Disentangling the effects of multidimensional monetary policy on inflation and inflation expectations in the euro area*

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Job Market Paper

This version: November 26, 2020
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Abstract

The European Central Bank (ECB) has adopted a mixture of conventional and unconventional tools in order to achieve its mandate of price stability in a low-inflation, low-interest-rate environment. This paper contributes to the existing literature by providing a taxonomy of the ECB's policy toolkit and by evaluating its implications on price stability and the anchoring of inflation expectations. Developing a novel high-frequency identification scheme for a large Bayesian Vector Autoregression, I find evidence that forecasters revise their long-term expectations upwards in response to quantitative easing and forward guidance shocks. Consequently, inflation increases and remains significant for over a year after the shock, which stresses the crucial role of expectations for the transmission of monetary policy.

Keywords: Inflation Expectations, Monetary Policy, Large BVAR, High-frequency identification

JEL classification: E52, C55, C11, C32, E31

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*This paper is part of the DFG project "The Anchoring of Inflation Expectations" at Freie Universität Berlin. I am grateful to Helmut Lütkepohl and Lars Winkelmann for great supervision and support. I thank Robin Braun, Flora Budianto, Matteo Ciccarelli, Max Diegel, Stefan Gebauer, Marc Giannoni, Enrique Martínez-García, Karel Mertens, Dieter Nautz, as well as the participants of the Tornow Seminar on Topics in Time Series Econometrics from Freie Universität Berlin, the 2019 Vienna Workshop on High-Dimensional Time Series in Macroeconomics and Finance and the brownbag seminars at the Federal Reserve Bank of Dallas for their comments and suggestions.

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1 Introduction

Under its mandate of price stability, the European Central Bank (ECB) conducts monetary policy with the goal of stabilising inflation to levels “below, but close to 2% over the medium term” in the euro area. For most of the 2010s, inflation and inflation expectations have remained low, on average lower than the ECB’s target.[1] Furthermore, there has been an era of low interest rates which, in turn, has limited the ECB’s space for steering short-term interest rates, its main policy tool. In order to provide an ample degree of accommodation, the ECB introduced several non-conventional tools. Although the rationale to deploy these tools may differ, they all share the ultimate goal to achieve price stability and to anchor inflation expectations to the ECB’s target.

In this paper, I study the effects of the ECB’s conventional, unconventional, and communication tools on inflation and inflation expectations of consumers and forecasters. In particular, this paper contributes to the existing literature by providing a taxonomy of the ECB’s policy toolkit and by comparing the individual effectiveness of the tools to influence inflation and inflation expectations. To do so, I carry out my analysis based on a two-step approach that combines a high-frequency identification strategy and the estimation of a large Bayesian Vector Autoregression (VAR).

I propose a novel high-frequency identification approach that considers three dimensions of monetary policy announcements - target, path, and the balance sheet. Specifically, I identify shocks related to the interest rate target, information, forward guidance, policies to ease lending conditions, and quantitative easing (QE).[2] My identification approach takes into consideration the 2016 changes in how the ECB communicates unconventional monetary policy. From this year onwards, decisions regarding both conventional and unconventional monetary policy are announced in a press release and further explained in a press conference. For this reason, I consider a wide range of surprises of asset and bond prices around a time window considering both events. I model the surprises through a factor model that fulfils a set of economic restrictions. In this way, I interpret the estimated factors as a measure of the underlying monetary policy shocks. My identification strategy hinges on the implementation of restrictions regarding short-term maturities of the Overnight Indexed Swap (OIS) term structure. Moreover, I integrate the characteristic that information shocks move interest rates and the stock market in the same direction. Conversely, these variables have a negative correlation

[1] See the graphs in appendix A.
[2] An economic explanation of these shocks is provided in section 3.

in the case of forward guidance.

In a second step, I consider a monthly data set containing twenty macroeconomic and financial variables, which allows me to have a comprehensive representation of the dynamics in the euro area economy. Furthermore, I integrate the estimated factors into the data set and estimate a large Bayesian VAR based on the methodology proposed by Giannone, Lenza, and Primiceri (2015). In this way, I further analyse the responses of inflation and inflation expectations to the five different types of monetary policy shocks.

My findings suggest that the long-term inflation expectations of forecasters anchor when expansionary forward guidance and QE shocks hit the economy. Furthermore, in response to stabilised inflation expectations, inflation increases and remains significant one year after a forward guidance shock. Nevertheless, for the case of QE, the response of inflation remains muted. My results stress the importance of the expectations channel of monetary policy transmission as the inflation response is considerably lower once long-term inflation expectations are excluded from the model.

Additionally, I find evidence of the ECB's information effect because, after an information shock that decreases interest rates and inflation, consumers and forecasters revise their inflation expectations downwards. Moreover, my results shed light on the finding in the literature that different types of agents in the economy do not interpret monetary policy announcements in the same way. I find that consumers and forecasters contemporaneously revise their short-term expectations in opposite ways when, responding to shocks related to QE and policies to ease lending conditions. Specifically, consumers' expectations decrease, which may suggest that they do not acquire all information regarding these policies or simply because they put more weight to other type of news. On the other hand, forecasters revise their expectations upwards. Overall, my results highlight the power of influencing inflation expectations for the transmission of monetary policy, bringing more evidence to the literature suggesting the use of policy tools for steering inflation expectations towards the ECB's target (see Coibion et al. (2020) and Candia, Coibion, and Gorodnichenko (2020)).

This paper proceeds as the follows. Section 2 reviews the exiting literature and highlights my contributions. In section 3, I present my identification strategy, while I explain the internal instrument approach and the estimation of a large Bayesian VAR in section 4. Section 5 provides an overview of the data, the main results of the paper, and its policy implications. Finally, section 6 concludes.

2 Related Literature

The influential analyses of Cook and Hahn (1989) and Kuttner (2001) have triggered a rising literature on the estimation of monetary policy shocks based on high-frequency data sets (e.g. Cochrane and Piazzesi (2002), Gürkaynak, Sack, and Swanson (2005), Swanson (2017), Nakamura and Steinsson (2018), Rogers, Scotti, and Wright (2018), Corsetti, Duarte, and Mann (2018), Hachula, Piffer, and Rieth (2019), Altavilla et al. (2019), among many others). This is due to the availability of asset prices at intra-daily and daily frequencies, whereby it is possible to exploit the rich information contained in futures and swap rates for identifying monetary policy shocks. In this paper, I compute a new set of monetary policy proxies (target, information, forward guidance, policies to ease lending conditions and QE) for the euro area inspired by the trilogy of papers: Gürkaynak, Sack, and Swanson (2005), Swanson (2017) and Altavilla et al. (2019).[3]

The first paper of the trilogy identifies US monetary policy shocks based on the surprises of intra-daily quotes of federal fed funds and eurodollar futures in a thirty-minute window around FOMC (Federal Open Market Committee) statements. Based on a rotated factor model, the authors find two significant factors reflecting a target (related to changes in the policy rate) and a path (forward guidance) dimension. They find that long-term yields respond more to the path than to the target factor which stresses the relevance of the central bank's communication strategy. In a follow-up paper, Swanson (2017) identifies a third factor which captures a balance sheet dimension. Particularly, he pins down the effects of QE by assuming it explains the least percentage of explained variance before the period of the Great Recession. He additionally imposes the restriction that the current level of the fed funds rate does not load onto this factor. He obtains that the QE factor has larger effects at the end of the yield curve in comparison to target and path factors. For the case of the euro area, Altavilla et al. (2019) construct the Euro Area Monetary Policy Event-Study Database (EA-MPD) which is a compendium of price changes for a wide range of assets like Overnight Indexed Swaps (OIS), exchange rates, stock market indices and sovereign bond yields. The database is available for three different windows regarding the communication of ECB's monetary policy decisions: The press release, the press conference, and the full monetary policy event window.[4] Based on a data set containing only surprises

[3] A monetary policy proxy is a measure of the underlying, unobservable monetary policy shock.

[4] Monetary policy decisions from the Governing Council meeting are communicated in two phases. First, a press release is published at 13:45 CET containing policy decisions. After-

of the OIS term structure, Altavilla and co-authors find evidence of a target component in the press release window; and timing, forward guidance, and QE components in the press conference window.

My contribution to this part of the literature is the estimation of a new set of factors based on the EA-MPD taking into consideration two important details. Firstly, since 2016 announcements about balance sheet policies and forward guidance are covered in the whole monetary policy event window. Secondly, an official forward guidance strategy was only implemented since 2013, therefore, in contrast to Altavilla and others, my forward guidance factor also includes timing effects. Furthermore, I identify an additional factor that isolates the effects of policies implemented to provide funding and to ease lending conditions in order to avoid a credit crunch in the aftermath of the Sovereign Debt Crisis.[5]

The second pillar of literature where this paper contributes concerns those papers empirically assessing the effects of several types of unconventional monetary policy shocks on key macroeconomic and financial variables.

From the side of shocks related to communication, Campbell et al. (2012) focus on the US economy and distinguish two types of forward guidance: Odyssean and Delphic. The first one is related to statements from a central bank regarding a commitment about certain policy actions such as the future path of interest rates, which in this paper I simply call forward guidance shock. The second concept is associated to the views of the central bank about the current and future state of the economy and throughout this paper I name it information shock. The main findings of Campbell et al. (2012) show that a contractionary information shock rises both interest rates and expectations about inflation and unemployment. Later, Nakamura and Steinsson (2018) find similar results and coined them as the Fed Information Effect. The rationale behind this concept is that the information sets of the Fed and private agents differ. Therefore, when the Fed releases new information to agents, they revise their expectations accordingly.[6] Unfortunately, evidence

wards, from 14:30-15:30 CET, there is a press conference where the ECB's president reads the Introductory Statement explaining the rationale of the decisions taken and communicating the ECB's view on current economic conditions. Afterwards, there is a Q&A session for the press. Consequently, the whole monetary policy event window spans from 13:45-15:30 CET.

[5]The finding of a similar factor is also obtained by Wright (2019). However, he does not implement restrictions in order to interpret it economically and do not assess its effects on the macroeconomy.

[6]In a recent paper, Bauer and Swanson (2020) give an alternative interpretation of these results and name it "Fed response to news" channel. Their reasoning centres on the idea that both the Fed and private sector agents have the same information set. However, there is a gap between the current Fed policy response function and the ex-ante estimation of that function from private-sector agents.

for the euro area remains scarce, some exceptions are the papers by Kerssenfischer (2019) (for high frequency variables), Jarociński and Karadi (2020) and Andrade and Ferroni (2020). They find that an information shock moves medium-term rates and stock market indices in the same direction. Moreover, the last two papers detect that this shock moves spreads in the opposite direction than interest rates. Turning to prices and expectations, Kerssenfischer (2019) and Andrade and Ferroni (2020) obtain evidence that inflation expectations (market-based for the former and forecasters for the latter) also react in the same direction than interest rates. Whereas for prices, only the latter study finds a significant increase in both, the one year interest rate and core prices. Moving to forward guidance shocks, Andrade and Ferroni (2020) find that a contractionary forward guidance shock (Odyssean in their terminology) increases medium-term rates and the spread of non-financial corporations, whereas it decreases stock market indices and output expectations. Furthermore, they find no response of neither prices nor inflation expectations of forecasters.

