their model are largely observationally equivalent to those of [Miranda-Agrippino and Ricco \(2021\)](#). However, their interpretation of the information effects appears ill-suited to explain the non-linear information effects documented in this work, and is also at odds with the fact that the ECB has more often been criticised for being too dovish rather than too hawkish. Finally, it is worth noting that information frictions of the type they discuss naturally give rise to autocorrelation in forecast revisions and to information effects from policy actions, as discussed in this paper.

⁸By incorporating additional asset prices, and particularly the stock market, when extracting policy surprises, we build on the work and insight of [Jarociński and Karadi \(2020\)](#).

⁹In Section L, of the Online Appendix we provide some comparison of the empirical results of these two approaches.

Figure 2: THE INFORMATION FLOW



Note: Each period t has a beginning \underline{t} and an end \bar{t} . At \underline{t} , agents (both private and central bank) receive a noisy signal $s_{i,\underline{t}}$ about inflation π_t , and update their forecasts $F_{i,\underline{t}}\pi_t$ based on their information set $\mathcal{I}_{i,\underline{t}}$. At \bar{t} , the central bank announces the policy rate r_t based on its forecast $F_{cb,\bar{t}}\pi_t$. Agents observe r_t , infer $F_{cb,\underline{t}}\pi_t$, and form $F_{i,\bar{t}}\pi_t$. Trade is a function of the aggregate expectation revision between \underline{t} and \bar{t} .

2 Information effects under market stress

To provide a framework for our empirical analysis, let us consider a model in which private agents and the central bank have imperfect information about the state of the economy, forming expectations conditional on private signals clouded by state-dependent observational noise. In doing so, we extend the model in [Miranda-Agrippino and Ricco \(2021\)](#) to the case where the variance of the noise is not constant.

Agents in the model live in discrete time, with each period t being divided into an opening and a closing stage, i.e. $t \in \{\underline{t}, \bar{t}\}$. The inflation process evolves over time with an AR(1) process:

$$\pi_t = \rho\pi_{t-1} + u_t^\pi, \quad u_t^\pi \sim \mathcal{N}(0, \sigma_\pi^2), \quad (1)$$

with normally distributed innovations, u_t^π , and $|\rho| < 1$.

At the beginning of time t , i.e. t , each agent i receives a private signal about inflation

contaminated by observational noise

$$s_{i,t} = \pi_t + v_{i,t}, \quad v_{i,t} \sim \mathcal{N}(0, \sigma_{v,z}^2), \quad (2)$$

with a state-dependent variance, $\sigma_{v,z}^2$, which is equal across agents and is characterised by the existence of two states, $z \in \{L, H\}$, respectively with high and low noise, i.e. $\sigma_{H,z}^v > \sigma_{L,z}^v$. Agents form and update their expectations about current and future inflation, conditional on the signals observed using a Kalman filter

$$F_{i,\underline{t}} \pi_t = K_{1,\underline{t}} s_{i,\underline{t}} + (1 - K_{1,\underline{t}}) F_{i,\overline{t-1}} \pi_t, \quad (3)$$

$$F_{i,\underline{t}} \pi_{t+h} = \rho F_{i,\underline{t}} \pi_t, \quad (4)$$

where $K_{1,\underline{t}}$ is the Kalman gain. Conditional on their expectations for inflation, agents forecast (and trade) the policy rate, that is set by the central bank following a Taylor rule,

$$i_t^{(0)} = r_t = \delta \pi_t + u_t^{mp}, \quad (5)$$

along with interest rates at longer horizons, $i_{\underline{t}}^{(h)}$ for $h \geq 0$

$$i_{\underline{t}}^{(h)} = \alpha_h F_{\underline{t}} \pi_{t+h} + \xi_t^{(h)}, \quad (6)$$

where $\xi_t^{(h)}$ captures risk premia, $\alpha_0 = \delta$, and $F_{\underline{t}}$ indicates the average expectations over the market.

Let us define $V_{t|\overline{t-1}} \equiv \text{Var}(\pi_t - F_{i,\overline{t-1}} \pi_t)$, i.e. the variance of the forecast errors for inflation at time t , made at time $\overline{t-1}$. The Kalman gain $K_{1,\underline{t}}$ is given by:

$$K_{1,\underline{t}} = \frac{V_{t|\overline{t-1}}}{V_{t|\overline{t-1}} + \sigma_{v,z}^2}. \quad (7)$$

From the expression for $K_{1,\underline{t}}$, it is clear that, for a given $V_{t|\overline{t-1}}$, the agents will update their

forecasts more in states of low noise, as compared to the states of high noise. The variance of the forecast of π_t made at \underline{t} will depend on $V_{t|\bar{t}-1}$ as¹⁰

$$V_{t|\underline{t}} = V_{t|\bar{t}-1} - \frac{(V_{t|\bar{t}-1})^2}{V_{t|\bar{t}-1} + \sigma_{v,z}^2}, \quad (8)$$

$$V_{t|\bar{t}-1} = \rho^2 V_{t-1|\bar{t}-1} + \sigma_\pi^2. \quad (9)$$

During period t , the central bank also receives a private signal about the state of the economy, contaminated by noise with constant volatility, and updates its forecast:

$$s_{cb,t} = \pi_t + v_{cb,t} \quad v_{cb,t} \sim \mathcal{N}(0, \sigma_{v,cb}^2), \quad (10)$$

$$F_{cb,t}\pi_t = K_{cb,t}s_{cb,t} + (1 - K_{cb,t})F_{cb,t-1}\pi_t. \quad (11)$$

The assumption of constant volatility captures in a stylised manner the fact that the central bank, differently from market operators which have to sample information from prices and data releases, can have a more direct access to data offices and survey directly financial and economic institutions to take the pulse of the economy. Given the constant noise in the central bank's signal, we consider the asymptotic value of the Kalman gain, denoted K_{cb} , with the time index dropped. Given its forecast for π_t , the central bank sets and announces the interest rate for the period:

$$r_t = \delta F_{cb,t}\pi_t + u_t^{mp}. \quad (12)$$

where u_t^{mp} is a monetary policy shock drawn from a normal distribution centred at zero and with variance σ_{mp}^2 .

At time \bar{t} , agents observe the interest rate, which conditional on the past interest rate, is

¹⁰Agents in the model know the model parameters, including the variance of the signal (either low or high).

a public signal on the state of the economy of the form:

$$\tilde{s}_{\bar{t}} = \pi_t + \tilde{v}_{cb,\underline{t}} \equiv \pi_t + v_{cb,t} + (\delta K_{cb})^{-1}[u_t^{mp} - (1 - K_{cb})\rho u_{t-1}^{mp}]. \quad (13)$$

Agents update their expectations with a Kalman filter, using the public signal delivered by the policy rate¹¹

$$F_{i,\bar{t}}\pi_t = K_{2,\bar{t}}\tilde{s}_{cb,\bar{t}} + (1 - K_{2,\bar{t}})F_{i,\underline{t}}\pi_t,$$

where the gain $K_{2,\bar{t}}$ is:

$$K_{2,\bar{t}} = \frac{V_{t|\underline{t}}}{V_{t|\underline{t}} + \sigma_{\tilde{v}}^2}, \quad (14)$$

and the forecast error variance is such that:

$$V_{t|\bar{t}} = V_{t|\underline{t}} - \frac{(V_{t|\underline{t}})^2}{V_{t|\underline{t}} + \sigma_{\tilde{v}}^2}. \quad (15)$$

Given their updated forecasts, agents revise the price of longer-horizon interest rates and trade. The following proposition links revisions in interest rates to current and past structural shocks and to past forecast revisions, and generalises results in [Miranda-Agrippino and Ricco \(2021\)](#) to the case in which the observational noise in public signal can vary.

Proposition 1. *The price revisions in interest rates at different maturities triggered by the policy announcement are*

$$\Delta i_{\bar{t}}^{(h)} = \alpha_h \rho^h (F_{\bar{t}}\pi_t - F_{\underline{t}}\pi_t) + \Delta \xi_t^{(h)}, \quad (16)$$

¹¹For the sake of simplicity, we assume that agents update with a standard Kalman filter without taking into account the structure in the noise of this public signal due to the moving average component in the monetary policy shock.

where

$$\begin{aligned}
F_{\bar{t}}\pi_t - F_{\underline{t}}\pi_t &= (1 - K_{1,\underline{t}})K_{2,\bar{t}}K_{2,\bar{t}-1}^{-1}(1 - K_{2,\bar{t}-1})[F_{\bar{t}-1}\pi_t - F_{\underline{t}-1}\pi_t] + (K_{2,\bar{t}})(1 - K_{1,\underline{t}})u_t^\pi \\
&\quad + K_{2,\bar{t}}[\nu_{cb,\underline{t}} - (1 - K_{1,\underline{t}})\rho\nu_{cb,\bar{t}-1}] + K_{2,\bar{t}}(K_{cb}\delta)^{-1}[u_t^{mp} - \rho(2 - K_{cb} - K_{1,\underline{t}})u_{t-1}^{mp} \\
&\quad + (1 - K_{1,\underline{t}})(1 - K_{cb})\rho^2u_{t-2}],
\end{aligned} \tag{17}$$

are the average revision in expectations across agents in the market, and $\Delta\xi_t^{(h)}$ are revisions to risk premia.

Proof. See Section A of the Online Appendix. \square

The expression in Eq. (17) shows that, after observing the policy decision, all agents update their expectations towards the view of the central bank, thereby inducing a market-wide information effect. The first term in the expression above represents the autocorrelation in revisions of expectations, which is due to the sluggish adjustment of expectations in models of imperfect information. The second term, $(K_{2,\bar{t}})(1 - K_{1,\underline{t}})u_t^\pi$, captures the information channel of monetary policy, that is the fact that the policy announcement delivers information about the shocks hitting the economy. The remaining terms include both monetary policy shocks and central bank noise (another source of policy shock), along with their lags.

In this setting, the coefficients of the different terms, particularly the information effects, are time-varying. Therefore, to control for information effects, it is insufficient to project the monetary policy surprises onto a set of central bank forecasts with a fixed-coefficient regression, and then retain the residuals as a measure of monetary policy.¹²

Our aim here is to understand how the economy being in a state of low or high variance alters the strength of information effects. To this end, let us consider how the asymptotic variance of the forecast errors depends on the variance of the observational noise. The idea is

¹²In this framework, the coefficient in front of the monetary policy shocks would also be time-varying. Hence, even if one manages to cleanse the policy surprises of their endogenous component, they may still represent a measure of the policy shock scaled by a time-varying coefficient. We abstract from this aspect in this analysis.

to compare information effects in states of low and high noise by assuming that the economy has remained in that state for an extended period.

Proposition 2. *The asymptotic variances of the forecast errors of the Kalman filter are increasing in the noise in the private signals received by the agents, i.e.*

$$\frac{dV}{d\sigma_{v,z}^2} > 0, \quad \frac{dW}{d\sigma_{v,z}^2} > 0, \quad \frac{dU}{d\sigma_{v,z}^2} > 0, \quad (18)$$

and hence

$$V^H > V^L, \quad W^H > W^L, \quad U^H > U^L. \quad (19)$$

Proof. See Section A of the Online Appendix. \square

Proposition 2 supports the intuition that, when private agents find it harder to infer the state of the economy due to market disruptions, their assessment of the economy becomes less precise. In fact, it indicates that, all else being equal, when the economy shifts to a state of higher noise, the variances of forecast errors begin to increase towards the asymptotic values of the high-variance state. Conversely, they decrease in a transition to lower noise. The increase in the variance of forecast errors makes the public signals obtained by the central bank relatively more valuable. This intuition is developed further in the next proposition.

Proposition 3. *The information channel of monetary policy strengthens with an increase in the noise in the economy, i.e.*

$$\frac{d}{d\sigma_{v,z}^2}(K_{2,\bar{t}}(1 - K_{1,t})) > 0, \quad (20)$$

and hence

$$K_2^H(1 - K_1^H) > K_2^L(1 - K_1^L), \quad (21)$$

where K_1^H , K_1^L and K_2^H , K_2^L are the asymptotic values of the Kalman gains in the states of high and low variance, respectively.

Proof. See Section A of the Online Appendix. □

This proposition is central to the empirical analysis in the remainder of this work. It predicts that, during periods of market stress and dislocation – which we interpret as periods of higher volatility in private signals – the information effects of central bank announcements become stronger, as market participants place more weight on the information contained in the central bank’s signal relative to their own assessment of the economy. In the following section, we empirically test the prediction of Proposition 3, adopting a non-linear regression model based on Eq. (17).

3 Monetary policy surprises in the euro area

In this section, we first provide an overview of the intraday market responses to monetary policy announcements in the euro area, as collected by [Altavilla et al. \(2025\)](#). We then present our methodology to construct the monetary surprises, and discuss some of the key choices in our specification. In doing so, we abstract from the correction for information effects, and postpone this discussion to the next section.

3.1 The Euro Area Monetary Policy Event-Study Database

Monetary policy decisions by the ECB are communicated to the markets in two stages, with the policy decision and a statement motivating the decision being delivered at different times. The press release, containing the main policy changes (including non-standard measures since March 2016) is released at 13.45 hours, followed by a press conference that begins at 14.30 hours, where the ECB President provides the policy committee’s view on the policy decision in an introductory statement and does a question-and-answer (Q&A) session.

The standard reference for the high-frequency reactions of asset prices to monetary policy announcements is the [Euro Area Monetary Policy Database \(EA-MPD\)](#) that the ECB maintains on its website, and which is built using the methodology proposed by [Altavilla](#)

et al. (2019). In this work, we employ an updated version of the dataset, constructed by Altavilla et al. (2025): the Euro Area Extended Monetary Policy Database (EA-EMPD).¹³ The database reports intraday price changes for several assets on policy announcement days, measured over two narrow windows: the ‘press release window’ and the ‘press conference window,’ which includes the President’s statement and the subsequent Q&A session. The combined interval, referred to as the monetary event window, captures the overall financial market response to these connected policy events.

The assets covered by the datasets are OIS rates with 1 week, 1, 3, 6 month and 1 to 10, 15, and 20 year maturities, German bund yields with 3 and 6 month and 1 to 10, 15, 20, and 30 year maturities, French, Italian, and Spanish sovereign yields with 2, 5, and 10 year maturities, the stock market price index and the stock price index comprising only banks, and the exchange rate of the euro.

The construction of monetary policy surprises, following Gürkaynak et al. (2005), involves two steps. First, we extract principal components (PCs) from the selected intraday price changes, and then we rotate them to allow for interpretability.

3.2 Common components in intraday price changes

To extract the meaningful common components in the price changes, we consider the total effect of the announcements over several assets by summing the price changes in the press release and press conference windows. In doing this, we deviate from Altavilla et al. (2019).¹⁴ The rationale for the summation of the surprise is to incorporate the revisions of expectations triggered by the press conference across the yield curve, and potentially reduce noise.

In particular, in our analysis, we extract principal components from 14 time series of price

¹³The EA-EMPD mitigates potential measurement biases in monetary policy surprises (Altavilla et al., 2025). We therefore use it to construct our monetary policy surprise series. While the EA-EMPD also covers policy communications outside Governing Council meeting dates, we restrict attention to meeting-related events in this paper and leave non-meeting communications for future work.

¹⁴In Section 5, we assess the empirical impact of this choice by comparing the transmission of policy shocks identified using as an IV the original factors of Altavilla et al. (2019), and the factors obtained with this approach.

Table 1: TEST OF NUMBER OF FACTORS

Press release and conference window			
Full sample (2002-2019)			
$H_0 : k = 0$	$H_0 : k = 1$	$H_0 : k = 2$	$H_0 : k = 3$
114.2679 (0.000)	98.4844 (0.000)	83.6753 (0.000)	69.8322 (0.000)

Notes: The table reports the Wald statistics and associated p-values (in parentheses) from the Cragg and Donald (1997) test of the null hypothesis $k = k_0$ factors against the alternative $k > k_0$. The full sample spans from January 2002 to December 2019. We find four statistically significant factors at the 5 percent level.

changes for every ECB Governing Council meeting from 2002 to 2019 ($T = 197$), obtained from the EA-EMPD:¹⁵

- OIS risk-free rates at 1-month, 3-month, 6-month, 1-year, 2-year, 5-year and 10-year maturities;
- spreads between Italian and German treasuries at 2-year, 5-year and 10-year maturity;
- the euro exchange rate against the US dollar, the pound sterling and the yen;
- the Euro STOXX 50 index.

In extracting the surprises, we do not exclude any observations over the sample period.

We assess the number statistically significant factors which capture commonalities in the dataset using Cragg and Donald (1997)'s test. Results point towards the presence of four factors after summing surprises (see Table 1). The test developed by Alessi et al. (2010) also confirms the existence of four factors.¹⁶

The factor model considered is therefore of the form

$$Y = F\Lambda + \epsilon, \quad (22)$$

¹⁵The terms ‘ECB Governing Council meeting dates’ and ‘ECB meeting dates’ are used interchangeably in the remainder of the paper.

¹⁶See Section D of the Online Appendix.

Table 2: VARIANCE DECOMPOSITION OF THE PRINCIPAL COMPONENTS

	1-m OIS	3-m OIS	6-m OIS	1-y OIS	2-y OIS	5-y OIS	10-y OIS
<i>PC1</i>	35.9865	69.3908	79.4581	82.3992	81.2865	75.8556	56.5171
<i>PC2</i>	0.1287	0.0052	0.1317	0.1148	0.0025	0.1200	0.0328
<i>PC3</i>	18.0087	16.6664	14.4069	8.6226	5.2972	0.0265	1.6199
<i>PC4</i>	29.1850	8.7194	0.8574	1.9631	7.4360	17.7616	25.5212
<i>Res</i>	16.6911	5.2182	5.1460	6.9004	5.9779	6.2362	16.3090
	2-y Spread	5-y Spread	10-y Spread	EURGBP	EURJPY	EURUSD	STOXX50
<i>PC1</i>	9.6644	7.1011	2.4091	48.9217	55.3321	49.0247	4.8723
<i>PC2</i>	68.5872	77.9559	81.3655	7.3245	1.8111	6.1400	56.6305
<i>PC3</i>	0.4740	5.9071	5.6852	28.6020	27.3279	33.3282	2.5477
<i>PC4</i>	3.8354	0.6972	0.5171	2.2911	0.7445	4.3116	6.7997
<i>Res</i>	17.4389	8.3386	10.0231	12.8608	14.7843	7.1955	29.1498

Notes: The table reports the Anova decomposition of the principal components of the prices revisions triggered by policy announcements. Values are in percentage.

where Y is a $T \times 14$ matrix of surprises. F denotes the $T \times 4$ matrix of principal components (or factors), Λ is the loading matrix (4×14), while ϵ is a $T \times 14$ matrix of idiosyncratic components. The four principal components extracted explain a large share of the variance of the assets considered (see Table 2), with some residual variance at the short and long end of the yield curve, in the stock index and sovereign spreads. It is also worth noticing that no factor appears to be idiosyncratic or variable-specific, since they all affect most of the variables considered, albeit the second principal component mainly moves the spreads and the stock market.

3.3 Monetary policy surprises

The factors in the model in Eq. (22) are unique up to a rotation matrix U , which in our case is a 4×4 orthonormal matrix. To pin down a unique representation of the model and give an interpretation to the factors, we need to specify 6 restrictions on a generic orthonormal

matrix U .¹⁷ To identify the factors we impose the following restrictions:¹⁸

- The first factor is the only factor that loads on the 1-month OIS rate, i.e. all the other factors have zero effect on the 1-month OIS rate.
- The variance of the third and fourth factors is minimal before the financial crisis (i.e. August 2008).¹⁹
- The fourth factor has zero impact on the 10-year OIS rate.

The first assumption is the standard assumption of [Gürkaynak et al. \(2005\)](#) that allows us to identify a target factor (F1) that relates to conventional monetary policy, being the only factor moving the short end of the yield curve. The second assumption is in line with the approach proposed by [Swanson \(2021\)](#) to identify a QE/QT factor that relates to unconventional monetary policy in the form of quantitative easing/tightening and possibly changes in risk premia triggered by policy communication. In our approach, this assumption isolates two factors (F3, F4).

The last assumption disentangles the QE/QT factor affecting the long end of the risk free yield curve from a factor that we call the asymmetric country risk factor (F4). It appears in the euro area after the financial crisis but does not move the long end of the OIS curve, hence it is different from QE for macroeconomic stability. We interpret this factor as capturing asymmetric increases (or decreases) in the sovereign risk premia between core and periphery countries in the euro area. In doing so, we take an approach similar in spirit to [Reichlin et al. \(2022\)](#) and [Motto and Özen \(2022\)](#), which we discuss in detail later. However, it is important to note that we impose no restrictions on government spread surprises. Hence, the fact that

¹⁷The condition of orthonormality, $U'U = UU' = I$, imposes $n(n+1)/2$ restrictions, which corresponds to 10 restrictions for $n = 4$. Hence, the space of orthonormal matrices of dimension n has $n(n - 1)/2$ free parameters.

¹⁸Additional details about the identification of the factors are reported in Appendix C.

¹⁹Since the 2007 financial crisis, the ECB began adopting various unconventional monetary policy measures. The first of these were long-term refinancing operations (LTROs), aimed at providing emergency liquidity to the financial system. These were followed in September 2014 by targeted longer-term refinancing operations (TLTROs), designed to stimulate bank lending to the real economy. The ECB's first explicitly defined quantitative easing program with a focus on price stability, the asset purchase programme (APP), was launched in March 2015. Further details are provided in Section N of the Online Appendix.

one of the factors captures spread dynamics is a feature of the data, and of the policy problem in the euro area.

To understand the rationale for this factor, one has to observe that monetary policy in all jurisdictions is about steering the yield curve via a variety of tools. In the euro area, the ECB faces an extra dimension to monetary policy since the policies which affect the common risk-free yield curve (typically proxied by the OIS curve) may differentially affect the risk premia associated with country-specific yield curves (countries face their own default risks), adding a second dimension to the policy problem (see discussion in [Reichlin et al., 2022](#)). In fact, a feature of the euro area is that, in bad times, there can be a flight to safety dynamics with investors moving to German bonds and away from the periphery countries' government bond markets (see, among others, [Beber et al., 2008](#) and [Costantini and Sousa, 2022](#))

Finally, the assumptions identify, by orthogonality to the others, a factor that by constructions moves the mid segment of the yield curve and hence relates to information about the path of monetary policy, i.e. a forward guidance factor (F2), potentially both conditional on the expected macro development and unconditionally to them (i.e. Delphic and Odyssean forward guidance as labelled by [Campbell et al., 2012](#)). The variance of the assets considered that is explained by the identified factors is reported in Table 3.

Figure 3 plots the time series of the identified factors, which line up nicely with vertical lines marking the related important events in the euro area.²⁰ It is interesting to notice that the volatility of the forward guidance factor declines markedly after the formal adoption of forward guidance by the ECB. Also, the target and QE factors correctly capture some of the largest surprises as related to large monetary policy announcements, and the beginning of the APP programme.

In Figure 4, instead, we report the loadings of the factors (i.e. Λ in Eq. 22) on different assets' price revisions. On the x-axis we plot the different market surprises, and on the y-axis we report the magnitude of the loadings by normalising the peak impact of the four factors

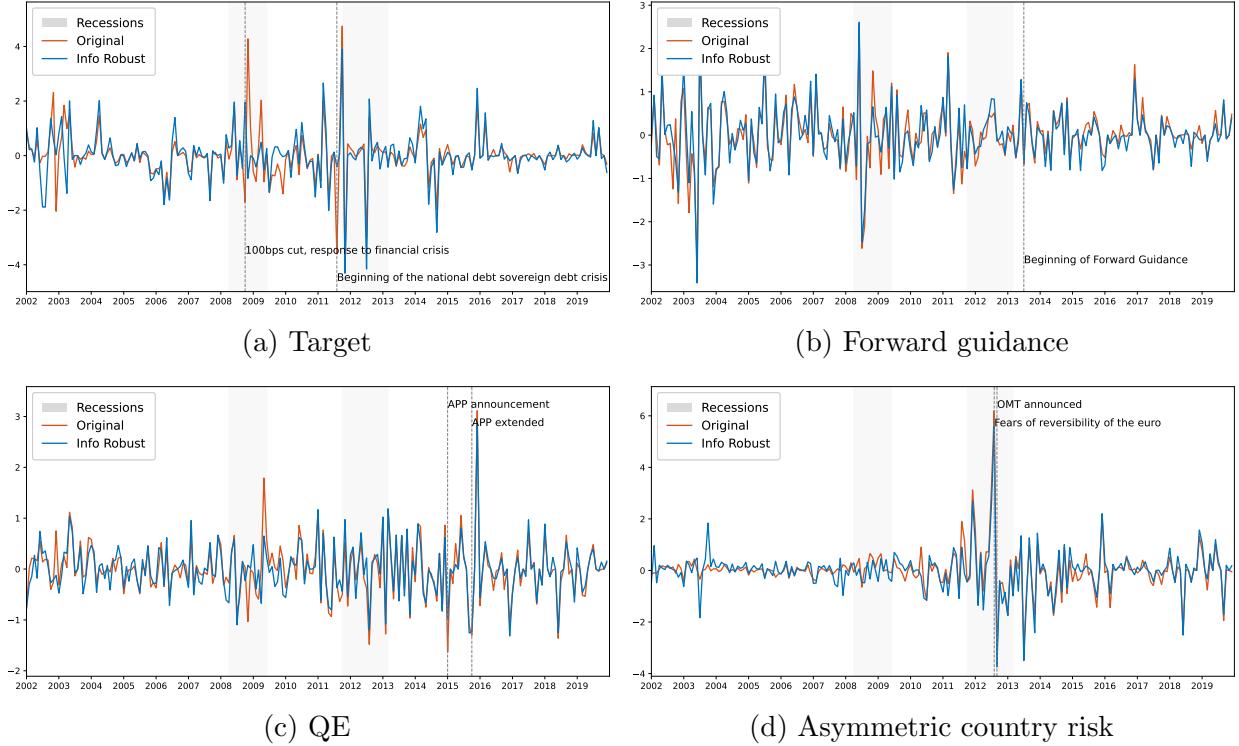
²⁰Details on the largest surprises are provided in Section M of the Online Appendix.

Table 3: VARIANCE DECOMPOSITION OF THE FACTORS

	1-m OIS	3-m OIS	6-m OIS	1-y OIS	2-y OIS	5-y OIS	10-y OIS
<i>F1</i>	83.3089	83.2393	66.5385	42.1029	28.9416	11.0168	1.8667
<i>F2</i>	0.0000	9.0547	23.3795	41.6461	52.1996	55.4678	49.6877
<i>F3</i>	0.0000	2.4359	4.6396	9.1701	12.8722	27.2440	32.1367
<i>F4</i>	0.0000	0.0519	0.2965	0.1805	0.0087	0.0353	0.0000
<i>Res</i>	16.6911	5.2182	5.1460	6.9004	5.9779	6.2362	16.3090
	2-y Spread	5-y Spread	10-y Spread	EURGBP	EURJPY	EURUSD	STOXX50
<i>F1</i>	6.5370	0.5907	0.0003	9.6890	9.1325	10.5243	6.4913
<i>F2</i>	0.1392	0.2231	0.0067	0.0314	0.5143	0.5777	5.4233
<i>F3</i>	1.4097	5.2027	2.4548	75.4117	75.5542	80.5216	12.1372
<i>F4</i>	74.4751	85.6449	87.5151	2.0071	0.0147	1.1809	46.7984
<i>Res</i>	17.4389	8.3386	10.0231	12.8608	14.7843	7.1955	29.1498

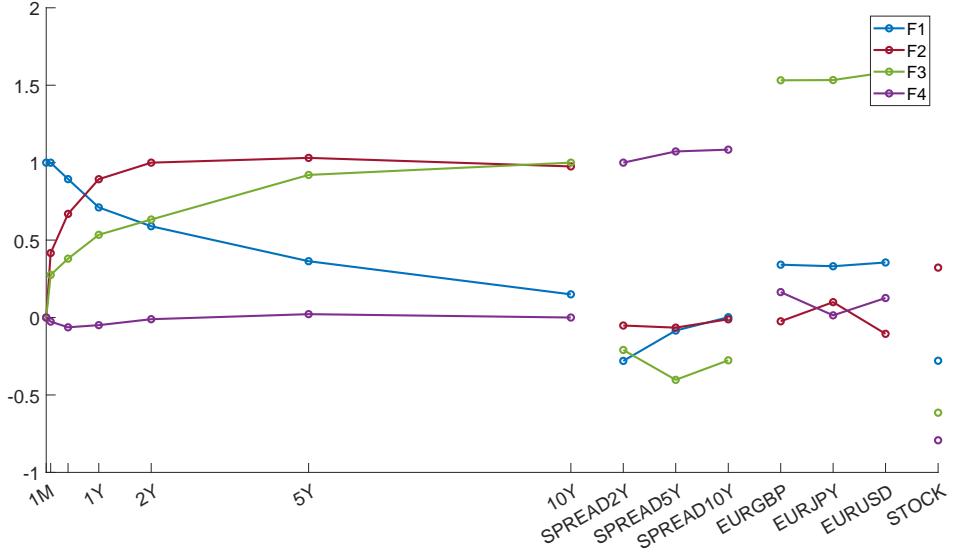
Notes: The table reports the Anova decomposition of the identified factors. Values are in percentage.