Concerning the effects of LTROs, Boeckx, Dossche, and Peersman (2017) consider expansionary balance sheet shocks without including the effects of QE. They find evidence of an increase in output and prices and a decrease of the spread between the EONIA and the Main Refinancing Operations rate. They specifically focus on the effects of the LTRO programme introduced in 2012 and estimate an scenario where the one and three year LTROs are not implemented. In both cases, inflation would have remained lower in comparison with the realised figures. Gambetti and Musso (2017) study the effects of QE shocks based on a mixture of sign, timing and magnitude identification restrictions. They obtain that a QE shock that decreases the ten year yield produces an increase in output and prices. Moreover, they find evidence of the “re-anchoring inflation expectations channel” because the response of inflation to a QE shock amplifies when they include long-term inflation expectations in their model. Therefore, this result suggests that inflation expectations are crucial for the transmission of monetary policy to prices.

This paper contributes to the second pillar of literature by teasing out the effectiveness of a conventional monetary policy and four different type of unconventional tools for increasing inflation and inflation expectations. Given the current low-inflation, low-interest-rates environment in the euro area, this isolation is crucial for a simultaneous comparison among policies.

3 High-frequency identification of monetary policy shocks

In this section, I construct a taxonomy of the monetary policy tools used by the ECB in order to achieve its mandate of price stability. In detail, I concentrate my analysis on the estimation of the following monetary policy proxies:[7]

Target. Before the effective lower bound, the main policy tool of the ECB was the change in its official rates (Deposit Facility, Main Refinancing Operations and the Marginal Lending Facility rates). This shock captures the surprises of an unexpected change in the official rates and therefore it corresponds to a conventional monetary policy shock.

Information. This shock represents the markets' response to the communication of the ECB's view on the current and future economic outlook. It is also known as Delphic forward guidance (see Campbell et al. (2012)).

Forward guidance (FG). It captures the markets' reaction to statements referring to the ECB's commitment to particular monetary policy actions, such as the future path of interest rates. In the terminology of Campbell et al. (2012), this shock is labelled as Odyssean forward guidance. Moreover, this shock also captures "timing" components which correspond to revisions of policy expectations regarding the following two meetings, therefore it is also interpreted as short-term forward guidance (see Gürkaynak, Sack, and Swanson (2007) and Altavilla et al. (2019)).

LTRO. This shock covers the surprises to announcements regarding policies implemented to reassure funding and to ease lending conditions. Examples of such policies are the Securities Purchase Programme (SMP), the announcements of Outright Monetary Transactions (OMT) and Longer-Term Refinancing Operations (LTRO).

Quantitative easing (QE). Since 2015, the ECB has conducted large purchases of assets. Their goal is to supply more liquidity to the banking system with the ultimate goal of addressing downward risks for medium-term inflation.[8] This shock contains the reaction of markets regarding announcements about the introduction and implementation of such programmes.

[7] A monetary policy proxy is a measure of the underlying, unobservable monetary policy shock.

[8] The ECB's Asset Purchase Programmes are the following: Corporate Sector Purchase Programme (CSPP), Public Sector Purchase Programme (PSPP), asset-backed securities Purchase Programme (ABSPP), the third Covered Bond Purchase Programme (CBPP3) and more recently the Pandemic Emergency Purchase Programme (PEPP)).

The policies above are a mixture of conventional, unconventional and communication tools. Their implementation aims at influencing different segments of the term structure of interest rates. Specifically, conventional monetary policy targets short-term maturities; communication tools, such as information and forward guidance, have the goal of moving medium- to long-term horizons; whereas QE affects the long end of the yield curve. In contrast, policies to ease lending conditions were effective in reducing spreads. In table 1, I summarise the previous properties. Moreover, based on the evidence found in the literature (see section 2), the table also shows my hypothesis regarding their individual effect on inflation (π_t^*) and inflation expectations (π_t^{e*}). I will further study these responses in section 5.

Table 1: Monetary Policy Shocks

Shock	MP type	Yield curve	π_t*	π_t^e*
Target	conventional	short	+	+
Information	communication	medium-long	/	-
FG	unc. & comm.	medium-long	+	+
LTRO	unconventional	spreads	/	/
QE	unconventional	long-end	+	+

Note: π_t^* and π_t^{e*} represent the prior hypothesis regarding the responses of inflation and inflation expectations to the individual policies. The symbol "/" represents an agnostic belief.

I base the construction of the monetary policy proxies on the EA-MPD. This data set contains the surprises of a wide range of asset and bond prices, whereas a surprise is defined as the difference between the median quote 10 minutes before and 10 minutes after a specified time window. As previously explained, Altavilla et al. (2019) provide the surprises for three windows: the press release, the press conference and the whole monetary policy event. The time dimension of these data sets is T^*, which corresponds to the frequency of ECB's governing council meetings, i.e. every six weeks.

Following Rogers, Scotti, and Wright (2018) and Altavilla et al. (2019), I define the target factor, F_t^{Target}, as the surprises of OIS prices at the one month maturity during the press release window. The rationale behind this is that the main reaction of market participants occur during the press release, given that in the press conference a larger emphasis is given to explaining changes in unconventional monetary policy.

In order to identify the proxies related to the ECB's communication and unconventional tools, I consider a subset of the EA-MDP covering the surprises of thirty four asset and bond prices over the whole monetary policy event window,[9] spanning from January 2002 to February 2020. This means that I consider a total of 199 governing council meetings. Particularly, I use a data set including the following surprises: the OIS at several maturities ranging between one, three, six months and one to twenty years; the three, six months and one, two, five and ten years maturities of German government bond yields; the government bond yields at two, five and ten years maturity of France, Italy and Spain; the STOXX50 and SX7 indices;[10] and exchange rates against the dollar, the pound sterling and the yen. Contrary to Altavilla et al. (2019), I do not estimate the second block of proxies exclusively using the surprises from the press conference window. This is because from March 2016 onwards information about unconventional policies is communicated in the press release. Moreover, starting in July 2016 an official forward guidance statement is also included in the release. Therefore, considering the whole monetary policy event window yields a more precise identification. In fact, as highlighted by Wright (2019), considering this window allows the distinction of an additional factor which does not appear in the other two windows, and that captures policies implemented in the aftermath of the Sovereign Debt Crisis. These policies aim at reassuring funding, especially in periphery countries. For this reason, Wright (2019) calls it *save the euro* factor. In contrast to Wright (2019), I will develop a formal identification of this factor and further use it for analysing its impact on price stability. In this study, I name it *LTRO*.

I assume that the 199×34 matrix of surprises, Z, evolves as the following factor model:

$$Z = F\Lambda' + \xi \quad \xi \sim \mathcal{N}(0, R), \tag{1}$$

where F is a matrix of latent factors of dimension $199 \times r$, Λ is a $34 \times r$ loading matrix and ξ is the idiosyncratic component with diagonal covariance matrix R. As it is common in factor models, I standardise the matrix of surprises to have mean zero and unit variance. As shown in figure 1, four factors explain around 58% of the variance and each of them contribute with more than 5%, therefore I set $r = 4$.

[9]This period covers the difference between the surprises of the median quote for the time 13:25-13:35 and 15:40-15:50, i.e. 10 minutes before the press release and 10 minutes after the press conference (see Altavilla et al. (2019)).

[10]The STOXX50 is a stock market index covering the largest fifty firms in the euro area, whereas SX7 is an index composed by the prices of the stocks of the largest banks in the euro area.

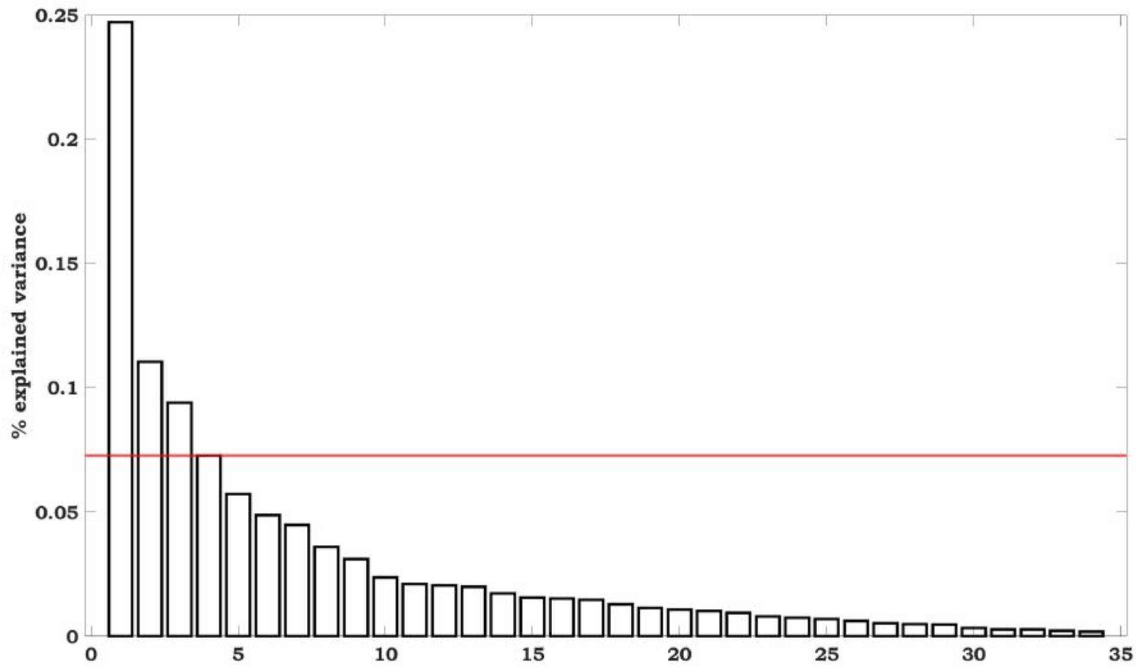

Figure 1: Scree plot (monetary policy event window)

The first part of the right-hand-side of equation (1) is called the common component, $\chi = F\Lambda'$, where the factors can be rotated freely. Therefore, in order to pin down the surprises concerning the different types of monetary policy tools, I must find a unique rotation matrix such that the parameters of the factor model fulfil a set of economic restrictions. Since the monetary policy event window integrates the communication of the complete set of monetary policy tools, I consider again a target factor, in order to clean the effects of conventional monetary policy onto the remaining factors. Nevertheless, for my final assessment I will consider the target factor from the press release.[11] I split the remaining three factors into two blocks. The first one corresponds to communication (path), whereas the second block contains two factors related to balance sheet tools, specifically to policies for easing lending conditions (denoted as LTRO) and QE.

I denote the balance sheet block as the $199^* \times 2$ vector $\mathcal{F}$. These policies were initially introduced during and after the Great Recession. Therefore, I impose the first restriction such that the LTRO and QE factors explain the least percentage of explained variance for the period before the crisis (Jan 2002-August 2008), in the spirit of Swanson (2017). Furthermore, following

[11] In subsection B.1 of appendix B, I present a figure depicting both factors. We can see that the factor from the whole monetary policy event window is noisier, however both factors commove. In fact, they have a correlation of 0.6.

Gürkaynak, Sack, and Swanson (2005), Altavilla et al. (2019) and Andrade and Ferroni (2020), I restrict the one-month OIS loadings to zero for the communication and balance sheet factors. The rationale behind these restrictions is that forward guidance and QE are implemented with the goal of influencing medium- and long-term rates, respectively. Moreover, there is broad evidence that the implementation of LTROs reduced a wide range of spreads, where the majority of the analyses focus on horizons larger than six months. In contrast, the target factor can affect the shortest maturity of the OIS.

The previous set of restrictions does not guarantee the identification between LTRO and QE factors. Given that QE aims at influencing the long end of the yield curve, I additionally restrict the loading of the six-months maturity OIS to zero. Moreover, it is important to highlight that the identification among the communication and LTRO factors is achieved since the latter is included in the block of factors that have more explanatory power only after the Great Recession.

I denote the rotated factors as $F^* = FQ$, such that Q is a rotation matrix. The subset of F^* containing the balance sheet factors is characterised by $\mathcal{F}^*$. Now we must find a rotation, Q^*, that incorporates the restrictions above. To do so, I consider the following optimisation problem for the pre-crisis period:

$$
\begin{aligned}
Q^* = \arg\min \frac{1}{T^*} \,\text{trace}(\mathcal{F}^{*\prime}\mathcal{F}^*) \qquad (2)\\
\text{s.t.}\\
Q'Q = I_r\\
\Lambda_{OIS1M,\bullet}Q_{\bullet,2} = 0, \quad \Lambda_{OIS1M,\bullet}Q_{\bullet,3} = 0 \quad \Lambda_{OIS1M,\bullet}Q_{\bullet,4} = 0\\
\Lambda_{OIS3M,\bullet}Q_{\bullet,5} = 0
\end{aligned}
$$

The syntax $\Lambda_{i,\bullet}$ denotes the i-th row of the loading matrix whereas $Q_{\bullet,i}$ is the i-th column of the orthogonal matrix. Therefore, the rotated matrix of factor loadings has the following structure:

$$
\Lambda^* = \begin{bmatrix}
\text{Target} & \text{Communication} & \text{LTRO} & \text{QE} \\
* & 0 & 0 & 0 \\
* & * & * & 0 \\
* & * & * & * \\
\vdots & \vdots & \vdots & \vdots \\
* & * & * & *
\end{bmatrix}
\begin{array}{c}
\\
\text{OIS1M} \\
\text{OIS3M} \\
\text{OIS6M} \\
\vdots \\
\\
\end{array}
$$

where the * denotes an unrestricted value.

As a second step, I further disaggregate the communication factor into information and forward guidance. To do so, I follow the literature on Delphic (information) and Odyssean forward guidance, where several studies find that the stock market and medium-term interest rate have a positive correlation for the former and a negative relation for the latter (see Kerssenfischer (2019), Jarociński and Karadi (2020), Andrade and Ferroni (2020)). I define the information factor to the observations in the communication factor such that the surprises of the STOXX50 and five-year OIS move in the same direction. In similar reasoning, when these surprises move in opposite directions, the observation of the communication factor is related to forward guidance.[12]

Summarising, we now have a target factor from the press release window and a set of four unconventional factors from the whole monetary policy event window. Due to the use of different data sets, the unconventional factors are not necessarily orthogonal to the target factor from the press release. As a next step, I construct the rotated factors $\tilde{F}_{k,t}$, through the following linear regressions:

$$F_{k,t} = \beta_k F_t^{Target} + \sum_{j=1}^{k-1} \gamma_j \tilde{F}_{j,t} + e_{k,t}, \quad e_{k,t} \sim \mathcal{N}(0, \sigma_k^2), \tag{3}$$

for $k = \{\text{information}, \text{forward guidance, LTRO, QE}\}$. I obtain the orthogonalised factors by defining them as the residual of each regression, i.e. $\tilde{F}_{k,t} = F_{k,t} - \hat{\beta}_k F_t^{Target} - \sum_{j=1}^{k-1} \hat{\gamma}_j \tilde{F}_{j,t}$. In order to obtain a monthly version of the orthogonalised factors, I set the months with no governing council meeting to zero. For the isolated cases where two meetings took place in one month, the sum of the surprises would correspond to the observation in that particular month.

I compute the orthogonalised loadings, $\tilde{\Lambda}$, based on 34 individual regressions:

$$Z_{i,t} = \tilde{\Lambda}_i \tilde{F}_t + v_{i,t}, \quad v_{i,t} \sim \mathcal{N}(0, \omega_i^2), \tag{4}$$

for $i = 1, \cdots, 34$. For each regression, I obtained draws of $\tilde{\Lambda}_i$ based on a Normal-inverse Gamma prior.

I normalise the loadings of the target and the QE factors to unity for the one-month and the twenty-year OIS, respectively. Both, the information and the forward guidance factors are normalised to the five-year maturity OIS. Moreover, I normalise the LTRO factor such that the five-year German bond

[12]As a robustness check, I imposed sign restrictions in the loadings matrix. However, in the estimation of the orthogonalised loadings the signs did not hold. These and other results based on alternative restrictions are available upon request.

yield equals one.

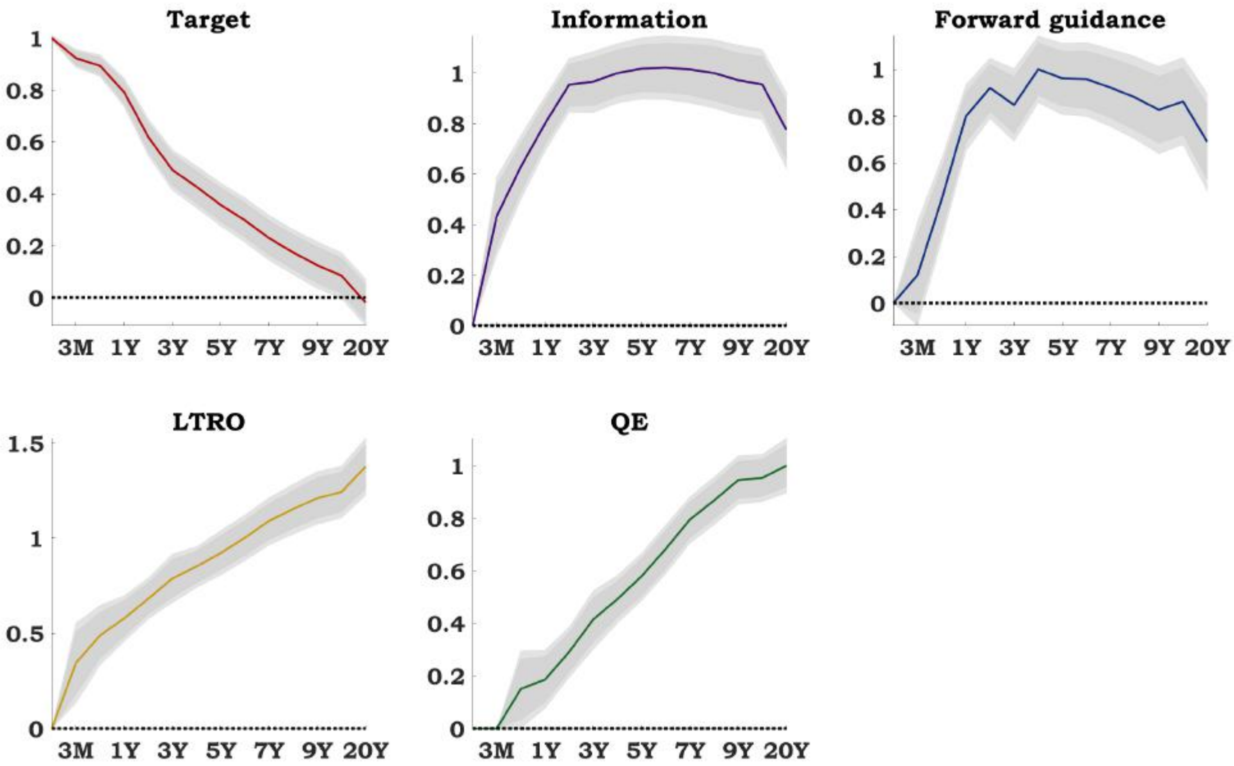

Figure 2: Loadings and the OIS term structure

Note: The shaded areas correspond to the 68% and 90% percentiles of the posterior distribution of the orthogonalised, normalised loadings. The solid lines are associated to the median.

Figure 2 depicts the normalised, orthogonalised loadings corresponding to the OIS term structure. The solid line is the median posterior distribution and the shaded areas cover the 68% (dark) and the 90% (light) percentiles. The maximum impact on the target factor corresponds to the one-month rate and the relevance of farther rates decreases the longer the maturity. The loadings associated to the information factor reach a plateau between the two and the ten-years maturities. Similarly, the forward guidance factor loadings peak at the five-years maturity and have a very slowly decrease along the end of the yield curve. The importance of longer-term maturities is greater for the loadings linked to the balance sheet factors.

In Table 2, I show the full set of orthogonalised and normalised loadings. A number with ** represents that its 90th percentile does not include zero, whereas those numbers with * mean that only the 68th percentile does not include zero. Therefore, we refer to a number without asterisks as *not significant*.

As expected from macroeconomic theory, in the presence of a conventional monetary policy shock (measured by the target factor), short-term interest rates and stock market prices react opposite directions. When the shock is contractionary (expansionary), sovereign bond yields increase (decrease) and the euro appreciates (depreciates). For the case of the information factor, I find a positive correlation between medium- to long-term maturities of the OIS and the stock market. However, the reaction of the EUROSTOXX and SX7 to forward guidance is not significant. Both communication factors depreciate the exchange rate with respect to the dollar, but only forward guidance has a significant depreciation effect with respect to the pound sterling and the yen.

Followed by the terminology in the Economic Bulletin ECB (2015), the LTRO and QE factors are considered proxies for active balance sheet shocks.[13] In this bulletin, the authors differentiate between two types of active balance sheets policies: Credit easing measures and quantitative easing. In fact, one feature that can distinguish them is that one of the goals of credit easing policies is to influence spreads. As pointed out by Altavilla, Giannone, and Lenza (2016) (for Outright Monetary Transactions (OMT)) announcements), Rogers, Scotti, and Wright (2014) (for LTROs) and Wright (2019), the introduction of credit easing policies moved the German government bond yields and the yields of crisis countries in opposite directions. I find evidence of this characteristic, and it is highlighted by the bold numbers in Table 2. This means that the LTRO factor increases the OIS and government bonds yields of core countries. At the same time, it reduces the government bond yields of Italy and Spain. Therefore, my identification achieves the differentiation between credit and quantitative easing policies.