Figure 3: IDENTIFIED AND INFORMATIONALLY CORRECTED FACTORS



Notes: The figure plots the identified factors extracted without any correction for information effects, along with the identified factors after the orthogonalisation of price surprises, obtained using the regression specification for non-linear information effects. Details on the largest surprises for each factor are provided in Section M of the Online Appendix.

Figure 4: LOADINGS FOR THE IDENTIFIED FACTORS



Notes: The figure reports the loadings of the identified factors on the market surprises, prior to information correction. F1 (blue) loads primarily on short-term OIS surprises, F2 (red) loads on medium-term OIS surprises, F3 (green) loads on long-term OIS surprises, and F4 (purple) loads on the markets surprises in the spreads between Italian and German government bonds.

on the 1-month, 2-year, 10-year, and 10-year spread, respectively, to one.

The target factor (blue) is by construction the only factor with loading different from zero on the 1-month rate, with a slowly decaying pattern of loading over increasing maturities. The flattening of the yield curve induced by this factor is typical of conventional monetary policy. The forward guidance factor (in red) loads mostly on medium-term maturities (2-year to 5-year OIS with a sizeable effect on longer maturities). These two factors also have a limited effect on governments spreads (mostly negative) and exchange rates (mostly positive). While the target factor has a negative impact on the stock market, the forward guidance factor has a positive effect. This is potential indication of a dominant information component in the forward guidance factor, following the intuition proposed by [Jarociński and Karadi \(2020\)](#). We shall discuss this point in the next section.

The QE factor (green) has the largest positive effect on 10-year OIS and exchange rates while it displays negative coefficients on government spreads and the stock market. Even if some of the government yields variation is captured by the asymmetric country risk factor, QE

has still a sizeable effect on those surprises by moving spread and risk-free rates in opposite direction.

The asymmetric country risk factor (purple) has almost zero effect on the yield curve and highest coefficients on government spread and stock market surprises. Consistent with our interpretation, we find a dimension orthogonal to conventional and unconventional monetary policy that has almost zero effect on risk-free rates and influences positively the spread between Italian and German bond yield and negatively the stock market.

Before discussing the presence of information effects in the market surprises in the next section, in the remainder of this section we detail the differences between our approach and other approaches in the literature and the potential empirical implications.

3.4 Comparison with other approaches

Our approach diverges from [Altavilla et al. \(2019\)](#) in several respects that are potentially important (see Table 4 for a summary). Let us highlight the four main differences below.

The assets considered. In addition to considering market surprises in risk-free rates across various maturities, ranging from 1 month to 10 years as in [Altavilla et al. \(2019\)](#), we also incorporate in our analysis surprises to the spreads between Italian and German treasury bonds, exchange rates, and the stock market index. By considering surprises to spreads, we want to capture the potentially divergent dynamics between core and periphery countries, which is a defining characteristic of the policy problem in the euro area that was particularly in evidence during the European sovereign debt crisis. In doing so, we follow the same intuition proposed by [Reichlin et al. \(2022\)](#) and [Motto and Özen \(2022\)](#).

The introduction of the stock market is potentially relevant to ‘sign’ the response of the markets to each of the factor extracted, which is key in the approach proposed by [Jarociński and Karadi \(2020\)](#) to disentangle information effects from policy shocks. It is interesting to observe that all factors bar F2 have a negative correlation between the response of the stock

Table 4: ASSUMPTIONS TO IDENTIFY FACTORS

	Sample	Ex. Dates	Assets	Std	Info	# Factors	Assumptions
Altavilla et al. (2019)	Jan2002 to Aug2018	8-Oct-2008 4-Nov-2008	1, 3, 6-month OIS 1, 2, 5, 10-year OIS	No	No	1 press release 3 press conf.	$\Lambda_{F2,OIS-1m} \equiv 0$ $\Lambda_{F3,OIS-1m} \equiv 0$ $F2, F3$ dropped $\Lambda_{F2,OIS-1m} \equiv 0$ $\Lambda_{F3,OIS-1m} \equiv 0$ $min_{t < Aug2008} var(F3)$
Motto and Özen (2022)	Jan2002 to Jun2020	8-Oct-2008 4-Nov-2008	1, 3, 6-month OIS 1, 2, 5, 10-year OIS 2, 5, 10-year ESP 2, 5, 10-year FRA 2, 5, 10-year ITA	No	No	4 press conf.	$\Lambda_{F2,OIS-1m} \equiv 0$ $\Lambda_{F3,OIS-1m} \equiv 0$ $\Lambda_{F4,OIS-1m} \equiv 0$ $min_{t < Aug2008} var(F3)$ $min_{t < Apr2010} var(F4)$ $min_{t \in [Jan2013, Dec2019]} var(F4)$ $\Lambda_{F4,ITA-5y} \times \Lambda_{F4,OIS-5y} \leq 0$
This work	Jan2002 to Dec2019	none	1, 3, 6-month OIS 1, 2, 5, 10-year OIS 2, 5, 10-year ITA-DEU FX rate EUR-USD FX rate EUR-GBP FX rate EUR-JPY stock mkt STOXX50	Yes	Yes	4 press release + press conf.	$\Lambda_{F2,OIS-1m} \equiv 0$ $\Lambda_{F3,OIS-1m} \equiv 0$ $\Lambda_{F4,OIS-1m} \equiv 0$ $min_{t < Aug2008} var(F3)$ $min_{t < Aug2008} var(F4)$ $\Lambda_{F4,OIS-10y} \equiv 0$

Notes: The table compares the main empirical choices in estimating the monetary policy surprises proposed in this work with those in Altavilla et al. (2019) and Motto and Özen (2022). In one of the many robustness exercises proposed about the identification assumptions, Motto and Özen (2022) impose that F4 has zero impact on both the 5y-OIS and 10y-OIS rates, similar to the restriction adopted in this work.

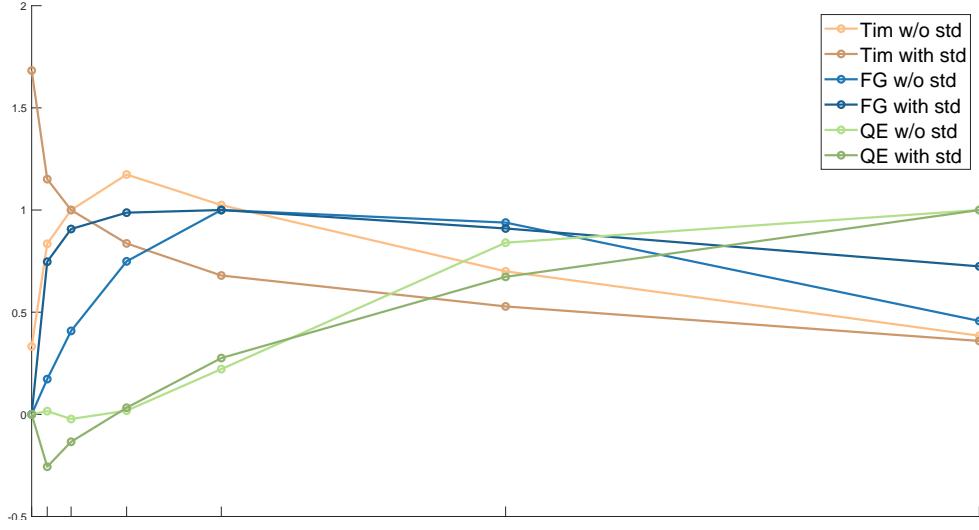
market and the factors.²¹

The exchange rates do not play a decisive role, with their reactions to the announcements being well captured by a rather standard number of monetary surprises. In fact, their presence in the analysis does not show the presence of an additional dimension of the policy communication. This in line with the declared objective of the ECB, which does not target the exchange rates. However, it is interesting to observe that conventional monetary policy affects exchange rates less than changes to long-term yields.

The windows. Differently from Altavilla et al. (2019) and Motto and Özen (2022), who analyse the press release and the press conference windows separately, we sum the surprises

²¹As showed in the rest of the paper, F2 has a strong information content, in line with the intuition proposed by Jarociński and Karadi (2020).

Figure 5: THE ROLE OF STANDARDISATION



Notes: The figure reports the loadings of the identified factors obtained with the procedure of [Altavilla et al. \(2019\)](#), where the price revisions are only demeaned, and compares them with the loadings obtained when the dataset is standardised before extracting the PCs.

across the two windows. [Altavilla et al. \(2019\)](#) extract a target factor that utilises surprises from the press release window, and a timing factor that utilises surprises from the press conference window. These two factors are identified by imposing the restriction that they are the only factors moving the short end of the yield curve.²²

Our approach of summing the two policy windows is potentially helpful in reducing the noise in the market reaction to the press release and captures the corrections generated by market participants as they revise and update their views during the press conference window. This is particularly important in the presence of information effects, which would also affect the first factor (target). Interestingly, the test on the number of factors present in the the 14 series obtained by summing across the two windows signals only four factors, one of which captures movements at the short end of the yield curve.

The standardisation of the price revisions. There is an additional specification in our approach which has a bearing for the short term factors: the standardisation of the price revisions. In [Altavilla et al. \(2019\)](#) price revisions are demeaned but not standardised before

²²The other factors, which are not significant for the press release window, in the analysis of [Altavilla et al. \(2019\)](#) are discarded.

extracting the principal components.

Figure 5 plots the factor loadings identified from OIS surprises in the press conference window with maturities ranging from 1 month to 10 years, as in [Altavilla et al. \(2019\)](#). Let us focus on the timing factor (orange and brown lines), which is identified as the only factor that loads on the 1-month OIS rate.

The timing factor in orange is obtained by the demeaned price revisions as in [Altavilla et al. \(2019\)](#). This factor peaks on the 1-year OIS rate (normalised to one), with a normalised value below 0.5 for 1-month OIS. This pattern of responses across maturities allows for an interpretation of it as capturing revisions of expectations about the next policy rounds.

The factor in brown corresponds to the same factor, obtained under identical assumptions and from the same assets, but extracted from principal components computed using standardised price revisions.²³ It displays a pattern of loadings comparable to that of the target factor extracted from the press release window.²⁴ This evidence suggests that, beyond being conveying information about the future path of monetary policy, the press conference window also contains information about short-term expectations of policy rates, which supports our choice to consider the combined effects of the two policy events.

The asymmetric country risk factor. This factor is additional to the ones discussed in [Altavilla et al. \(2019\)](#). As mentioned, it follows the intuition proposed by [Reichlin et al. \(2022\)](#), and is close to the market stabilisation QE factor of [Motto and Özen \(2022\)](#). Differently from [Motto and Özen \(2022\)](#), we do not directly impose restrictions on the European sovereign debt crisis or on sovereign yield curves, but only on the OIS rates. The effect of our F4 factor on the spread is hence a result and not an assumption.²⁵

²³The PCA criterion is based on the variance of the matrix which is not a scale-invariant measure. It is therefore generally recommended to standardise the data before extracting PCs (see for instance [Hastie et al., 2009](#)).

²⁴Figure E.9 in Appendix E provides a similar comparison for the target factor extracted from the press release window using standardised rather than demeaned data.

²⁵In one of the many robustness exercises proposed about the identification assumptions, [Motto and Özen \(2022\)](#) impose that F4 has zero impact on both the 5y and 10y OIS rates, similarly to the restriction imposed in this work.

4 Information effects in the euro area

The literature on US monetary policy has pointed to the presence of information effects in monetary surprises as the source of puzzles in the dynamic responses of macroeconomic variables obtained when such surprises are used as instrumental variables for the identification of policy shocks (see, for example, [Jarociński and Karadi, 2020](#); [Miranda-Agrippino and Ricco, 2021](#)). To control for these effects and isolate the pure policy component, the most common approaches are to either use the differences in the co-movements of the yield curve with the stock market, as proposed by [Jarociński and Karadi \(2020\)](#), or to use the central bank or private forecasts about the economic conditions that pre-date the policy decision, as discussed in [Miranda-Agrippino and Ricco \(2021\)](#).²⁶

In line with the predictions of the model presented in Section 2, we follow an approach similar to the one proposed by [Miranda-Agrippino and Ricco \(2021\)](#) to control for information effects, but with some important differences.

4.1 Linear and non-linear information effects

Instead of employing only the central bank's pre-meeting forecast as in [Miranda-Agrippino and Ricco \(2021\)](#), we consider both the ECB's and professional forecasts. The ECB forecasts that we consider are quarterly projections for GDP and inflation.²⁷ We supplement these forecasts, that can be stale with respect to the information set of the policymakers at the moment of the policy decision, with the pre-meeting monthly polls from Reuters, on inflation, GDP and the MRO policy rate (main refinancing operations rate) and which consist of quarterly and annual growth rates forecasts. While the use of the private sector forecasts may

²⁶[Bauer and Swanson \(2023\)](#) propose a related approach that regresses monetary policy surprises onto past financial variables. While they interpret information effects as arising from market participants' forecast model being based on a misspecified Taylor rule, from the point of view of the correction of the surprises their approach and predictions are equivalent to those of [Miranda-Agrippino and Ricco \(2021\)](#).

²⁷The forecasts are produced before, but published after the monetary policy meetings of the ECB Governing Council (in March, June, September, and December), and are disseminated in the form of a projections article on the ECB's website. We retrieve them from the [Macroeconomic Projection Database \(MPD\)](#) of the ECB.

seem surprising in dealing with information effects in central bank communication, it is in fact fully in line with the predictions of Proposition 1, and in particular of Eq. (17). They show that private forecast revisions are correlated with past private forecasts, as well as with any variable, be it forecasts or financial variables, capturing both lagged and current structural shocks. This observation provides justification for our approach, given the limitations of the ECB’s forecasts. Let us finally observe that the use of the Fed’s Greenbook forecasts is convenient since they provide a simple and direct measure of the central bank’s expectations, and provides a clear test of information effects since the forecasts are published with a five year lag. However, in the framework dispersed information presented in Section 2, it is not strictly speaking necessary and other variables can be adopted.