Lastly, in figure 3, I present the plots of the five rotated and normalised factors. The impact of target shocks decreased significantly after the beginning of the Sovereign Debt Crisis. This coincides with the decision of the ECB to set the deposit facility and the main refinancing operations rates to zero in July 2012 and March 2016, respectively. The LTRO shock has a strong concentration during the period of the Sovereign Debt Crisis. The small movements in this factor before 2007 reflect other type of market operations that are implemented for correcting malfunctions in the financial markets. Finally, the large spikes of the QE factor coincide with main announcements regarding

[13] A passive balance sheet is considered as the transactions that the ECB conducts to supply liquidity with the goal of restoring the appropriate transmission of monetary policy in malfunctioning markets (see also ECB (2010)). On the other hand, an active balance sheet concerns those transactions that have the goal to provide additional monetary policy accommodation.

the different large-asset purchasing programmes introduced by the ECB.[14]

Table 2: Orthogonalised and normalised factor loadings

		Target	Information	FG	LTRO	QE
OIS	OIS1M	1.00**	0.00	0.00	0.00	0.00
	OIS3M	0.92**	0.43**	0.12	0.34**	0.00
	OIS6M	0.89**	0.63**	0.44**	0.49**	0.15**
	OIS1Y	0.79**	0.80**	0.80**	0.58**	0.19**
	OIS2Y	0.62**	0.95**	0.92**	0.68**	0.29**
	OIS3Y	0.49**	0.97**	0.85**	0.79**	0.42**
	OIS4Y	0.43**	1.00**	1.00**	0.85**	0.49**
	OIS5Y	0.36**	1.02**	0.96**	0.92**	0.58**
	OIS6Y	0.30**	1.02**	0.96**	1.00**	0.68**
	OIS7Y	0.23**	1.01**	0.92**	1.09**	0.79**
	OIS8Y	0.17**	1.00**	0.88**	1.15**	0.87**
	OIS9Y	0.12**	0.97**	0.83**	1.21**	0.95**
	OIS10Y	0.08*	0.96**	0.86**	1.24**	0.95**
	OIS20Y	-0.02	0.78**	0.69**	1.38**	1.00**
Gov. bond yields	DE3M	0.64*	-0.03	-0.01	-0.12	0.05
	DE6M	0.70**	0.41**	0.31**	0.32**	0.13*
	DE1Y	0.74**	0.67**	0.77**	0.57**	0.19*
	DE2Y	0.51**	0.88**	1.01**	0.72**	0.34*
	DE5Y	0.28**	0.96**	0.93**	1.00**	0.60*
	DE10Y	0.02	0.87**	0.73**	1.29 **	1.16*
	FR2Y	0.52**	0.86**	0.92**	0.65**	0.38*
	FR5Y	0.37**	0.91**	0.89**	0.58**	0.79*
	FR10Y	0.12**	0.83**	0.67**	0.57**	1.41*
	IT2Y	0.31**	0.62**	0.92**	**-0.96****	0.84*
	IT5Y	0.25**	0.57**	0.82**	**-1.16****	1.07*
	IT10Y	0.13**	0.45**	0.49**	**-1.16****	1.40*
	ES2Y	0.39**	0.73**	1.06**	**-0.43****	0.57*
	ES5Y	0.26**	0.77**	0.94**	**-0.80****	0.96*
	ES10Y	0.21**	0.58**	0.64**	**-0.95****	1.30*
Stock Market	STOXX50	-0.35**	0.58**	-0.09	0.98**	-1.18**
	SX7	-0.18**	0.35**	-0.11	1.53**	-0.71**
Exchange rates	EURUSD	0.16**	-0.24**	-0.26**	1.22**	0.95**
	EURGBP	0.21**	-0.09	-0.31**	1.14**	0.93**
	EURJPY	0.18**	0.05	-0.22**	1.29**	1.01**

[14]In subsection B.2 of appendix B, I associate spikes of some of the factors to selected policy announcements.

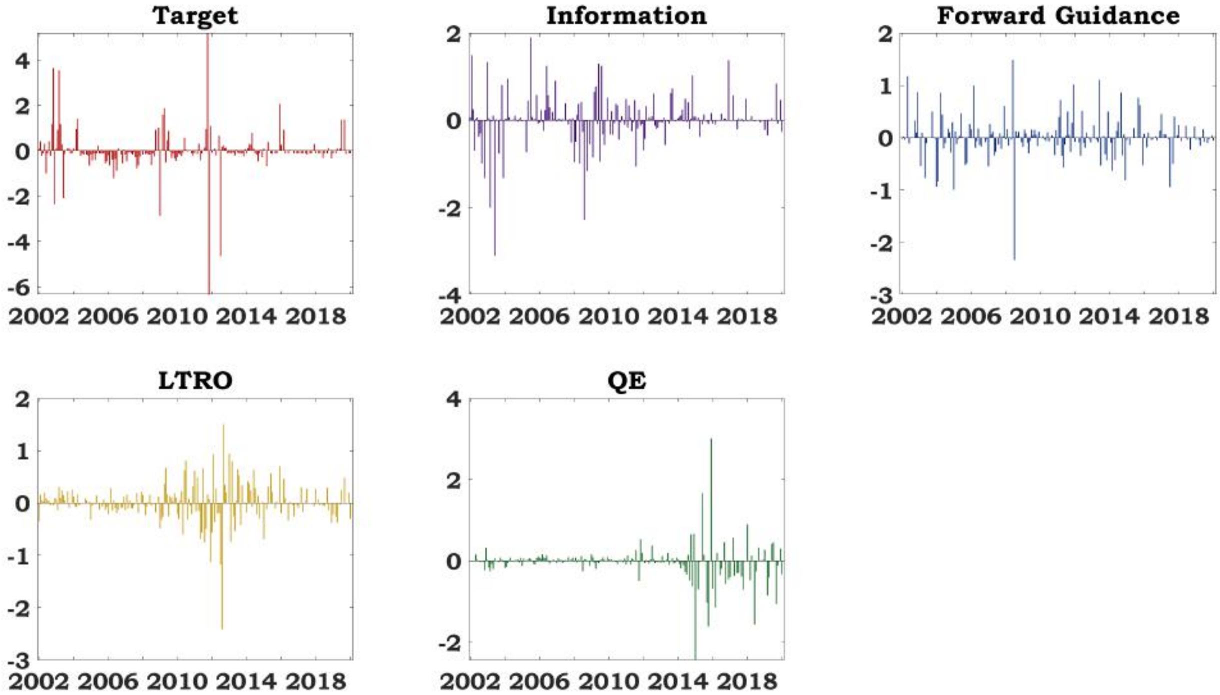

Figure 3: Proxies for conventional and unconventional monetary policy shocks

Note: The bars represent the median posterior distribution of the orthogonalised, normalised factors.

4 Monetary policy in a data-rich environment

The conduct of monetary policy in the euro area requires monitoring a large set of variables. In order to have a comprehensive representation of the full dynamics in the euro area economy, I consider a wide range of macroeconomic and financial variables. Due to a high degree of parametrisation in large systems, the estimation of VARs is not feasible under conventional methods. Therefore, we must apply a dimension reduction (sparse) or a shrinkage (dense) technique.[15] A popular approach to cope with the curse of dimensionality is to set up a factor based model like a Factor Augmented VAR (Bernanke and Boivin (2003), Bernanke, Boivin, and Eliasz (2005)) or a structural factor model (Forni et al. (2009)). This type of dense models summarise the common information of a large number of variables into a strictly smaller number of factors. A second common approach is the set up of a large Bayesian VAR, where the econometrician relies on the implementation of Bayesian shrinkage. In this paper, I consider the second approach since it neither relies on

[15] See Giannone, Lenza, and Primiceri (2018) for an assessment of dense and sparse models in a forecasting framework.

stationary transformations of the variables nor in normalisation of the factors for analysing the results of the model.[16] Moreover, I integrate the factors from the previous section into a large Bayesian VAR, in order to achieve the identification of monetary policy shocks. I describe the methodology in the following subsections.

4.1 The large Bayesian VAR

Let us consider a large vector of endogenous variables, y_t, of dimension $N \times 1$. We jointly model its dynamics through a VAR with p lags described as in equation (5):

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{5}$$

where $A_1, \cdots, A_p$ are $N \times N$ matrices of autoregressive coefficients, c is a vector of constant terms and $u_t \sim \mathcal{N}(0, \Sigma)$ are the reduced-form errors. The VAR can also be written in compact form:

$$y_t = A_+ x_t + u_t, \tag{6}$$

where $x_t = [1, y'_{t-1}, \ldots, y'_{t-p}]'$ is a $(Np+1) \times 1$ vector containing all the lagged values of y_t and the constant term, the matrix $A_+ = [c, A_1, \cdots, A_p]$ has all stacked coefficients of dimension $N \times (Np+1)$. Additionally, we also express the model in matrix form:

$$Y = XA'_+ + U, \tag{7}$$

where Y is a $T \times N$ matrix of data, $X = [x_1, \ldots, x_T]'$ is a $T \times (Np+1)$ matrix of lagged endogenous variables and U is a $T \times N$ matrix of stacked reduced-form errors.

The literature on large Bayesian VARs can be tracked back to the articles of Litterman (1986) and Doan, Litterman, and Sims (1984). Their main contribution is the proposal of an informative prior distribution - popularly known as the Minnesota prior- for the estimation of a ten-variable VAR. A proposal for selecting the degree of shrinkage for larger models was made by Bańbura, Giannone, and Reichlin (2010). The authors propose selecting the shrinkage parameter over a grid in a data-driven approach for a set of 131 variables.

[16] Other possible approaches are Panel VAR (see Canova and Ciccarelli (2013) for a survey), Global VAR (Pesaran and Smith (2006), Dees, Mauro, Pesaran, and Smith (2007)), Stochastic Search Variable Selection (George and McCulloch (1995)), LASSO (Tibshirani (1996), Park and Casella (2008)), among others.

In more detail, they estimate a large Bayesian VAR based on priors where the hyperparameter governing the overall degree of shrinkage is selected such that it gives the best in-sample fit. This approach takes into consideration the cross-sectional dimension of the data, i.e. the larger the number of time series, the larger the tightness of the prior. Nevertheless, when Bańbura, Giannone, and Reichlin (2010) additionally consider a sum of coefficients prior (see below), they arbitrarily set the hyperparameter ruling this prior.

More recently, Giannone, Lenza, and Primiceri (2015) (GLP, henceforth) propose a hierarchical model where they treat the shrinkage hyperparameters as an additional vector to estimate. In particular, the authors consider priors taking the Normal-inverse Wishart form as follows:

$$\Sigma \sim iW(\Psi, d) \tag{8}$$

$$\alpha|\Sigma \sim \mathcal{N}(a, (\Sigma \otimes V_a)), \tag{9}$$

where $\alpha = \mathrm{vec}(A'_+)$ and the inverse Wishart distribution is parametrised with degrees of freedom $d = N + 2$ such that the mean of Σ exists.[17] The authors also set the scale matrix to be a diagonal matrix, i.e. $\Psi = \mathrm{diag}(\psi_1, \cdots, \psi_N)$. Typically, the diagonal elements are constructed with the variances resulting from fitting an autoregressive model (AR) to each variable. The matrices $\underline{A}$ and V_a correspond to the prior mean and variance, where $a = \mathrm{vec}(\underline{A})$ of dimension $N(Np+1) \times 1$. These parameters are functions of a vector of hyperparameters θ (which I define below). Assuming a Gaussian likelihood, the great computational advantage of considering Normal-inverse Wishart priors is that the posterior distribution is from the same distributional family as the prior, i.e. the priors are conjugate.

GLP consider three types of priors: The Minnesota, sum of coefficients and single unit root prior. The Minnesota prior was initially proposed by Litterman (1986) and its broad idea is to treat the variables in the VAR as independent random walks by setting the diagonal elements of A_1 to one and the off-diagonal elements to zero. Furthermore, GLP assume that the more distant lags have a smaller weight in the equation of $y_{i,t}$, for $i = 1, \cdots, N$. Following the notation in GLP, the Minnesota structure sets the prior belief that the matrices of coefficients are independent and follow a Normal distribution

[17] This choice of degrees of freedom is the minimal condition such that $\mathbb{E}[\Sigma]$ exists and equals $\frac{\Psi}{d-N-1}$, as explained in Kadiyala and Karlsson (1997).

with the following moments:

$$\underline{A} := \mathbb{E}[(A_\ell)_{i,j}|\Sigma] = \begin{cases} \delta_i, & i = j \quad \& \quad \ell = 1 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$V_a := \mathrm{cov}\left((A_\ell)_{i,j}, (A_k)_{r,s}|\Sigma\right) = \begin{cases} \frac{\theta_1^2}{\ell^{\theta_2}} \frac{\Sigma_{i,r}}{\psi_j/(d-N-1)} & j = s \quad \& \quad \ell = k \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

This version of the Minnesota prior is more flexible than the traditional set up since it allows a mixture of stationary and non-stationary variables. Specifically, the parameter δ_i equals one when variable y_i is not stationary and zero otherwise. The crucial hyperparameter of the prior is θ_1 since it governs the overall degree of shrinkage. When $\theta_1 = 0$ the data is not informative enough and the posterior perfectly coincides with the prior distribution. On the other extreme, as $\theta_1 \to \infty$ the posterior mean draws converge to Least Squares estimates. For lags $\ell > 1$, the hyperparameter θ_2 penalises the more distant lags.

The last two considered priors are refinements of the Minnesota prior and both are implemented by adding artificial or dummy observations to the original data.[18] The first extension is the sum-of-coefficients prior (also known as inexact-differencing or no-cointegration-prior) which was proposed by Doan, Litterman, and Sims (1984). To understand this extension, let us rewrite the VAR from equation (5) in an error-correction form:

$$\Delta y_t = c - (I_N - A_1 - \cdots - A_p)y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1}\Delta y_{t-p} + u_t. \tag{12}$$

The combination of the Minnesota with the sum-of-coefficients prior shrinks the term $(I_N - A_1 - \cdots - A_p)$ to zero. The shrinkage of this relationship is ruled by hyperparameter θ_3. When θ_3 is zero the VAR is set in first differences, which implies a unit root equation for each variable. Therefore, in this case, there are no cointegration relationships among the variables. On the other extreme, if $\theta_3 \to \infty$ the prior is diffuse and no additional shrinkage is imposed.

Sims (1993) recognised that the sum-of-coefficients prior is too strict in the limits. In the extremes, the model either completely eliminates long-run relationships or assumes no cointegration. To refine this issue, he proposed the dummy-initial-observation prior (also known as single-unit-root or co-persistence prior). This prior allows the possibility of unit roots in all variables without eliminating cointegration relations. As explained by Sims and Zha (1998), this prior represents the belief that the average over an initial

[18] For a detailed explanation of the construction of the dummies, see Del Negro and Schorfheide (2011).

sample T_0, $\bar{y}_{0,i}$, is a good model to forecast y_i. The tightness of the prior is scaled by hyperparameter θ_4. When $\theta_4 \to 0$ the variables are shrunk to their mean, whereas if $\theta_4 \to \infty$ the prior becomes diffuse. As stressed by Del Negro and Schorfheide (2011), the two refinements of the Minnesota prior introduce correlation among coefficients' priors in each equation.

We now embed the sum-of-coefficients and single-unit-root priors in form of T_d artificial observations, denoted as Y^* and X^*. They are constructed as follows:

$$Y^* = \begin{bmatrix} \text{diag}(\bar{y}_1, \cdots, \bar{y}_N)/\theta_3 \\ (\bar{y}_1, \cdots, \bar{y}_N)/\theta_4 \end{bmatrix} \quad X^* = \begin{bmatrix} 0_{N\times 1} & (1_{1\times p} \otimes \text{diag}(\bar{y}_1, \cdots, \bar{y}_N)/\theta_3) \\ 1/\theta_4 & (\bar{y}_1, \cdots, \bar{y}_N)/\theta_4 \end{bmatrix},$$

where the first column of X^* correspond to the prior for the constant term. We concatenate the original data with the artificial (dummy) observations in the matrices $\tilde{Y} = [Y', Y^{*\prime}]'$ and $\tilde{X} = [X', X^{*\prime}]'$, whose time dimension equals $\tilde{T} = T + T_d$. Since the priors are conjugate, the posterior distributions of the VAR parameters and the error covariance matrix take the following form:

$$\alpha|\Sigma, Y \sim \mathcal{N}\left(\tilde{\alpha}, \tilde{V}_\alpha\right) \tag{13}$$

$$\Sigma|Y \sim iW\left(\Psi + \tilde{u}'\tilde{u} + (\tilde{A} - \underline{A})'V_a^{-1}(\tilde{A} - \underline{A}), \tilde{T} - p + d\right) \tag{14}$$

with

$$\tilde{A} = \left(\tilde{X}'\tilde{X} + V_a^{-1}\right)^{-1}\left(\tilde{X}'\tilde{Y} + \tilde{V}_a^{-1}\underline{A}\right) \quad \text{and} \quad \tilde{V}_\alpha = \Sigma \otimes \left(\tilde{X}'\tilde{X} + V_a^{-1}\right)^{-1}.$$

Therefore, $\tilde{\alpha} = \text{vec}(\tilde{A}')$ and $\tilde{u} = \tilde{Y} - \tilde{X}\tilde{A}'$. Notice that under this setup it is possible to implement the Minnesota, the sum-of-coefficients and the single-unit-root priors simultaneously.

GLP estimate the parameters based on the optimisation of the marginal data density $p(Y|\theta)$, which is a function depending on the hyperparameters governing the priors, $\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$. The direct optimisation of the marginal likelihood is possible since the authors provide a closed-form solution formula. The simulation of the posterior parameters is carried out in two parts. First, they numerically optimise the marginal data density which is equivalent to maximising the one-step-ahead forecast likelihood. GLP use the results from the likelihood optimisation to draw the hyperparameter's vector from gamma distributions in a Metropolis-Hastings step.[19] Secondly, given the hyperparameters, they draw the parameters of the VAR based on (13) and

[19] For further detail about the functional form of the marginal data density and the MCMC algorithm, see the web appendices of Giannone, Lenza, and Primiceri (2015).

(14).

4.2 The *internal* instrument approach

The literature studying large Bayesian structural VARs has relied on identifying macroeconomic shocks through a recursive approach.[20] Nevertheless, justifying the order of the variables in a data-rich environment can be cumbersome since the ordering needs to be backed up with economic theory. In this paper, I use the factors computed in section 3 as proxies (instruments) for achieving identification of the underlying monetary policy shocks.[21] The formal use of instruments for identification in a VAR context was introduced by Stock and Watson (2012) and Mertens and Ravn (2013), known as Proxy-VAR.[22] The main idea of this model is to augment the VAR by additional equations representing the relationship between instruments and the shocks of interest.

In a further paper, Stock and Watson (2018) stress the relevance of invertibility for obtaining consistent impulse response functions, in the context of Proxy-VARs. When this assumption holds, the econometrician is able to recover the shocks using current and past values of the data (see Kilian and Lütkepohl (2017), Chapter 17). For the particular case of forward guidance shocks, Noh (2017) and Plagborg-Møller and Wolf (2019) independently show that these type of shocks are not invertible. The main reason is that they can be interpreted as a type of news shocks, since the central bank releases "news" about the *future* path of interest rates. As highlighted by Leeper, Walker, and Yang (2013), in this case, consumers discount more recent news heavily, in comparison to older news. In contrast, the econometrician discounts older news relative to the latest available information. Given that forward guidance is a central part of my analysis, the use of a Proxy-VAR would not be feasible. For this reason, I rely on the methodology known as the "internal" instrument approach.

As highlighted by Plagborg-Møller and Wolf (Forthcoming), the internal instrument approach returns valid impulse responses regardless the invertibility properties of the shocks. The idea is to augment the vector of endogenous variables by the instruments m_t, a vector of dimension $T \times 5$. The most general

[20]An exception is the recent paper by Korobilis (2020), where he proposes a methodology based on sign restrictions.

[21]Throughout this paper, I use the words proxies and instruments as synonyms.

[22]In the Bayesian framework, the estimation of a Proxy-VAR was introduced by Caldara and Herbst (2019) for a single proxy analysis and later on extended for multiple proxies by Arias, Rubio-Ramírez, and Waggoner (2020) and Drautzburg (2020).

version of this model is portrayed in equation (15):

$$\begin{bmatrix} m_t \\ y_t \end{bmatrix} = \begin{bmatrix} \kappa \\ c \end{bmatrix} + \begin{bmatrix} B_1 & C_1 \\ \Gamma_1 & A_1 \end{bmatrix} \begin{bmatrix} m_{t-1} \\ y_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} B_p & C_p \\ \Gamma_p & A_p \end{bmatrix} \begin{bmatrix} m_{t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} w_t \\ u_t \end{bmatrix} \tag{15}$$

where

$$\tilde{u}_t = \begin{bmatrix} w_t \\ u_t \end{bmatrix} \sim \mathcal{N}(0, \Omega).$$

In this approach, the proxies are embedded in the VAR and for this reason it is also known as hybrid VAR. As pointed out by Stock and Watson (2018), a special case of this equation is the so-called observed shock case. In this situation, the vector $\kappa = 0$ and the matrices $B_i = 0$ and $C_i = 0$, for $i = 1, \cdots, p$. As long as the proxies are unpredictable and serially uncorrelated, the zero restrictions are plausible (see Jarociński and Karadi (2020)).

Noh (2017) and Paul (2019) develop the conditions under which the internal instrument approach and the Proxy-VAR are equivalent. These conditions are the following: (i) invertibility of the shocks of interest must hold; (ii) the proxies must be serially uncorrelated and (iii) $\Gamma_i = 0$, for $i = 1, \ldots, p$.

I denote the $(N+5) \times 1$ vector of structural shocks as ε_t, with the property that $\varepsilon_t \sim \mathcal{N}(0, I)$. Without loss of generality, I split the vector ε_t into two blocks:

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix},$$

where $\varepsilon_{1,t}$ corresponds to the 5×1 block of shocks of interest. In a similar fashion, $\varepsilon_{2,t}$ is the $N \times 1$ vector of remaining shocks. In the same way as in standard structural VARs, we can bridge the reduced-form errors $\tilde{u}_t$ with the structural shocks as follows:

$$\begin{aligned} \tilde{u}_t &= H\varepsilon_t \\ &= H_1\varepsilon_{1,t} + H_2\varepsilon_{2,t}. \end{aligned} \tag{16}$$

The nonsingular impact matrix $H = [H_1 \quad H_2]$ captures the impact effects of structural shocks on $\tilde{y}_t = [m_t', y_t']'$. The dimensions of the blocks H_1 and H_2 are $(N+5) \times 5$ and $(N+5) \times N$, respectively. The impact matrix is obtained by decomposing the reduced-form covariance matrix as $\Omega = HH'$. Thus, the identification of the shocks of interest $\varepsilon_{1,t}$ is achieved through the identification of the columns of matrix H_1. In this setup, the computation of the impulse response function relies on the Choleski decomposition of the covariance matrix

Ω.

I treat equation (15) as a large Bayesian VAR and carry out its estimation based on the technique described in subsection 4.1.