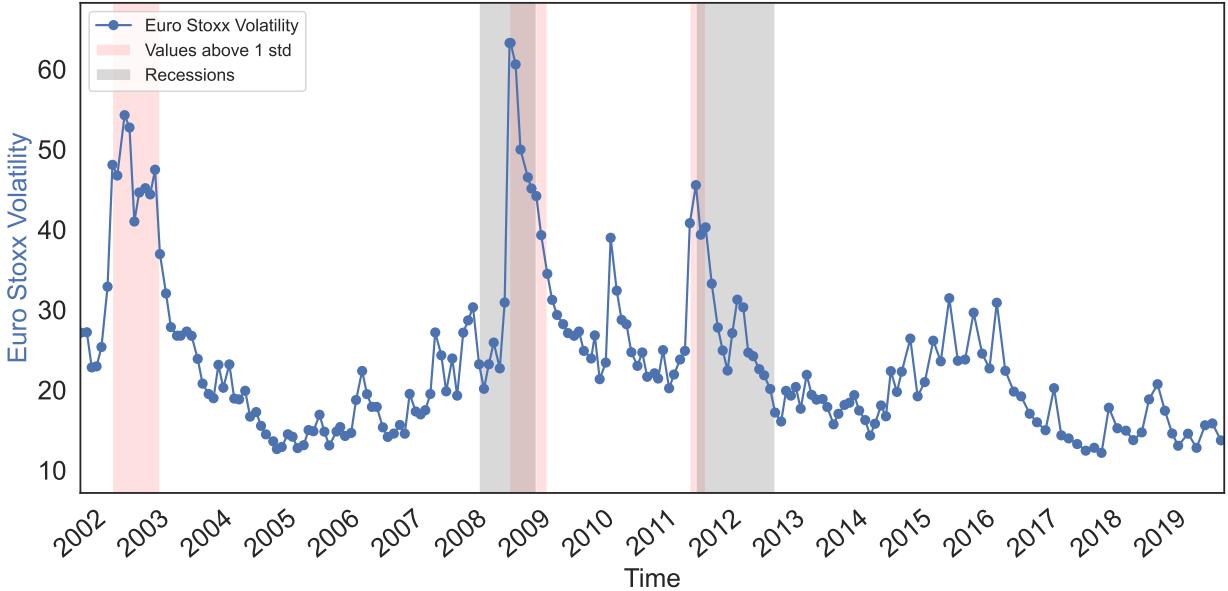
To address the issue of information effects along the OIS yield curve and other assets that we consider, we operate in two steps. First, we project the price revisions of each asset – the risk-free yield curve, the government spreads, the exchange rates and the stock market – on ECB and Reuters forecasts and forecast revisions, and obtain residuals that are orthogonal to economic shocks other than monetary policy. We then extract the monetary policy factors from the residuals of these ‘information’ regressions, using the restrictions detailed in the previous section.

In controlling for information effects, we consider two OLS regression specifications, both at the ECB Governing Council meeting’s frequency. The first is a linear regression, of the form

$$ms_t^i = \beta_0 + \sum_{j=0}^J \theta_j^i F_t x_{q+j} + \sum_{j=0}^{J-1} \eta_j \Delta F_t x_{q+j} + \tilde{ms}_t^i \quad (23)$$

where ms_t^i (i.e. the monetary surprises) are the price revisions of the assets i in the monetary window related to the Governing Council meeting at t . $F_t x_{q+j}$ denotes the forecast for variable x at horizon $q+j$, and $\Delta F_t x_{q+j} = F_t x_{q+j} - F_{t-1} x_{q+j}$ denotes revisions to forecasts between consecutive ECB meetings. The index j denotes the period to which the forecast refers, i.e. one period ahead, two periods ahead, and so on. \tilde{ms}_t^i is the residual of the regression and represents the informationally robust monetary policy surprises. As mentioned, we run a

Figure 6: VSTOXX INDEX AND DATES SELECTED



Notes: The figure plots the Euro STOXX Volatility index (blue), with vertical red shaded areas marking dates when the index is one standard deviation above its mean. The vertical grey shaded areas indicate recessions dates for the euro area, as defined by the [CEPR-EABCN Euro Area Business Cycle Dating Committee](#).

separate regression for every asset we consider: risk-free rates, government spreads, exchange rates, and the stock market.

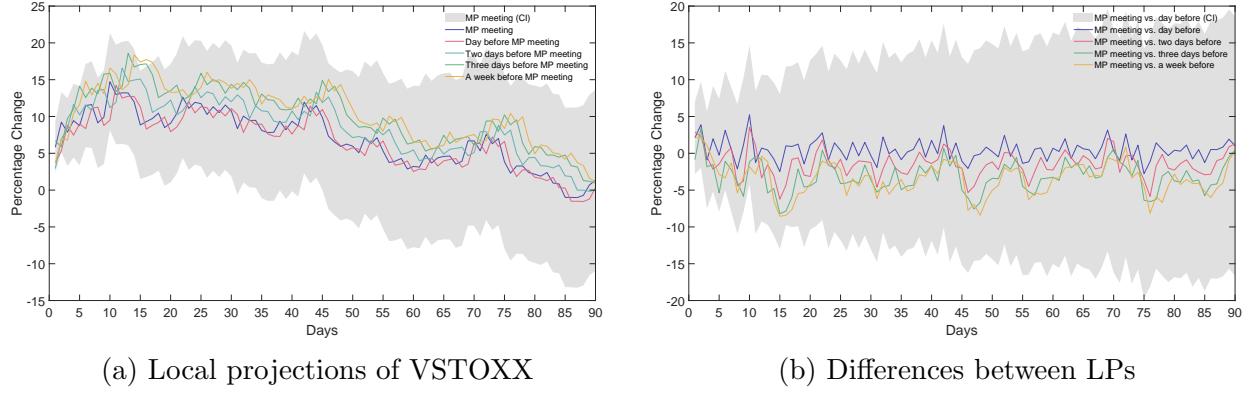
The second specification is a non-linear threshold regression of the form

$$ms_t^i = \beta_0 + \sum_{j=0}^J \theta_j F_t x_{q+j} + \sum_{j=0}^{J-1} \eta_j \Delta F_t x_{q+j} + I(S_t > \bar{s}) \left[\sum_{j=0}^J \kappa_j F_t x_{q+j} + \sum_{j=0}^{J-1} \psi_j \Delta F_t x_{q+j} \right] + \tilde{ms}_t^i \quad (24)$$

where $I(S_t > \bar{s})$ is a Heaviside step function that takes value one when an indicator of market stress, S_t , is above the threshold, \bar{s} . We interpret the residuals from the second regression, i.e. \tilde{ms}_t^i , as a measure of monetary policy shocks corrected for non-linear information effects.

This second regression specification tests the predictions of Proposition 3 obtained from of the model presented in Section 2. When there is a state of high stress and dislocation in financial markets, which can be thought of as an increase in the noise in the private signals

Figure 7: THE IMPACT OF MONETARY POLICY ANNOUNCEMENT ON VSTOXX



Notes: Panel (a) presents local projection IRFs of the daily VSTOXX index during periods of high volatility for (i) a dummy variable set to one on the days of monetary policy announcements and (ii) placebo dummies set to one on the day before, two days before, three days before, and one week before the policy announcement. Panel (b) shows the differences between the IRFs for the placebo dates and for the actual monetary policy announcement date.

obtained by market participants, the model predicts information effects to be stronger. In such a state, private agents place greater weight on the public signal conveyed by the central bank's monetary policy decision. This is possibly a salient characteristic of the euro area, evident during the financial crisis and the subsequent sovereign debt crisis, and later during the COVID-19 crisis.

To capture these conditions, we use the Euro STOXX Volatility index (VSTOXX) as an indicator of market stress in the euro area, and set the threshold level at one standard deviation above the index's mean (Figure 6).²⁸ The chart reports the time series of the VSTOXX index from 2002 to 2019, with the recession bands for the euro area, and in light blue the periods selected by our indicator. From Figure 6, it is clear that the indicator does not simply coincide with the recession indicator, but instead it captures moments of turbulence on the markets not necessarily associated to the two large recessions in the sample.

A potential concern is the endogeneity between observed high stock market volatility and monetary policy decisions – some of which may have disappointed or even caused panic in

²⁸Varying this threshold within large limits does not lead to different results in terms of both information effects and the transmission of monetary policy shocks. This is due to the clear non-linear nature of this index with very localised spikes above its average level.

the market during crisis periods. Figure 7 addresses this concern by showing that during high-volatility periods, ECB's monetary policy decisions were not the primary cause of market volatility. Figure 7a reports local projections of the daily VSTOXX index during high-volatility periods for (i) a dummy variable set to one on the days of monetary policy announcements, and (ii) placebo dummies set to one on the day before, two days before, three days before, and one week before the policy announcement. While stock market volatility tends to increase following a monetary policy announcement, this is not due to the decision itself, as the response to placebo dummies preceding policy decisions follows a similar pattern. Indeed, the differences between the IRFs for the announcement dummy and the placebo dummies are not statistically different from zero, as shown in Figure 7b.

4.2 Information robust monetary surprises

Table 5 presents the results of the non-linear regression specification in Eq. (24) for the OIS curve. It also reports the adjusted R^2 of the regressions, as a measure of predictability of the surprises and, as a reference, the adjusted R^2 of the related linear specification. Results for the spreads, the exchange rates and stock market surprises are reported in Section G of the Online Appendix, along with the results of the linear regression specification in Eq. (23). Let us here summarise some noteworthy findings.

By including a larger set of forecasts, we have qualitatively the same results as the baseline where we observe limited information effects for these surprises.

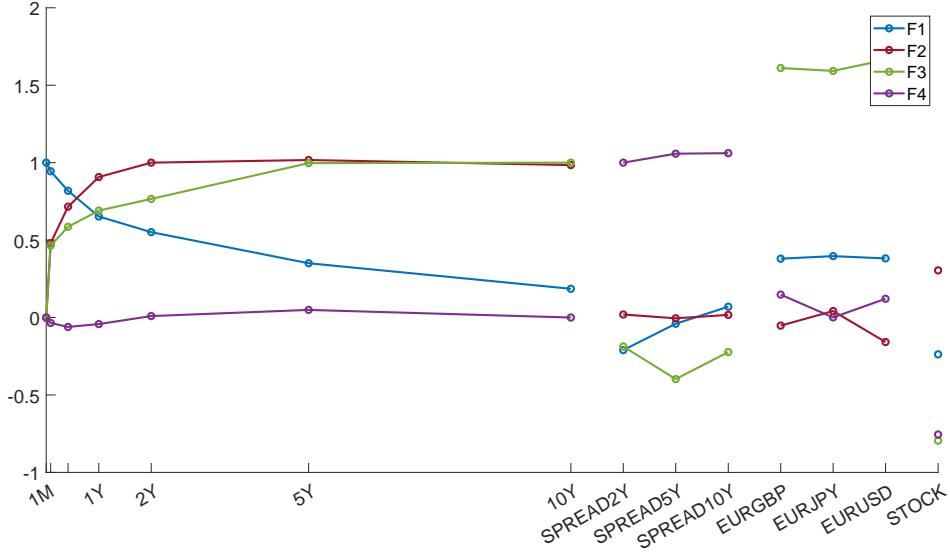
Overall, the results confirm the predictions of the model: both the linear and the threshold regression coefficients indicate predictability in the monetary policy surprises, in line with the presence of imperfect information. While many of the regressors are correlated, making the interpretation of their coefficients not straightforward, many of them are significant. Similarly, to what reported by [Miranda-Agrippino and Ricco \(2021\)](#) for the U.S., the linear information regression explains around nine per cent of the surprises on the yield curve. The explanatory power of the regressors for the other assets is limited, possibly indicating a larger role for

Table 5: PROJECTION OF YIELD CURVE SURPRISES ON FORECASTS - NON-LINEAR

	(1) 1m-OIS	(2) 3m-OIS	(3) 6m-OIS	(4) 1y-OIS	(5) 2y-OIS	(6) 5y-OIS	(7) 10y-OIS
$MRO_{q=0}$	-0.094 (0.138)	-0.019 (0.252)	0.081 (0.340)	0.004 (0.468)	0.100 (0.508)	0.449 (0.510)	0.436 (0.296)
$\Delta MRO_{q=0}$	1.453 (1.935)	2.112 (1.990)	1.779 (2.403)	1.956 (3.185)	2.465 (3.818)	3.712 (3.491)	3.451** (1.719)
$HICP_{q=1}$	-0.200 (0.562)	0.305 (1.019)	-0.106 (1.315)	-0.747 (1.705)	-1.536 (1.816)	-1.851 (1.608)	-1.265 (1.165)
$GDP_{q=0}$	-1.300 (1.354)	-1.863 (1.846)	-1.355 (2.378)	-1.277 (3.047)	-1.594 (3.452)	0.021 (3.193)	0.417 (2.404)
$GDP_{q=1}$	-2.107 (1.746)	1.514 (2.679)	0.939 (3.913)	1.269 (5.503)	3.372 (6.309)	1.967 (5.288)	-0.352 (3.539)
$GDP_{q=2}$	2.906 (1.958)	0.477 (2.519)	0.271 (3.624)	-0.199 (5.165)	-2.198 (5.940)	-3.310 (4.707)	-3.935 (3.353)
$GDP_{y=0}$	0.481** (0.195)	0.320 (0.237)	0.342 (0.304)	0.277 (0.354)	0.156 (0.472)	0.195 (0.420)	0.252 (0.325)
$HICP_{y=0}$	0.056 (0.507)	-0.166 (0.747)	-0.503 (0.970)	-0.611 (1.322)	-0.565 (1.508)	-0.103 (1.477)	0.232 (1.080)
$HICP_{y=1}$	-0.608 (1.088)	-1.398 (1.726)	-0.628 (2.139)	0.165 (2.747)	0.469 (3.147)	-1.112 (2.712)	-2.138 (2.097)
$\Delta HICP_{y=0}$	-0.101 (1.163)	0.439 (1.555)	1.667 (2.107)	2.756 (2.988)	3.597 (3.464)	4.078 (3.831)	6.565** (2.954)
$HICP_{ECB}^{ECB}_{q=0}$	0.093 (0.824)	-0.036 (1.306)	-0.242 (1.768)	1.043 (2.414)	2.696 (2.555)	3.589 (2.365)	3.344** (1.657)
$\Delta HICP_{ECB}^{ECB}_{q=0}$	0.118 (0.872)	0.694 (1.383)	-0.263 (1.678)	-0.524 (2.338)	-1.305 (2.438)	0.088 (2.292)	0.333 (1.608)
$GDP_{y=0}^{ECB}$	-0.046 (0.210)	0.148 (0.338)	0.288 (0.493)	0.297 (0.646)	0.055 (0.764)	-0.417 (0.643)	-0.528 (0.486)
$HICP_{y=0}^{ECB}$	0.041 (0.919)	0.438 (1.532)	1.025 (2.112)	0.129 (2.879)	-1.248 (3.056)	-2.555 (2.759)	-2.933 (1.825)
$GDP_{q=0}^{ECB}$	-0.853 (1.393)	-1.204 (2.096)	-1.975 (2.918)	-1.738 (3.929)	-1.776 (4.334)	0.841 (3.751)	3.119 (2.474)
$I(index) * MRO_{q=0}$	0.051 (2.865)	-1.605 (2.107)	-3.144 (2.180)	-2.531 (3.158)	-2.496 (3.126)	-2.283 (1.450)	-0.474 (0.574)
$I(index) * \Delta MRO_{q=0}$	-17.492*** (5.704)	-21.754*** (4.626)	-19.817*** (5.293)	-16.204** (7.032)	-15.013** (7.454)	-7.612 (4.879)	-2.368 (2.516)
$I(index) * HICP_{q=1}$	-8.049 (13.772)	-24.989** (9.926)	-36.097*** (9.735)	-38.936*** (13.456)	-35.200** (13.894)	-12.376 (7.594)	1.363 (3.856)
$I(index) * GDP_{q=0}$	-14.902 (17.408)	-13.265 (12.448)	-11.959 (12.886)	-14.419 (15.620)	-20.697 (15.011)	-11.413 (7.780)	-2.338 (4.087)
$I(index) * GDP_{q=1}$	42.479 (36.294)	46.046* (25.279)	48.003** (23.667)	49.661* (27.848)	59.861** (27.497)	21.391 (14.139)	-3.478 (7.711)
$I(index) * GDP_{q=2}$	-24.469 (23.762)	-25.185 (19.054)	-27.000 (20.755)	-31.834 (27.078)	-37.676 (29.062)	9.738 (17.580)	22.828** (9.132)
$I(index) * GDP_{y=0}$	0.870 (3.372)	4.402* (2.440)	6.848*** (2.498)	8.081** (3.489)	7.394** (3.559)	-0.256 (2.053)	-2.871*** (1.035)
$I(index) * HICP_{y=0}$	1.109 (9.100)	9.739 (6.914)	16.496** (6.785)	18.257** (8.000)	18.696** (8.121)	14.039*** (4.450)	6.074** (2.370)
$I(index) * HICP_{y=1}$	5.711 (6.626)	12.133** (5.761)	16.116** (7.683)	16.885 (11.060)	13.372 (11.073)	-5.504 (6.814)	-10.673*** (3.131)
$I(index) * \Delta HICP_{y=0}$	19.911*** (5.763)	10.777** (5.409)	8.952 (8.961)	11.445 (13.460)	4.086 (13.542)	-6.958 (8.944)	-11.078** (4.619)
$I(index) * HICP_{ECB}^{ECB}_{q=0}$	22.282*** (6.403)	19.311*** (5.491)	19.343*** (7.147)	9.133 (10.430)	1.283 (11.595)	-0.554 (7.410)	-1.140 (3.850)
$I(index) * \Delta HICP_{ECB}^{ECB}_{q=0}$	-17.923** (8.452)	-10.304 (6.886)	-5.618 (7.528)	10.486 (10.175)	25.740** (12.182)	16.285** (7.923)	6.748 (4.295)
$I(index) * GDP_{y=0}^{ECB}$	19.415*** (3.694)	11.005*** (2.831)	7.969*** (2.792)	2.440 (3.935)	-2.682 (4.994)	-0.818 (3.196)	0.675 (1.770)
$I(index) * HICP_{y=0}^{ECB}$	-28.867*** (6.597)	-22.368*** (5.899)	-22.077*** (8.053)	-9.893 (11.966)	-0.330 (13.291)	0.565 (8.473)	0.784 (4.297)
$I(index) * GDP_{y=0}^{ECB}$	-25.640* (13.903)	-16.300 (11.472)	-15.244 (11.788)	-15.098 (13.550)	-12.009 (14.484)	-12.046 (8.615)	-7.060 (4.679)
<i>Constant</i>	0.942 (1.447)	1.428 (2.051)	1.213 (2.516)	0.991 (3.229)	1.690 (3.652)	4.088 (3.297)	5.375** (2.550)
\mathcal{R}_{adj}^2	0.356	0.334	0.234	0.103	0.077	0.019	0.072
N	197	197	197	197	197	197	197
Linear Info - \mathcal{R}_{adj}^2	0.048	0.067	0.037	0.015	0.011	0.019	0.087