5 Empirical Assessment

5.1 Data

I consider a medium-scale monthly data set containing twenty variables spanning from January 2007 to February 2020.[23] The data set contains information about industrial production, unemployment, the Purchasing Managers Index (PMI), the harmonised index of consumer prices, the EURIBOR at one month maturity, euro area yields (one, two and ten years), stock market index (EUROSTOXX50), corporate and banks spreads from Gilchrist and Mojon (2018), loans to non-financial corporations (NFC) and households (HH), an indicator of cost of borrowing for NFCs and the nominal effective exchange rate (NEER) against the currencies of the main trading partners of the euro area.[24] For capturing downward risks in global inflation, I also include oil and commodity price indices (see Ciccarelli and Osbat (2017)). From the side of expectations, I consider two sources: the qualitative data from the consumers' survey collected by the European Commission and the consensus median of short-term (one year ahead) inflation forecasts of the Eurozone Barometer (EB) gathered by MJEconomics.[25] Moreover, I include the long-term (five years ahead) inflation forecast from the ECB's survey of professional forecasters. The latter data set is available at quarterly frequency which I transform into a monthly time series through a Chow-Lin decomposition (Chow and Lin (1971, 1976)). I use monthly expectations at one year horizon and monthly perceptions from EB as bridge variables.[26]

[23] I do not consider the period of extreme observations as consequence of the COVID-19 pandemic since their size can compromise the inference of the VAR. For a methodology handling with such episodes see the recent work of Lenza and Primiceri (2020).

[24] For detailed information about the data set see appendix C.

[25] Arioli, Bates, Dieden, et al. (2017) transform the European Commission's survey into quantitative data, however the available data sets spans only from January 2004 to July 2015.

[26] I use the toolbox on temporal disaggregation written by Enrique M. Quilis and available at https://www.mathworks.com/matlabcentral/fileexchange/69800-temporal-disaggregation.

5.2 Results and policy implications

This section presents results from the estimation of the hybrid Bayesian VAR from equation (15) with three lags.[27] As robustness check, I estimated the model using one through thirteen lags. However, my parsimonious selection already eliminates the serial correlation among the block of reduced-form errors linked to the structural shocks (see top panel of graph 9 from Appendix D). The estimation is based on 50000 draws where I keep the last 25000 for inference.[28] In all figures, I present the median of the posterior distribution of impulse responses together with 68% point-wise credibility intervals. Moreover, I normalise the shocks such that an expansionary target shock is related to a 25 basis points decrease in the short-term rate; the information and forward guidance shocks are associated to a 15 basis points decrease in the one- and two-year yield, respectively; the LTRO shock is associated to a 0.10 basis points decrease in the spreads between Italian and German Government Bond yields and the QE shock is linked to a 10 basis points decrease in the ten-year yield.

Figure 4 presents the responses of prices and inflation expectations of consumers and forecasters to expansionary monetary policy shocks in the euro area. Furthermore, figures 11-15 from appendix F depict results from the remaining variables in the VAR, which are also important to analyse for identification purposes.

In line with macroeconomic theory, I find evidence that a target shock increases prices and expectations of forecasters and consumers. From the side of forward guidance, an expansionary shock increases inflation and inflation expectations of forecasters. Particularly, consumers' expectations decrease contemporaneously but pick up three months after the shock. Moreover forecasters revise their short- and long-term expectations upwards. The later piece of results is crucial, since it suggests evidence in favour of the anchoring of inflation expectations.

Additionally, I obtain evidence of the ECB's information channel. This is because an expansionary information shock causes a downward revision of inflation forecasts and a decrease in inflation. The rationale of the "opposite-sign-revision" is the following: When the ECB releases private information regarding a negative economic outlook, professional forecasters become more pessimistic and revise their short- and long-term expectations downwards. In

[27] I carry out the estimation of the large BVAR through modifications to the MATLAB files from Giannone, Lenza, and Primiceri (2015) and available at Giorgio Primiceri's website: http://faculty.wcas.northwestern.edu/~gep575/GLPreplicationWeb.zip.

[28] Appendix E presents a convergence test of the MCMC algorithm.

the signalling channel literature, some studies such as Nakamura and Steinsson (2018), Jarociński and Karadi (2020) and Andrade and Ferroni (2020) also find further evidence that output and economic activity forecasts react in the same direction than interest rates for the case of information shocks and in the opposite direction for forward guidance shocks. Similarly to the evidence of these papers, in Figure 13 I show that industrial production decreases contemporaneously and a few months after an information shock, whereas output and the PMI increase after an expansionary forward guidance shock. Contrary to the findings in the mentioned papers, I do not find evidence that the stock market index reacts to information shocks. Additionally, I find a weak negative response of the stock market to a forward guidance shock.

Turning to balance sheet shocks, one of the effects of policies implemented after the Sovereign Debt Crisis for “saving the euro” was the reduction of spreads (see Wright (2019)). However, there is no consensus regarding their effects on inflation and expectations.[29] This paper sheds new light on the impact of such policies summarised in the LTRO shock. As shown in the fourth column of figure 4, the LTRO shock strikingly decrease inflation and expectations. In particular, its effect on short-term expectations is mild and not long-lasting. However, in spite of the small scale of the response of long-term expectations, it is persistent and remains significant two years after the shock. The previous results have strong policy implications because the introduction of LTROs could potentially introduce risks of de-anchored expectations. On the other hand, QE shocks are effective in increasing long-term inflation expectations of forecasters.

In summary, I obtain a re-anchoring of long-term inflation expectations conditional on forward guidance and QE shocks. In order to have a better understanding of the role of inflation expectations for monetary policy transmission, I re-run the same hybrid VAR with the difference of eliminating long-run inflation expectations of forecasters. The impulse responses of inflation and short-term inflation expectations are depicted in figure 5. The key result from this experiment is the muted response of inflation conditional on the occurrence of a forward guidance shock. Therefore, I find evidence of the *re-anchoring inflation expectations channel* because in response of stabilised inflation expectations, inflation increases.

The effectiveness of forward guidance stresses the “combined arms” strategy of the ECB (see Rostagno et al. (2019)). Between 2016-2018, forward guidance was mainly composed by state- and time-contingent statements regarding the implementation of the Asset Purchasing Programmes. However

[29]See the comments of Lucrezia Reichlin in Financial Times (2020).

after this period, its composition has been concerning statements about the future path of monetary policy. Therefore in this paper, we shed more light on the importance of expectations for achieving the goal of price stability.

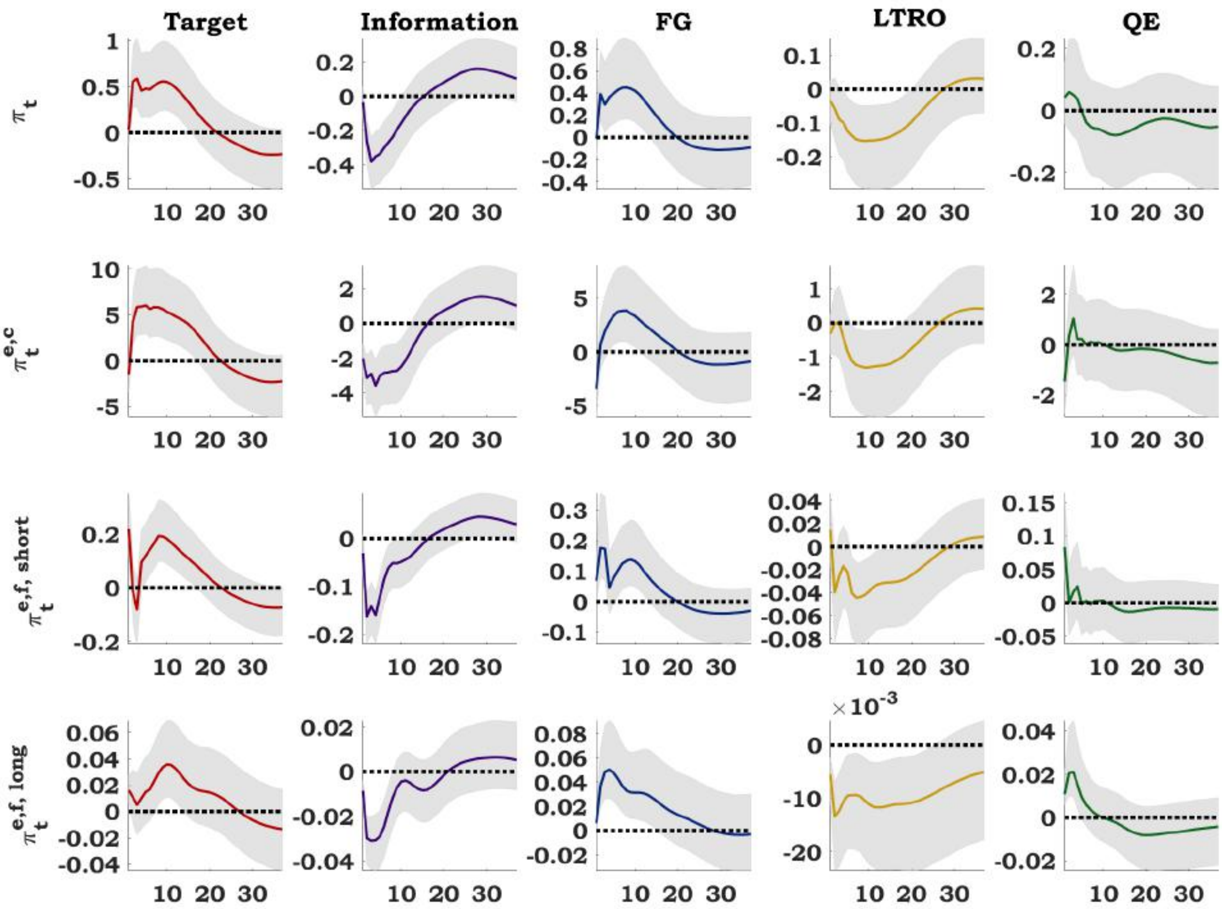

Figure 4: Responses of euro area inflation and expectations to multi-dimensional monetary policy

Note: This figure shows the impulse responses of expansionary target (red), information (purple), forward guidance (blue) and QE (green) shocks, normalised to a decrease of 25 basis points in the one month rate, 20 basis points in the one and two year rate and 10 basis points in the 10 year rate, respectively. The LTRO shock (yellow) correspond to a 10 basis point decrease in the spread between Italian and German Government bond yields. Bands represent the 68% point-wise credibility sets. Same note apply for the following figures.

An additional interesting result is the opposite contemporaneous reaction of consumers and forecasters to LTRO and QE shocks. Specifically, consumers revise their expectations downwards, whereas forecasters revise them upwards. A possible explanation of these results follows the logic in Cavallo, Cruces, and Perez-Truglia (2017). They explain that consumer's expectations are more heterogeneous than those of professional forecasters. This is due to a higher degree of rational inattention or that they simply put higher weight to personal purchases and experiences which may deviate them from realised inflation. Overall, it seems that the expectations of consumers are still driven by changes in policy rates in comparison to other policies.