Notes: The table reports regression results for a test of non-linear information effects along the yield curve surprises. We also report, for references, the adjusted R^2 for the linear specification.

Figure 8: LOADINGS WITH NON-LINEAR INFORMATION EFFECTS



Notes: The figure reports the loadings of the identified factors on the market surprises, after controlling for non-linear information effects. F1 (blue) loads primarily on short-term OIS surprises, F2 (red) loads on medium-term OIS surprises, F3 (green) loads on long-term OIS surprises, and F4 (purple) loads on the markets surprises in the spreads between Italian and German government bonds.

changes in risk premia.

The R^2 of the non-linear specification explains a much larger share at short maturities (Table 5). This confirms the prediction of the model in terms of stronger information effects in phases of market stress. The coefficients on the forecast of GDP are generally positive, as well as the coefficients on the inflation forecast, with some exceptions. Overall this is in line with the model predictions – despite having many collinear regressors. Interestingly, past revisions to forecasts of the MRO appear with a negative signs, as is the coefficient of past monetary policy shocks in Eq. (17) of Proposition 1.²⁹

4.3 Informationally robust IVs for monetary policy

The informationally robust policy factors we adopt in our benchmark specifications are obtained from the residuals of the regressions employing the restrictions described in the previous section. Figure 3 reports the times series of these factors along with the factors obtained before the information correction, while Figure 8 plots their loadings. The interpretation for each factor is the same as the one that we have when we extract factors without information effects, and their magnitude remains very similar. This shows that the convolution of structural shocks to which the ECB responds, and that determines the information effects, appears as an unspanned ‘information factor’ in the data.

In particular, the target factor (i.e. conventional monetary policy) loads more strongly on the short-term rates with declining weights over the yield curve, with a positive impact on the exchange rates and a negative impact on the stock market. The forward guidance factor has the largest weight on the medium maturities, while a tightening in the QE factor lifts the long end of the yield curve, has a large positive impact on the exchange rates and a large negative impact on the stock market. The asymmetric risk factor has no effect on the OIS curve but strongly affects country spreads.

5 Policy shocks and information

This section discusses the macroeconomic propagation of the four monetary shocks that are identified by the information robust IVs we proposed: conventional monetary policy, forward guidance, quantitative easing/tightening and country risk shocks. We identify these structural shocks in a rich VAR model with the external IV approach of [Stock and Watson \(2012\)](#) and

²⁹Results are robust both in terms of the properties of the residuals of the non-linear regressions, and of the macroeconomic effects obtained from the IV thus obtained. In Section G of the Online Appendix, we report results obtained with a larger set of regressors and a LASSO or RIDGE regression specification. The information effects for longer maturities of the yield curve are stronger, as compared to the baseline results (the adjusted R^2 for the 10y-OIS exceeds 11%). However, the impact of these on the IRFs obtained in an identified VARs using the IVs obtained from residuals of the regressions is marginal.

Mertens and Ravn (2013), which is valid under mild conditions of relevance and exogeneity, and the invertibility of the shocks of interest for the model adopted (see Miranda-Agrippino and Ricco, 2023).

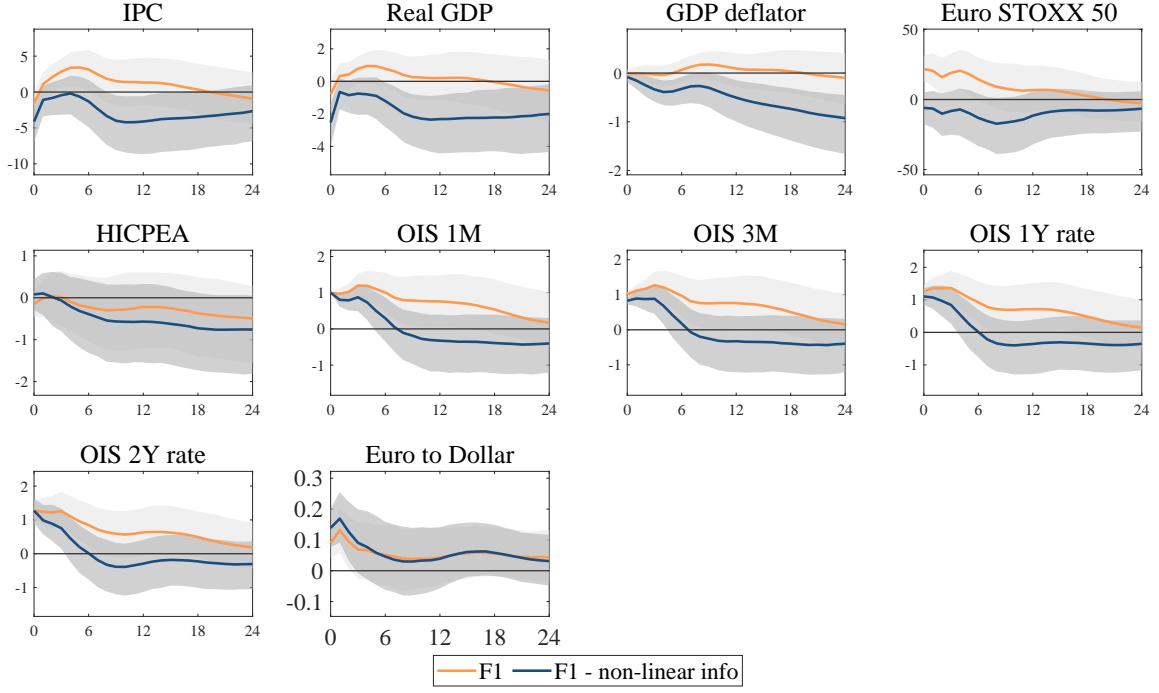
For each shock, we estimate a monthly Bayesian VAR with 12 lags and standard Minnesota priors over the sample 2002 to 2019. The informativeness of the priors is set following Giannone et al. (2015). Our baseline specification includes a rich set of real, nominal and financial variables. We choose industrial production including construction (IPC) and a measure of real GDP as proxies for economic activity in the euro area. We use seasonally adjusted series for headline inflation (HICPEA), together with the GDP deflator as indicators of the price dynamics in the euro area.³⁰ The VAR also include the Euro STOXX 50 index as a measure of the stock market, a range of risk-free OIS rates with maturities from 1 month to 10 years, and the euro-US dollar ($\text{€}/\text{\$}$) exchange rate. All variables, with the exception of rates, are in log-levels.

For each of the four shocks, we compare the impulse response functions (IRFs) obtained using as IVs the factors that are extracted from market surprise (in amber) with those obtained after correcting for non-linear information effects (in blue). We report IRFs over a horizon of 24 months. As discussed below, using the raw market-based factors as IVs deliver responses with several puzzles – notably for prices, output and the stock market. In contrast, the information-robust IVs generates dynamic responses in line with the expected effects of monetary policy.

Finally, we show the propagation of the information component of the monetary policy announcements. This cannot strictly speaking be thought of as a structural shock, but rather as a bundle of structural shocks (and potentially their lags) to which monetary policy responds. The IRFs are obtained from the VAR using as an instrument the principal components of the fitted values of Eq. (24).

³⁰Real GDP and its deflator are obtained by interpolating quarterly measures to obtain monthly frequency as in Stock and Watson (2010); Jarociński and Karadi (2020). Results for IP excluding construction are almost indistinguishable from those for IPC (see Section B of the Online Appendix).

Figure 9: CONVENTIONAL MONETARY POLICY SHOCK



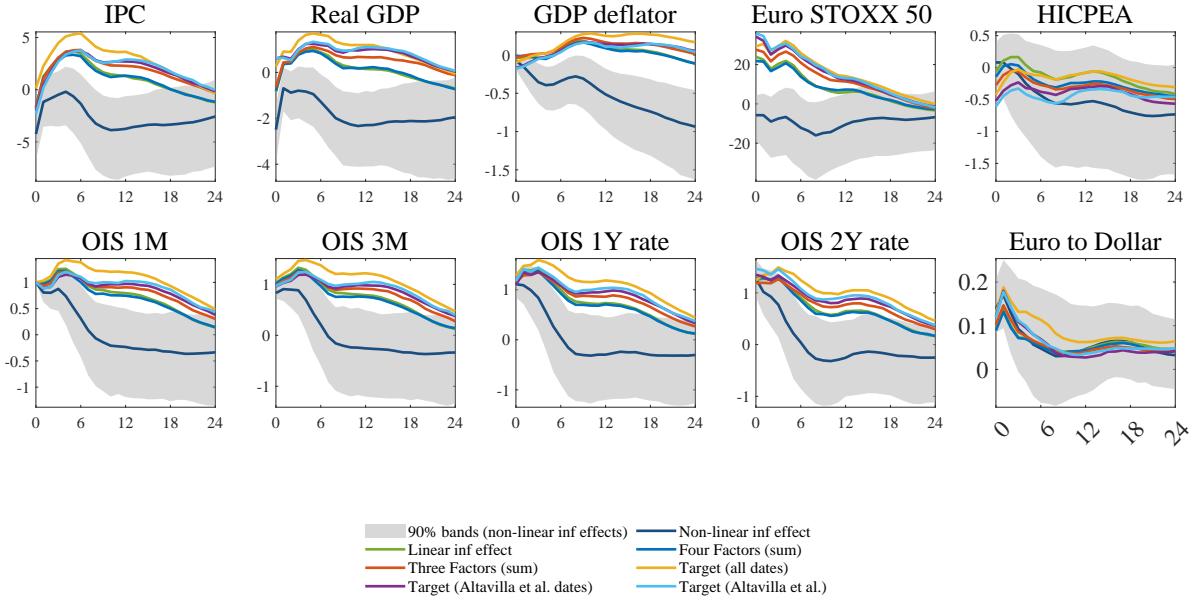
Notes: The figure reports the IRFs to a conventional monetary policy shock, normalised to induce a 100 basis points increase in the 1m-OIS rate. In amber, it reports the responses obtained with the original F1 factor, without any correction for information effects. In blue, it reports the IRFs by using the informationally robust F1 factor. The grey shaded areas are 90% coverage bands. The sample considered is 2002-2019.

5.1 Conventional monetary policy shocks

Let us start by discussing the effects of a conventional monetary policy shock, normalised to induce a 100 bps tightening of the 1-month OIS (Figure 9). The informationally robust IV, obtained from correction in the non-linear regression setting, delivers impulse response functions to a monetary tightening with significant contractionary effects (blue IRFs). IPC and real GDP contract, with real GDP reaching a trough of about 2% after 12 months, and industrial production contracts by roughly 4% over the same horizon. The different measure of prices indicates deflationary pressure, with HICP contracting by 1% over 24 months. The stock market contracts by 17%, while the euro appreciates against the dollar, and the short-to-medium term segment of the OIS yield curve is lifted for roughly 6 months.³¹

³¹The variables present significant responses for the 68% coverage bands (not shown), with several also significant for the 90% coverage bands, shown in Figure 9.

Figure 10: CONVENTIONAL MONETARY POLICY SHOCK – COMPARISON ACROSS METHODS



Notes: The chart reports the IRFs to a conventional monetary policy shock, normalised to induce a 100 basis points increase in the 1m-OIS rate. The blue IRFs are the baseline median responses to a shock identified with the target factor (F1) corrected for non-linear information effects. The green IRFs are the responses to a shock identified with target factor (F1) with a linear information correction. The orange IRFs are the median responses to a shock identified with a target factor obtained by only considering the market surprises on the OIS curve, and not employing other assets. The yellow IRFs are the median responses to a shock identified with a target factor identified only on the OIS market surprises of press release window, without excluding any date. The purple IRFs are the median responses to a shock identified with a target factor obtained from the OIS market surprises of press release window, but excluding the surprises associated with the ECB meetings of 8 October 2008 and 6 November 2008 (as in Altavilla et al., 2019). In light blue, we report the responses of the target factor identified by Altavilla et al. (2019), obtained on from the press release window, by excluding the surprises associated to the ECB meetings of 8 October 2008 and 6 November 2008, demeaning, but not standardising, the market surprises. The grey shaded areas are 90% coverage bands of the baseline specification. The sample considered is 2002-2019.

This picture contrasts with the one obtained when using the factor extracted without taking into account information effects (amber IRFs). In that case, we find strong output and prices puzzles, as well as a strong positive response of the stock market – a clear illustration of the strength of the information effects in the original monetary policy surprises.

To gauge the importance of the non-linear information effects, against other choices in the construction of the instrument, we report a detailed comparison of different approaches in Figure 10. In particular we compare IRFs for the following IVs:

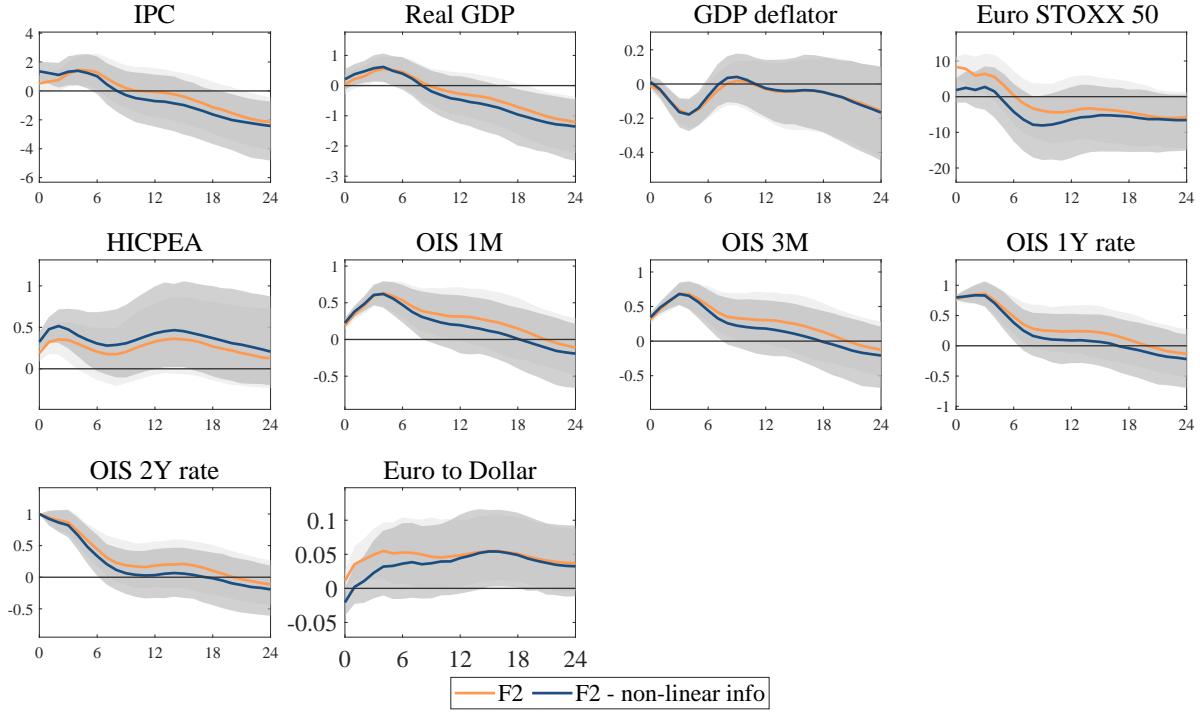
- the target factor corrected for non-linear information effects (blue), our baseline specification;
- the target factor corrected for linear information effects (green);
- the target factor obtained by only considering OIS market surprises, and excluding other assets (orange);
- the target factor identified using only OIS market surprises from the press release window, without excluding any date (yellow);
- the target factor obtained by using OIS market surprises of the press release window, but excluding the surprises associated with the ECB meetings of 8 October 2008 and 6 November 2008 (purple);
- the target factor constructed from demeaned OIS surprises in the press release window, as in [Altavilla et al. \(2019\)](#), and excluding the ECB meetings of 8 October 2008 and 6 November 2008 (light blue).

The results show that while the various approaches to build the target factor – as for example excluding some dates – marginally reduce the extent of the puzzles, they do not change the overall picture, differently from the IVs corrected for non-linear information effects. It is worth observing that the charts provide a visual validation of the predictions of the model presented in Section 2.

5.2 Forward guidance

The informationally robust forward guidance factor offers result that are overall in line with economic theory and with the effects reported for conventional monetary policy (Figure 11). The non-linear information correction mitigates most of the puzzles in the raw F2 factor, with the notable exception of HICP inflation.

Figure 11: FORWARD GUIDANCE POLICY SHOCK

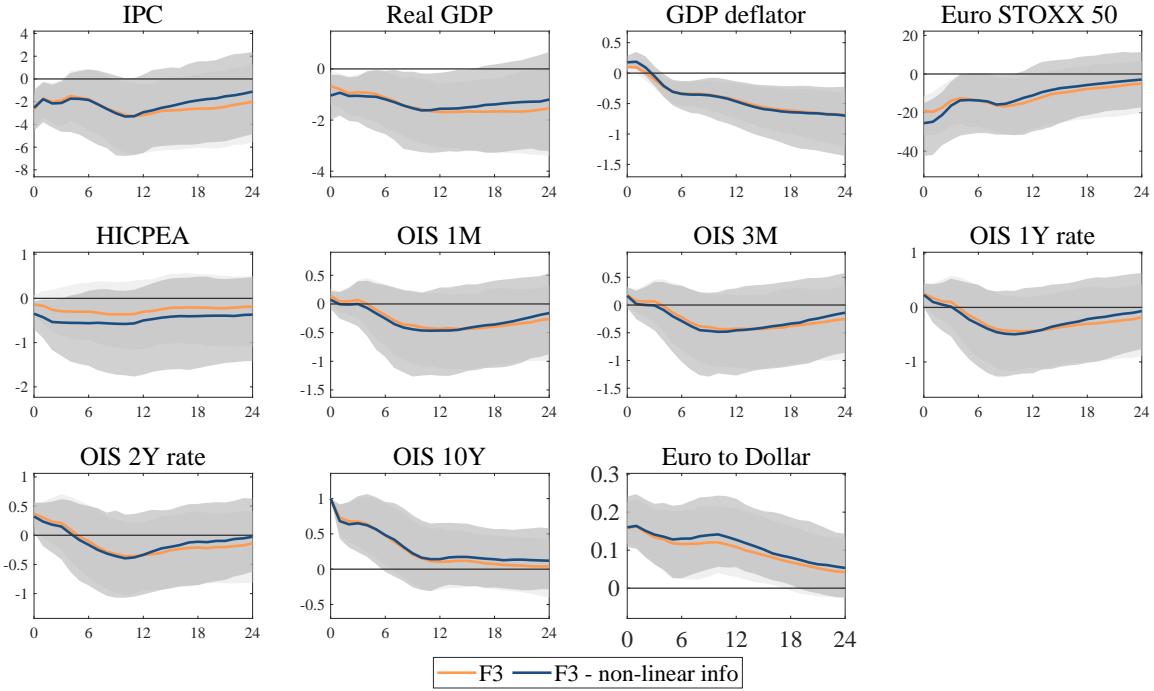


Notes: The figure reports the IRFs to a forward guidance shock, normalised to induce a 100 basis points tightening in the 2y-OIS rate. In amber, we report the responses to a shock identified with the forward guidance factor (F2), without any correction for information effects. In blue, we report the responses to a shock identified with the informationally robust F2 factor, obtained correcting for non-linear information effects. The grey shaded areas are 90% coverage bands. The sample considered is 2002-2019.

A positive forward guidance shock lifts the short-medium segment of the yield curve for about 12 months, with the 1-month OIS rate peaking at the 4-months horizon. Industrial production and real GDP decline over a 2 year horizon, as does the stock market, while the euro appreciates against the US dollar. While the GDP deflator indicates deflationary pressure, HICP displays a puzzling response.

While overall, the responses are of the expected signs, the puzzling response of inflation may be due to either measurement issues in HICP or residual information effects that cannot be fully address given the limited coverage of the available ECB forecasts. We explore potential measurement issues of the euro area measures of inflation in Section B of the Online Appendix.

Figure 12: QUANTITATIVE EASING/TIGHTENING POLICY SHOCK



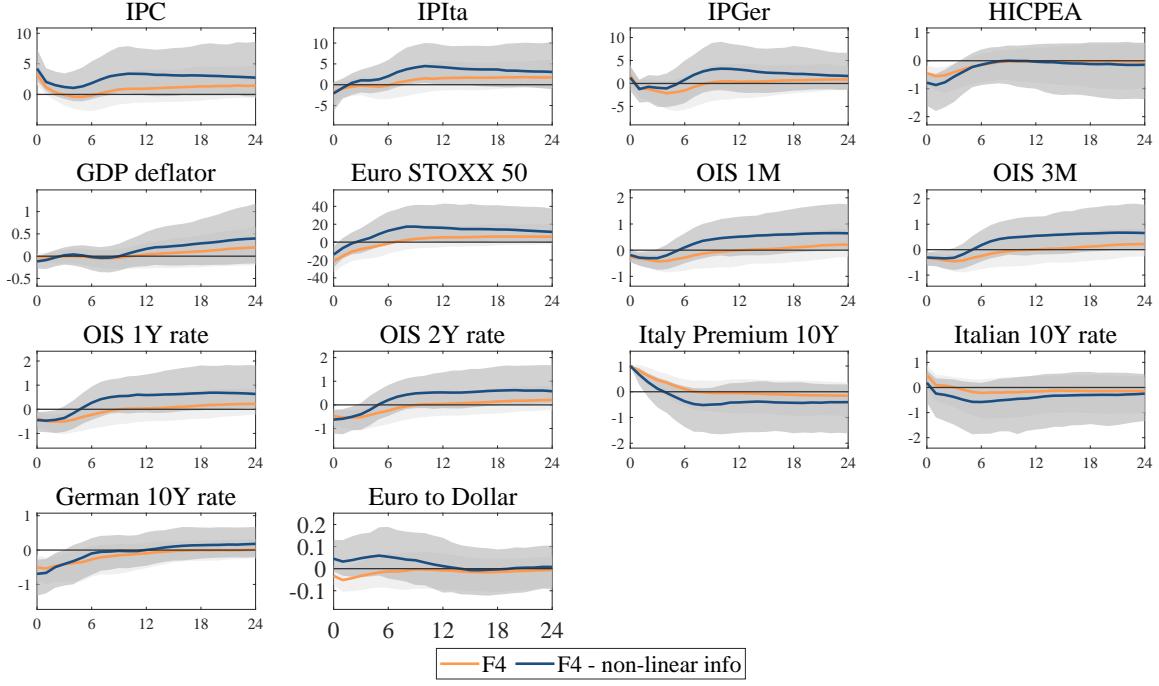
Notes: The figure reports the IRFs to a quantitative tightening shock, normalised to induce a 100 basis points tightening in the 10y-OIS rate. In amber, we report the responses to a shock identified with the QE/QT factor (F3), without any correction for information effects. In blue, we report the responses to a shock identified with the informationally robust QE/QT factor, obtained correcting for non-linear information effects. The grey shaded areas are 90% coverage bands. The sample considered is 2002-2019.

5.3 Quantitative easing/tightening

A quantitative tightening has powerful contractionary effects, with results significant at 90% confidence bands (Figure 12). The shock lifts the long end of the OIS curve, normalised to a 100 basis points increases at the 10-year maturity, while depressing the short end of the curve over the medium run, thereby inducing a steepening of the yield curve. The decline in the short-term OIS likely reflects the weakening of the economy following the monetary tightening.

Output and prices contracts, as well as the stock market, while the euro appreciates against the dollar. GDP contracts sharply with a trough of 2% after about one year, while industrial production contracts by around 3% at its trough. The response of the stock market is significantly negative for the whole period, with the largest decrease of about 20% on

Figure 13: ASYMMETRIC COUNTRY RISK SHOCK



Notes: The figure reports the IRFs to an asymmetric country risk shock, normalised to induce a 100 basis points increase in the spread between the 10y Italian government bond yield and the 10y German government bond yield (Italy Premium 10y in the figure). In amber, we report the responses to a shock identified with the asymmetric country risk factor (F4), without any correction for information effects. In blue, we report the responses to a shock identified with the informationally robust asymmetric country risk factor, obtained correcting for non-linear information effects. The grey shaded areas are 90% coverage bands. The sample considered is 2002-2019.

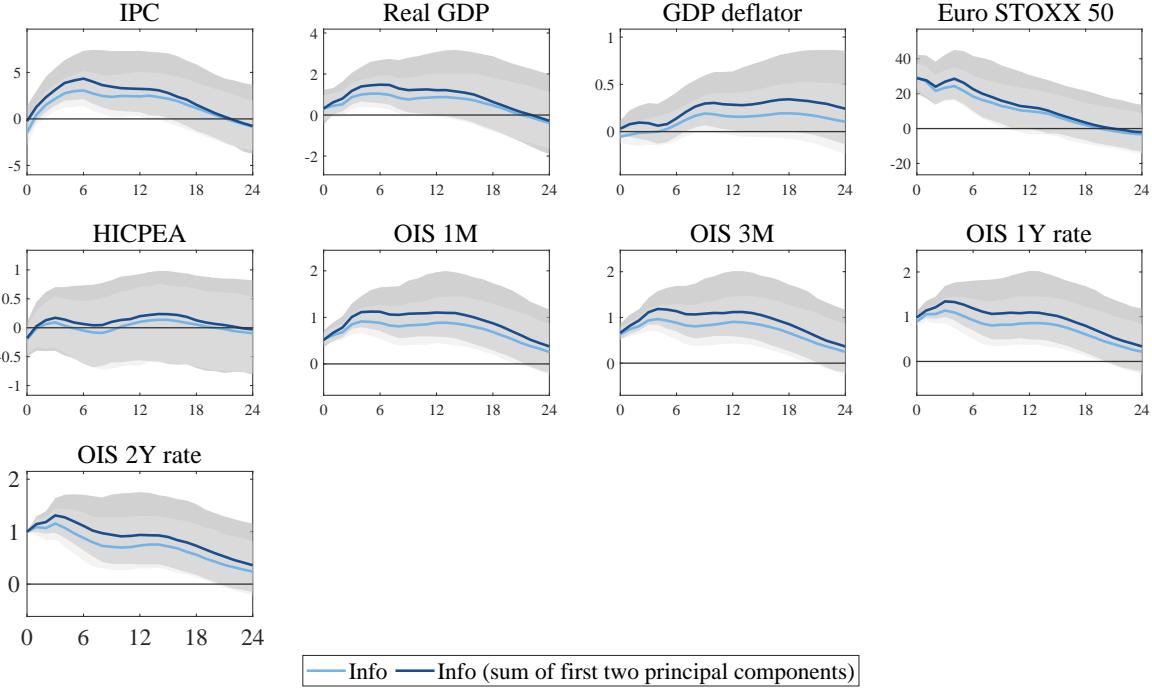
impact. There is little difference between the IRFs obtained from the informationally robust and the original instrument.