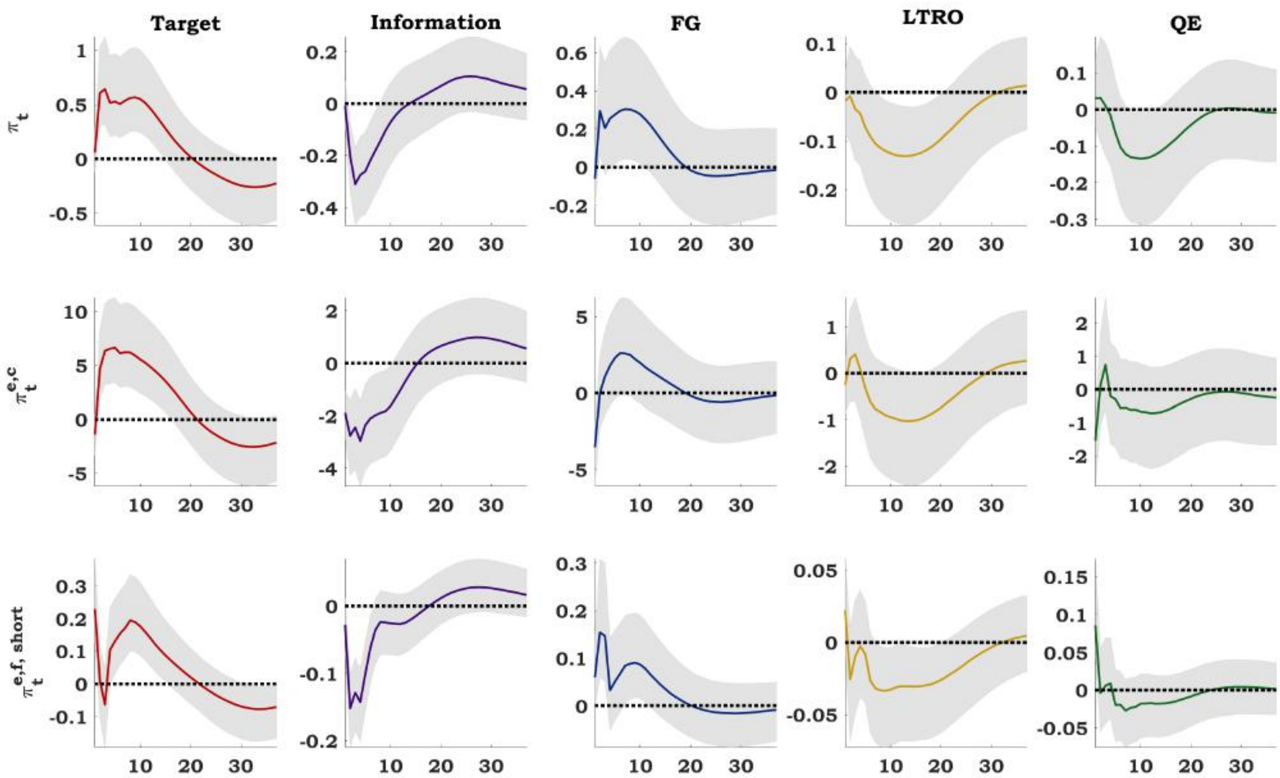

Figure 5: Responses of euro area inflation and short-term expectations of consumers and forecasters to multi-dimensional monetary policy.

The current low-inflation-low expectations scenario combined with the effective lower bound exacerbates the fear among market participants about the *japanification* of the euro area. With current increasing risks of deflation due to the impact of the novel coronavirus, the current challenge for the ECB is to design appropriate monetary policy tools for avoiding a deflation trap. My results therefore bring new evidence to the literature suggesting the use of inflation expectations as a policy tool (see Coibion et al. (2020), Candia, Coibion, and Gorodnichenko (2020)). In the previous papers, the authors also find contrary reactions among consumers and forecasters. They urge for a reform in the communication strategy of central banks such that the monetary policy tools can be understood by all agents in the economy.

6 Conclusions

In response to the Great Recession and the Sovereign Debt Crisis, the ECB has implemented a series of unconventional monetary policy tools in order to provide economic stimulus that addressed the undershooting of inflation and inflation expectations. Despite the high degree of policy accommodation, inflation remained low. For this reason, it is crucial to pin down the response of inflation and expectations to the individual policies implemented by the ECB. In this paper, I study the reaction of inflation and inflation expectations to conventional and unconventional monetary policy shocks. Given the ongoing low-inflation-low-expectations environment combined with the effective lower bound, this study crucially analyses the effectiveness of each of the considered policies for pushing up inflation and expectations of consumers and forecasters. To the best of my knowledge, this is the first paper to jointly assess this issue empirically.

The main result of this paper is that the long-term inflation expectations of forecasters anchor in response to forward guidance and quantitative easing shocks. Moreover, inflation increases and remains significant one year after a forward guidance shock hits the economy. In a further experiment, I re-estimate my model excluding inflation expectations and obtain a muted response of inflation. This result has strong policy implications because inflation expectations can be a powerful tool to achieve monetary policy transmission. Additionally, I find evidence of the ECB's information channel since after an information shock, consumers and forecasters revise their expectations downwards. The main message I extract from these results is that agents listen. Therefore, how the ECB communicates its view on current economic conditions is significant for the transmission of monetary policy through the expectations channel. These results provide additional support to the paper by Candia, Coibion, and Gorodnichenko (2020) which urges for more transparent communication strategies in order to avoid misinterpretation of monetary policy announcements.

Whilst this paper distinguishes between several types of unconventional monetary policies, there is still space for an even deeper analysis. For instance, studying the transmission of negative interest policy rates and by further differentiating out the effects of the Targeted Longer-Term Refinancing Operations (TLTRO).

Although the results of this paper exclusively isolate the effects of monetary policy, there are other structural factors contributing to the low-inflation-low-expectations environment. Some examples are the impact of digitalisation, demographic conditions, and climate change on the economy. The evaluation of the interaction of these factors with monetary policy are crucial for the design and development of further monetary policy tools. However, this topic is left for future research.

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A Inflation and Inflation expectations in the euro area

Figure 6: Inflation and inflation expectations of professional forecasters in the euro area

Note: The upper panel presents the year-on-year inflation in the euro area. The bottom panel shows the short-term (one-year-ahead) inflation expectations of forecasters from the EuroZone Barometer of MjEconomics in the blue, continuous line. The time series of long-term inflation expectations from the ECB's Survey of Professional Forecasters is depicted in the discontinuous, green line. The latter was transformed from a quarterly to a monthly frequency through a Chow-Lin decomposition.

Figure 7: Inflation expectations of consumers in the euro area

Note: The chart depicts the short-term (one-year-ahead) expectations of consumers based on the qualitative index computed by the European Commission.