5.4 Asymmetric country risk shock

An asymmetric country risk shock (Figure 13), triggered by ECB communication, brings about an increase in the spread between 10-year Italian and 10-year German bonds (Italy Premium 10Y), which we interpret as an increase in sovereign risk for southern-European countries with the associated flight to safety towards the core countries of the union. The OIS curve remains relatively flat.

Following the shock, industrial production contracts for Italy, while it expands for Germany

Figure 14: INFORMATION IN MONETARY POLICY



Notes: The figure reports the IRFs to an ‘information surprise’, normalised to induce a 100 basis points increase in the 2y-OIS rate. In light blue, we report the responses to a shock identified with an information factor defined as the first principal component of the fitted values of the non-linear information effects regressions. In blue, we report the responses to a shock identified with an information factor defined as the sum of the first two principal components of the fitted values of the non-linear information effects regressions. The grey shaded areas are 90% coverage bands. The sample considered is 2002-2019.

and for the euro area economy. The stock market contracts on impact, with a 10% reduction to its value, before recovering rapidly. Headline inflation contracts, with a significant impact response of around -0.8% . The differences between the IRFs obtained from the informationally robust and the original instrument are minor.

5.5 Information propagation

We conclude the presentation of the macroeconomic transmission of the shocks extracted from the ECB communication, by looking at the information component (Figure 14). It is important to stress, once again, that this component cannot be interpreted as an ‘information’ structural shock delivered by the central bank. The correct interpretation of this component, in line with the model in Section 2, is as an ‘information surprise’ bundling different structural

shocks to which the ECB responds via its systematic reaction function. The presence of imperfect information delivers contamination of the market surprises by these shocks. While the policy decision and communication inform the market participants the central bank's assessment of economic conditions, they cannot be seen as 'delivering' the shocks but only as being part of their transmission through the economy. Hence, the IRFs in Figure 14 should be seen to be informative of the reaction function of the ECB, and not as structural response functions to a given shock. This observation is also important when looking at the variance decomposition for this component for which a correct identification of a given shock it is not possible.

The IRFs to the information component are normalised to induce a 100 basis points increase in the 2y-OIS rate. They are obtained using either (i) the first, or (ii) the sum of the first and the second principal components of the fitted values of the non-linear information effects regressions. The pattern of responses indicates that the ECB primarily reacts to a bundle of business cycle shocks with aggregate effects similar to those of demand shocks. Industrial production and real GDP expands, as well as prices. The stock market value increases, while the short-medium term maturities of the OIS curve all respond positively with a hump-shaped response.

5.6 How powerful are monetary shocks?

An important question is how powerful the effects of monetary policy shocks are at business cycle frequency. Several interesting findings emerge from the variance decomposition analysis reported in Table 6.³² First, conventional monetary policy shocks explain around 7% of the variance in real activity and around 3% for prices at business cycle frequencies, consistent with results reported for the U.S. on a similar sample (see, for example, Forni et al., 2022). Second, forward guidance and QE shocks account for approximately 10% and 6% of the variance in GDP, and 7% and 4% of the variance in headline inflation, respectively. Third,

³²Section J, in the Online Appendix reports the contributions of the different identified shocks to the variances of the variables of interests, at shorter and longer periods.

Table 6: VARIANCE DECOMPOSITION AT BUSINESS CYCLE FREQUENCIES

<i>Variables</i>	<i>Target</i>	<i>Forward Guidance</i>	<i>QE</i>	<i>Asymmetric Country Risk</i>	<i>Information</i>
IP	4.80 (1.36, 8.75)	9.06 (4.05, 14.05)	4.48 (1.39, 8.97)	7.57 (2.59, 14.17)	18.18 (10.16, 27.65)
Real GDP	7.64 (3.10, 13.08)	10.41 (4.72, 16.44)	6.52 (2.32, 12.74)	— —	12.06 (6.38, 20.90)
Stock Market	3.11 (0.94, 6.82)	6.20 (1.82, 13.66)	6.52 (2.87, 11.54)	9.76 (4.01, 16.38)	29.36 (18.11, 42.76)
HICP	2.87 (0.75, 6.92)	7.38 (2.11, 16.83)	3.75 (1.00, 9.01)	2.57 (0.97, 6.16)	4.33 (1.01, 11.66)
1m-OIS	3.92 (1.76, 6.78)	10.78 (5.49, 16.83)	2.87 (0.81, 7.14)	6.55 (2.04, 12.73)	41.77 (26.38, 54.54)
1y-OIS	3.45 (1.50, 6.17)	13.26 (7.31, 18.86)	2.77 (0.70, 6.18)	7.77 (2.78, 13.76)	41.65 (26.16, 54.88)
2y-OIS	3.21 (1.39, 5.94)	14.52 (8.33, 20.69)	2.51 (0.67, 5.73)	8.47 (3.25, 14.09)	41.82 (26.53, 55.37)
10y-OIS	— —	— (2.69, 12.86)	6.65 —	— —	— —
Spread 10Y	— —	— —	— —	3.61 (1.14, 8.32)	— —
IP Italy	— —	— —	— —	7.60 (2.77, 13.62)	— —
IP Germany	— —	— —	— —	3.89 (1.02, 8.42)	— —

Notes: The table reports the percentage share of the variance of each variable attributable to each monetary policy shock, in the range of business cycle frequencies (i.e. 24 and 96 months), following the approach of Forni et al. (2022). 68% confidence bands are reported in parentheses.

QE shocks have a modest impact on the stock market, explaining around 6% of its variance, with forward guidance explaining an additional 6%.

Notably, information disturbances explain a significant portion of the variance across the variables considered. It is important to stress that the information component should not be interpreted as a structural shock, as it captures a combination of contemporaneous (and potentially lagged) macro shocks to which central banks respond. Thus, interpreting the variance decomposition results is less straightforward. However, the findings indicate that the ECB responds to the primary sources of business cycle fluctuations, consistent with its mandate for macroeconomic stabilisation. Furthermore, the pervasiveness of the information component explains the observed extent of the puzzles in the IRFs derived from policy factors,

despite the limited R^2 of some of the information regression reported in Section 4.³³

6 Robustness of the results

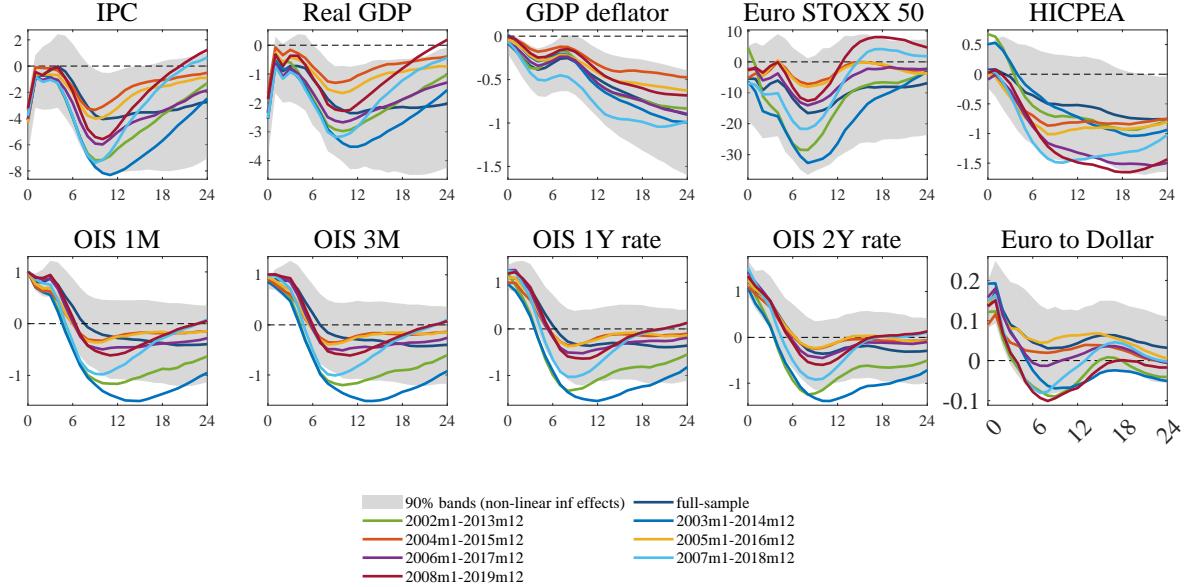
We conclude our empirical analysis by providing some robustness exercises, by considering a subsample analysis, and the sensitivity of our results to the methodology used in the information regressions. In this section, we focus on conventional monetary policy shocks, while Section H in the Online Appendix provides additional charts and results relating to the other shocks identified in this paper.

6.1 Subsample analysis

Figure 15 plots the median and confidence bands of the IRF for the benchmark sample (2002-2019, blue), together with the median responses for a set of rolling subsamples starting in a different year of the sample, and each spanning ten years of data. The chart shows the high degree of robustness of the benchmark results, and almost all the IRFs for each subsample are within 90% coverage bands of the baseline model. The textbook effects of contractionary monetary policy in the euro area are confirmed in each subsample.³⁴

Figure 16 presents a similar exercise for the information-robust QE/QT factor, showing the effects of the shock in a VAR estimated over expanding samples starting from 2008 – when the ECB began deploying several unconventional monetary policy instruments – and extended by one year in every new specification. The results reported in the baseline specification are confirmed across the different samples.

Figure 15: CONVENTIONAL MONETARY POLICY – ROLLING SAMPLES



Notes: The figure reports the IRFs to a conventional monetary policy shock for the full sample along with a set of rolling subsamples. The shock is identified with the informationally robust target factor, corrected for non-linear information effects, and normalised to induce a 100 basis points increase in the 1m-OIS rate. The grey shaded areas are 90% coverage bands of the baseline specification.

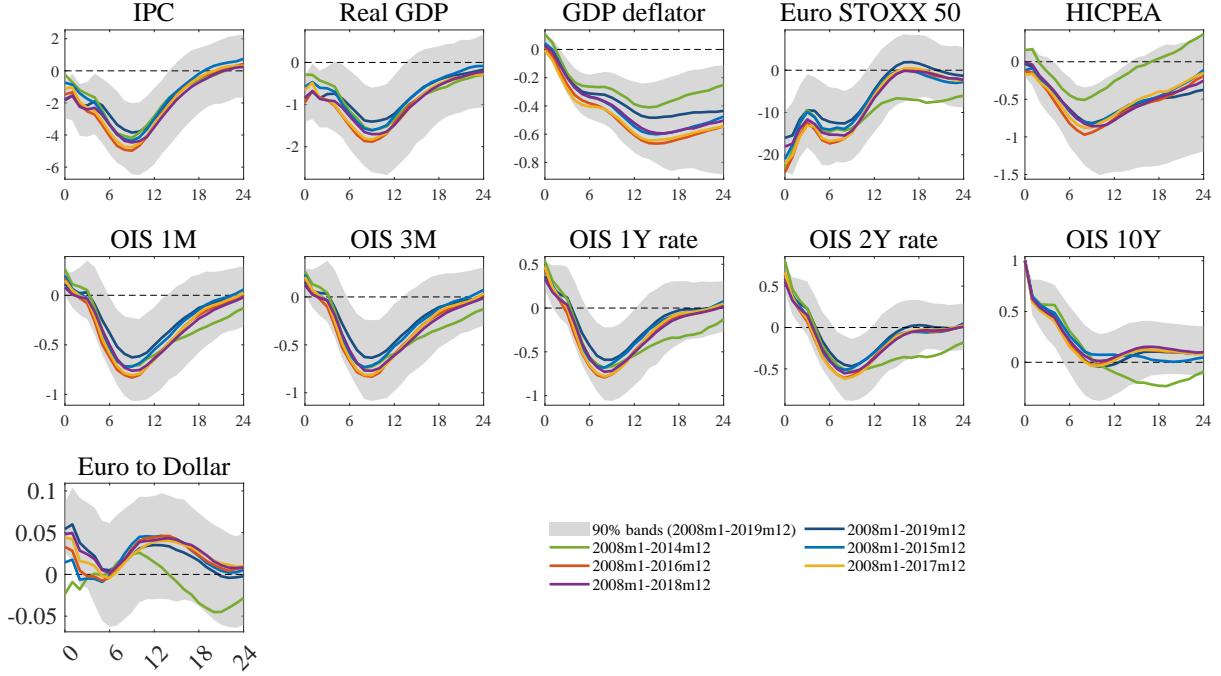
6.2 Information regression specification

Are the results sensitive to the non-linear regression specification adopted, or the set of regressors? To a large extent, they are not. Figure 17 reports the IRFs to a conventional monetary policy shock identified with three variants of the information robust target factor with the non-linear information correction in (i) the baseline OLS specification (blue), (ii) a Ridge regression approach (green), and a (iii) a Lasso regression (light blue). All three specifications adopt the same set of regressors. The resulting IRFs are qualitatively similar across the specifications. Expanding the set of regressors changes, to some extent, the share

³³As shown by [Miranda-Agrippino and Ricco \(2023\)](#), the bias due to contamination of the instrument depends both on the extent to which the share of variance of the IV due to non-policy shocks, and on the variance of the variables of interest that these shocks explain.

³⁴Section I in the Online Appendix reports similar results for the target and timing factors of [Altavilla et al. \(2019\)](#).

Figure 16: QUANTITATIVE EASING/TIGHTENING – EXPANDING SAMPLES



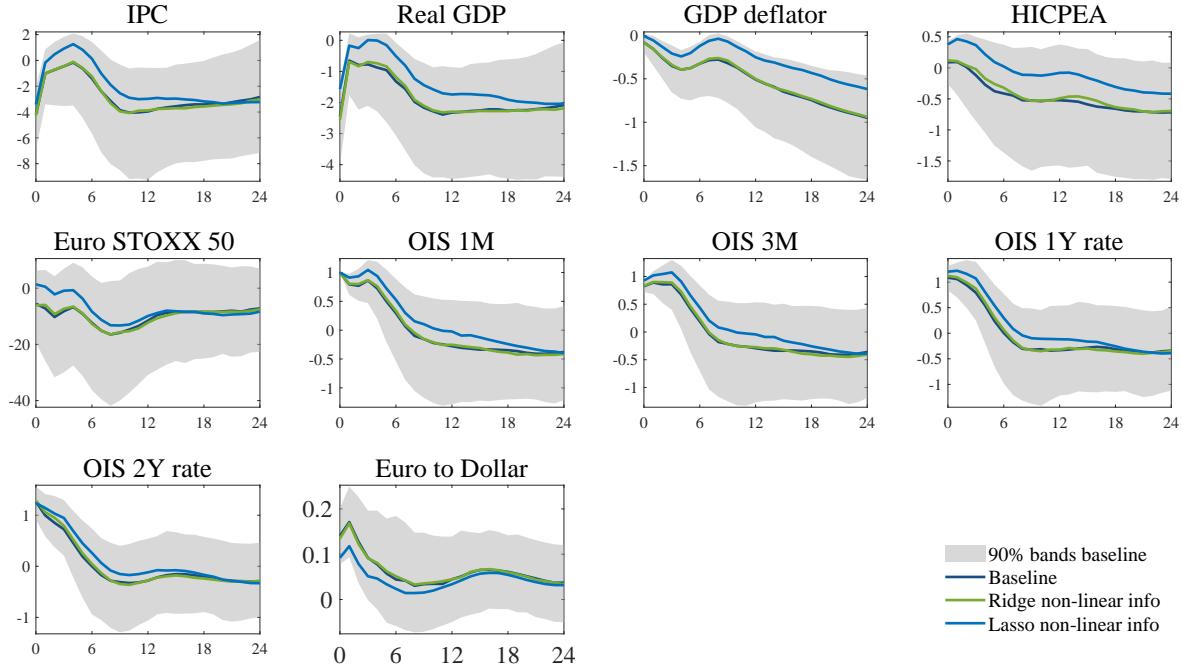
Notes: The figure reports the IRFs to a quantitative tightening shock for a set of subsamples beginning from 2008. The shock is identified with the informationally robust QE/QT factor, corrected for non-linear information effects, and normalised to induce a 100 basis points increase in the 10y-OIS rate. The grey shaded areas are 90% coverage bands of the baseline specification.

of the surprises at longer maturities that is explained by information effects, but leaves macroeconomic results unchanged (see Section G, in the Online Appendix).

6.3 Pandemic period and extended sample

Our baseline analysis consider a pre-COVID-19 pandemic sample, which terminates in 2019, to avoid ad hoc adjustments (see [Lenza and Primiceri, 2022](#)). Figure 18 assesses robustness to including both the pandemic recession and a longer post-pandemic period. Specifically, it compares the baseline estimates (2002m1–2019m12, blue) with results obtained from three alternative samples: an extended sample up to 2024m12 (2001m1–2024m12, light blue), an extended sample that includes the pandemic but ends before the subsequent tightening cycle (2001m1–2021m12, green), and an extended sample that excludes the early part of the

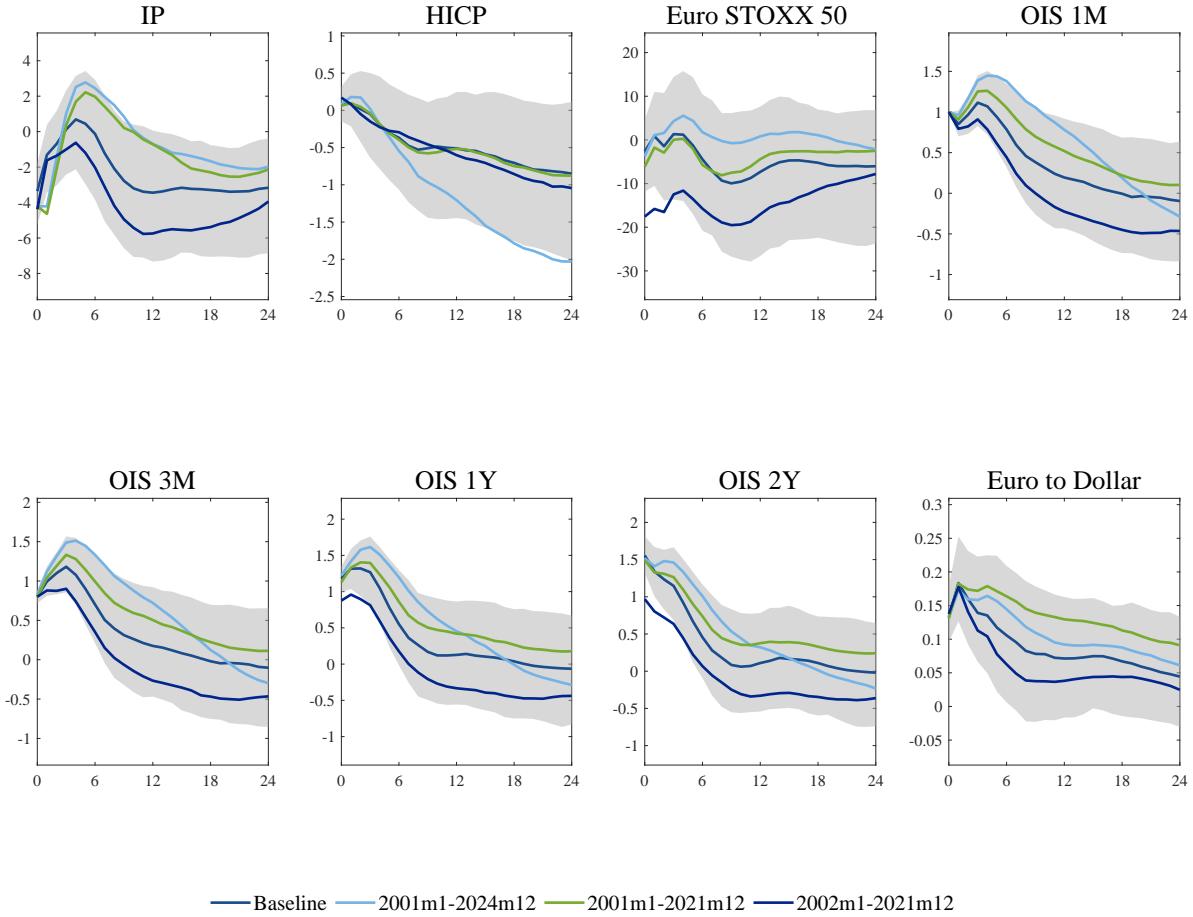
Figure 17: CONVENTIONAL MONETARY POLICY – INFO CORRECTIONS



Notes: The figure reports the IRFs to a conventional monetary policy shock, normalised to induce a 100 basis points increase of the 1m-OIS rate. The shock is identified with three informationally robust target factors, corrected for nonlinear information effects adopting different regression models and the same set of regressors: baseline OLS specification (blue), Ridge regression (green), Lasso (light blue). The grey shaded areas are 90% coverage bands of the baseline specification. The sample considered is 2002-2019.

euro-area sample (2002m1–2021m12, dark blue). Across specifications, the impulse responses remain largely within the baseline 90% coverage bands.

Figure 18: CONVENTIONAL MONETARY POLICY – DIFFERENT SAMPLES



Notes: The figure reports impulse responses to a conventional monetary policy shock, normalised to induce a 100 basis points increase in the 1m-OIS rate. The shock is identified using informationally robust target factors corrected for nonlinear information effects. Responses are shown for the baseline sample 2002m1–2019m12 (baseline, blue) and for alternative samples 2001m1–2024m12 (light blue), 2001m1–2021m12 (green), and 2002m1–2021m12 (dark blue). The grey shaded areas are 90% coverage bands of the baseline specification.

7 Conclusions

Information frictions play a significant role in the transmission of policy shocks, and consequently in the methods that have to be used to identify their effects. The findings reported in this paper align with the predictions of imperfect information models: during periods of elevated market stress, agents increasingly rely more heavily on central bank policy signals to track and forecast economic developments.

In the euro area, these non-linear information effects appear to contribute to the pronounced puzzles in the dynamic responses to policy shocks identified through high-frequency interest rate changes triggered by policy announcements. By accounting for these non-linear information effects, it is possible to identify the effects of both conventional and unconventional policy shocks, as well as to understand the transmission of information disturbances – i.e. the bundle of shocks to which the central bank responds. Our results demonstrate that the ECB’s multidimensional policy toolkit has powerful effects on the European economy, with policy tightenings producing contractionary effects on real economic activity, prices, and financial markets.

References

- Alessi, L., M. Barigozzi, and M. Capasso (2010). Improved penalization for determining the number of factors in approximate factor models. *Statistics & Probability Letters* 80(23-24), 1806–1813.
- Altavilla, C., L. Brugnolini, R. S. Gürkaynak, R. Motto, and G. Ragusa (2019). Measuring euro area monetary policy. *Journal of Monetary Economics* 108, 162–179.
- Altavilla, C., R. S. Gürkaynak, L. Laeven, and T. Kind (2025). Monetary transmission with frequent policy events.
- Badinger, H. and S. Schiman (2023). Measuring monetary policy in the euro area using svars with residual restrictions. *American Economic Journal: Macroeconomics* 15(2), 279–305.
- Bauer, M. D. and E. T. Swanson (2023). An Alternative Explanation for the “Fed Information Effect”. *American Economic Review* 113(3), 664–700.
- Beber, A., M. W. Brandt, and K. A. Kavajecz (2008). Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *The Review of Financial Studies* 22(3), 925–957.

Bocola, L. and A. Dovis (2019). Self-fulfilling debt crises: A quantitative analysis. *American Economic Review* 109(12), 4343–77.

Campbell, J. R., C. L. Evans, J. D. Fisher, A. Justiniano, C. W. Calomiris, and M. Woodford (2012). Macroeconomic effects of federal reserve forward guidance [with comments and discussion]. *Brookings papers on economic activity*, 1–80.

Cieslak, A. and H. Pang (2020, May). Common shocks in stocks and bonds. CEPR Discussion Papers 14708, C.E.P.R. Discussion Papers.

Cieslak, A. and A. Schrimpf (2019). Non-monetary news in central bank communication. *Journal of International Economics* 118(C), 293–315.

Coibion, O. and Y. Gorodnichenko (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy* 120(1), 116 – 159.

Coibion, O. and Y. Gorodnichenko (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review* 105(8), 2644–78.

Corsetti, G. and L. Dedola (2016). The Mystery of the Printing Press: Monetary Policy and Self-Fulfilling Debt Crises. *Journal of the European Economic Association* 14(6), 1329–1371.

Costantini, M. and R. M. Sousa (2022). What uncertainty does to euro area sovereign bond markets: Flight to safety and flight to quality. *Journal of International Money and Finance* 122, 102574.

Cragg, J. G. and S. G. Donald (1997). Inferring the rank of a matrix. *Journal of Econometrics* 76(1), 223–250.

Fornaro, L. and C. Grosse-Steffen (2025). Fragmented monetary unions.

Forni, M., L. Gambetti, and G. Ricco (2022). External instrument svar analysis for noninvertible shocks.

- Gertler, M. and P. Karadi (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics* 7(1), 44–76.
- Giannone, D., M. Lenza, and G. E. Primiceri (2015). Prior selection for vector autoregressions. *The Review of Economics and Statistics* 97(2), 436–451.
- Gürkaynak, R. S., A. H. Kara, B. Kısacıkoglu, and S. S. Lee (2021). Monetary policy surprises and exchange rate behavior. *Journal of International Economics* 130, 103443. NBER International Seminar on Macroeconomics 2020.
- Gürkaynak, R. S., B. Sack, and E. Swanson (2005). Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking* 1(1).
- Hastie, T., R. Tibshirani, J. H. Friedman, and J. H. Friedman (2009). *The elements of statistical learning: data mining, inference, and prediction*, Volume 2. Springer.
- Jarociński, M. and P. Karadi (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics* 12(2), 1–43.
- Jouvanceau, V. and I. Mikaliunaite-Jouvanceau (2023). ECB monetary communications: Market fragmentation at stake. *Economics Letters* 225(C).
- Kerssenfischer, M. (2022). Information effects of euro area monetary policy. *Economics Letters* 216, 110570.
- Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics* 47(3), 523–544.
- Lenza, M. and G. E. Primiceri (2022). How to estimate a vector autoregression after march 2020. *Journal of Applied Econometrics* 37(4), 688–699.
- Leombroni, M., A. Vedolin, G. Venter, and P. Whelan (2021). Central bank communication and the yield curve. *Journal of Financial Economics* 141(3), 860–880.

- Lorenzoni, G. and I. Werning (2019). Slow moving debt crises. *American Economic Review* 109(9), 3229–63.
- Melosi, L. (2017). Signalling effects of monetary policy. *The Review of Economic Studies* 84(2), 853–884.
- Mertens, K. and M. O. Ravn (2013). The dynamic effects of personal and corporate income tax changes in the united states. *American Economic Review* 103(4), 1212–47.
- Miranda-Agrippino, S. and G. Ricco (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics* 13(3), 74–107.
- Miranda-Agrippino, S. and G. Ricco (2023). Identification with external instruments in structural vars. *Journal of Monetary Economics* 135, 1–19.
- Motto, R. and K. Özen (2022). Market-stabilization QE. Working Paper Series 2640, European Central Bank.
- Nakamura, E. and J. Steinsson (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics* 133(3), 1283–1330.
- Pirozhkova, E., G. Ricco, and N. Viegi (2024). Trouble Every Day: Monetary Policy in an Open Emerging Economy. CEPR Discussion Papers 19094, C.E.P.R. Discussion Papers.
- Ramey, V. (2016). Chapter 2 - Macroeconomic Shocks and Their Propagation. Volume 2 of *Handbook of Macroeconomics*, pp. 71–162. Elsevier.
- Reichlin, L., G. Ricco, and A. Tuteja (2022). The two-dimensional feature of ecb monetary policy. <https://cepr.org/voxeu/columns/two-dimensional-feature/ecb-monetary-policy>.

Rostagno, M., C. Altavilla, G. Carboni, W. Lemke, R. Motto, A. Saint Guilhem, and J. Yiaygou (2021). *Monetary Policy in Times of Crisis. A Tale of Two Decades of the European Central Bank*. Oxford University Press.

Stock, J. H. and M. Watson (2012). Disentangling the channels of the 2007-09 recession. *Brookings Papers on Economic Activity* 43(1 (Spring)), 81–156.

Stock, J. H. and M. W. Watson (2010). Monthly gdp and gni–research memorandum. *Manuscript, Princeton University*.

Stock, J. H. and M. W. Watson (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal* 128(610), 917–948.

Swanson, E. T. (2020). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*.

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics* 118, 32–53.

Wright, J. H. (2019). Comment on ‘measuring euro area monetary policy’ by carlo altavilla, luca brugnolini, refet gürkaynak, giuseppe ragusa and roberto motto. *Journal of Monetary Economics* 108, 180–184. ‘Central Bank Communications: From Mystery to Transparency’, May 23-24, 2019, Annual Research Conference of the National Bank of Ukraine organized in cooperation with Narodowy Bank Polski.