B High-frequency identification: Further figures

B.1 Monetary policy event window vs Press release factor

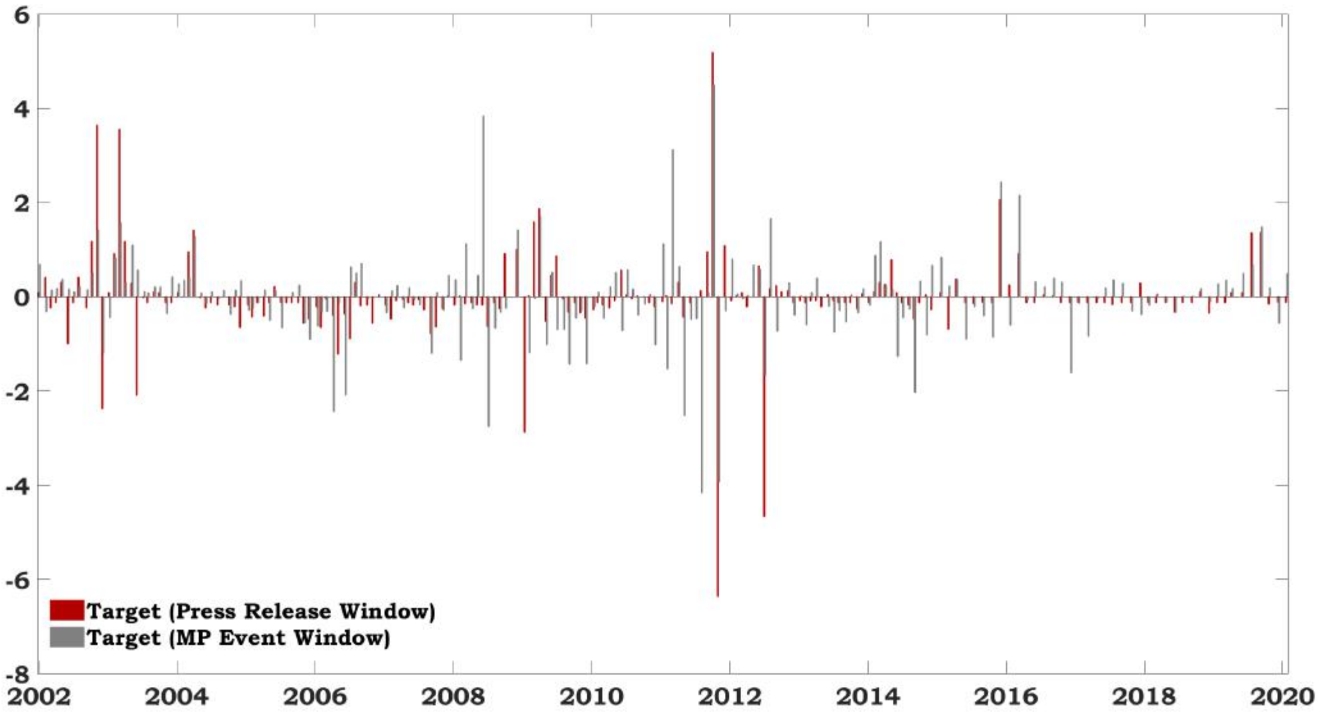
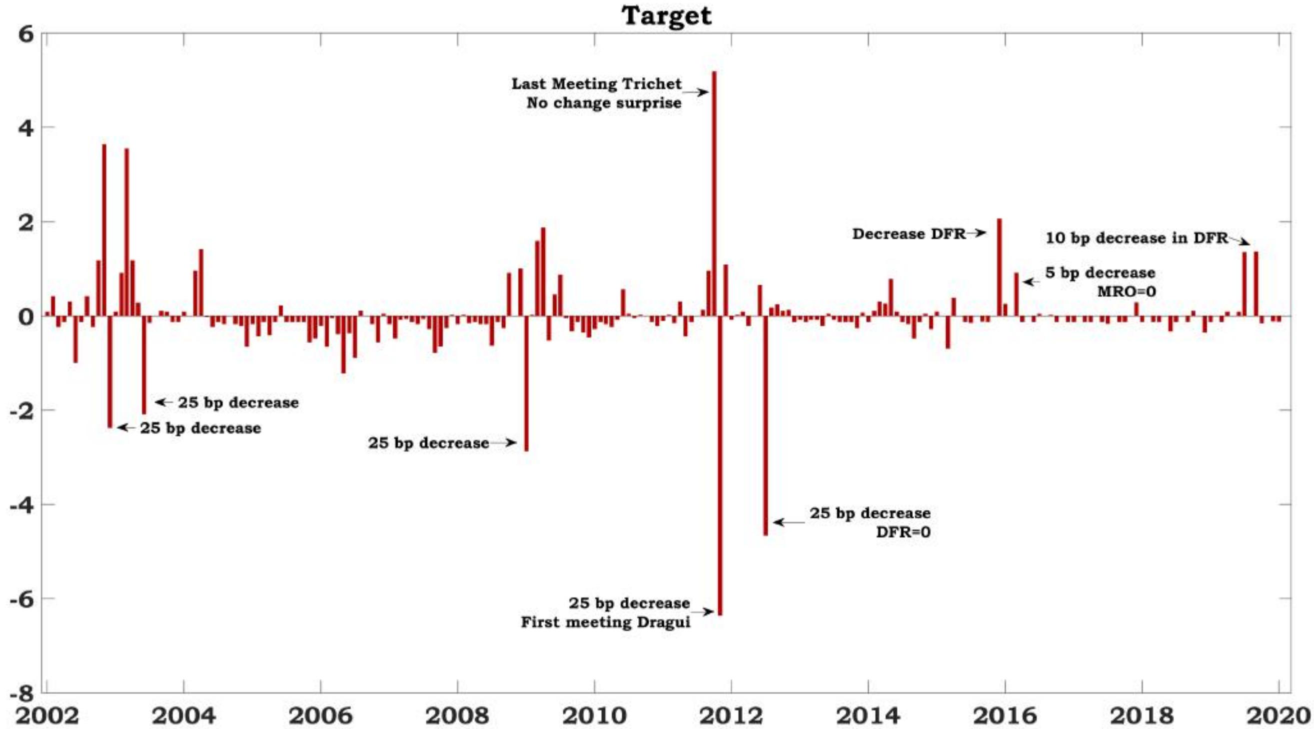
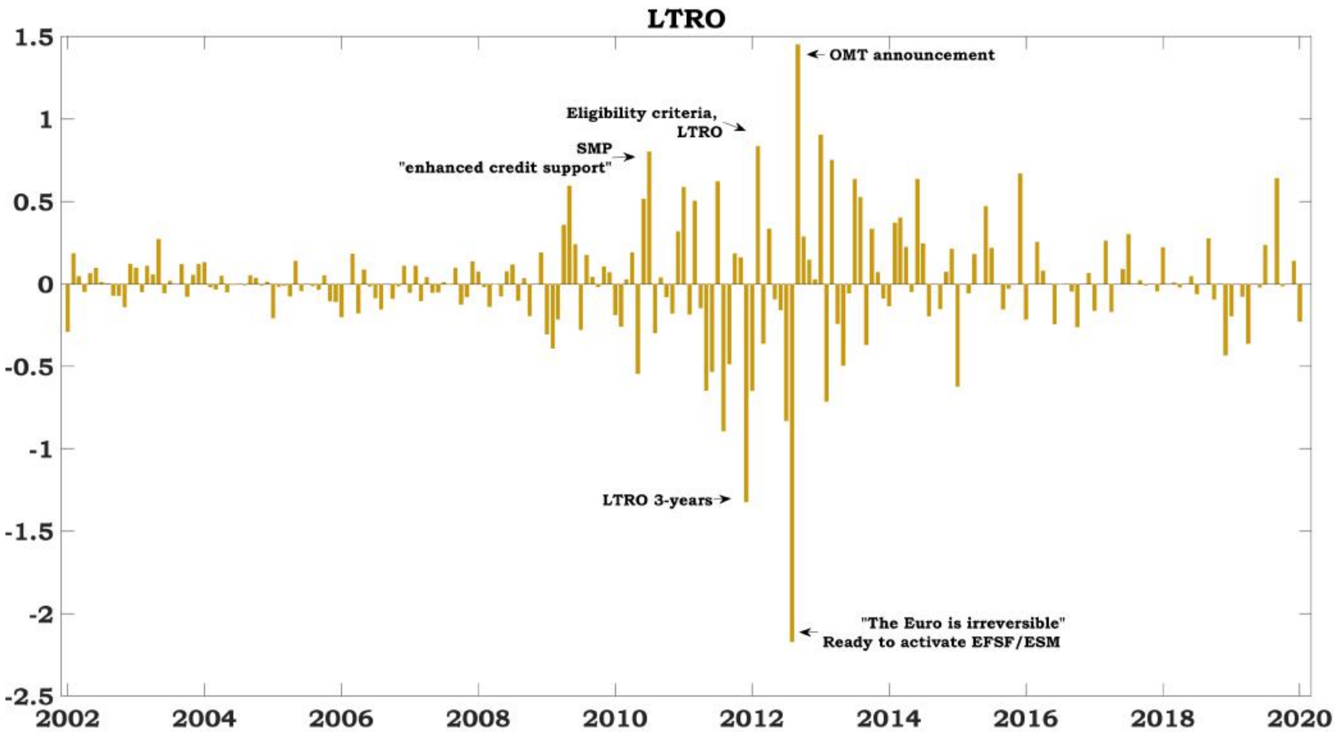
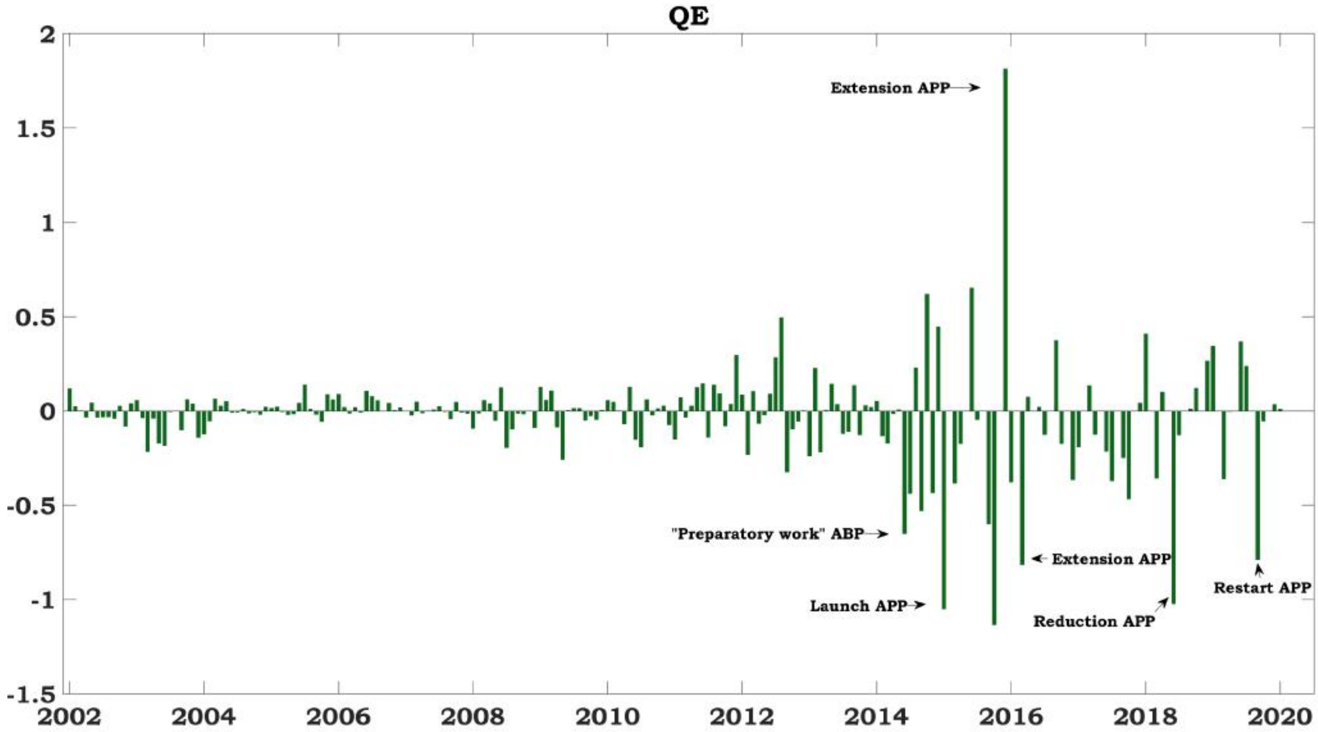


Figure 8: Target factors

B.2 Monetary Policy Proxies and selected Governing Council Meetings







C Data description

Table (3) shows the description of the macroeconomic and financial data used in the large hybrid VAR (15) as endogenous variables. The majority of variables were transformed to the year-over-year rate, i.e. $y_{i,t}^{yoy} = 100 \times ((\ln(y_{i,t}) - \ln(y_{i,t-12})))$. We leave interest rates, spreads and variables already expressed as annualized rate in levels.

Table 3: Data Description

Name	Description	Source	Transformation
IP	Volume index of production; Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; Seasonally and calendar adjusted data; Index, 2015=100	Eurostat	YoY
HICP	All-items HICP; Index, 2015=100; not seasonally adjusted	Eurostat	YoY
OILPRICE	Crude Oil Prices: Brent - Europe, Dollars per Barrel, Monthly, Not Seasonally Adjusted	FRED	YoY
COMPRICE	Euro area 19 (fixed composition)- ECB Commodity Price index Euro denominated, import weighted, Total non-energy commodity; European Central Bank; Neither seasonally nor working day adjusted	ECB-SWH	YoY
EC	Price trends over the next 12 months; Seasonally adjusted data, not calendar adjusted data; Balance Index	European Commission	Levels
CE1Y	Eurozone Barometer; Inflation forecast over the next year; consensus mean	MjEconomics	Levels
SPF	Survey of Professional Forecasters, HICP Inflation; Average of Point forecasts - Longer term	ECB-SWH	Levels
EURIBOR1M	Euro area (changing composition) - Money Market - Euribor 1-month - Historical close Euro, provided by Reuters ;Average of observations through period	ECB-SWH	Levels
EURIBOR6M	Euro area (changing composition) - Money Market - Euribor 6-month - Historical close, Euro, provided by Reuters; Average of observations through period (A)	ECB-SWH	Levels
YLD1Y	Euro area (changing composition)-Money Market-Euribor 1-year-Historical close, average of observations through period, Euro, provided by Reuters	ECB-SWH	Levels
YLD2Y	Euro area (changing composition)-Benchmark bond - Euro area 2-year Government Benchmark bond yield Yield, Euro, provided by ECB; end of period	ECB-SWH	Levels
LTREA	Euro area 19 (fixed composition) as of 1 January 2015, Long-term interest rate for convergence purposes Unspecified rate type, Debt security issued, 10 years maturity, New business coverage, denominated in Euro	ECB-SWH	Levels
SPNFCEA	Spread non financial corporations, Euro area with respect to Bund	Banque de France	Levels
SPBKEA	Spread banks, Euro area with respect to Bund	Banque de France	Levels
NEER	ECB Nominal effective exch. rate of the Euro against, EER-19 group of trading partners: AU,CA, DK, HK, JP, NO, SG,KR,SE,CH,GB,US and BG,CZ,HU,PL,RO,CN and HR excluding the Euro; Average of observations through period	ECB-SWH	YoY
EUROSTOXX50	Euro area (changing composition) - Equity/index - Dow Jones Euro Stoxx 50 Price Index - Historical close, average of observations through period - Euro, provided by DataStream	ECB-SWH	YoY
LOANSNFC	Euro area (changing composition), Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector, Loans, Total maturity, Euro - Euro area (changing composition) counterpart, Non-Financial corporations (S.11) sector, denominated in Euro, data Neither seasonally nor working day adjusted	ECB-SWH	YoY
LOANSHH	Euro area (changing composition), Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector ; Loans, Total maturity, Euro area (changing composition) counterpart, Households and non-profit institutions serving households sector, denominated in Euro, data Neither seasonally nor working day adjusted	ECB-SWH	YoY
COSTNFC	Euro area (changing composition), Annualised agreed rate (AAR) / Narrowly defined effective rate (NDER), Credit and other institutions (MFI except MMFs and central banks) reporting sector - Loans (defined for cost of borrowing purposes, sum of A2A and A2Z (both related to non-financial corporations)), Total calculated by weighting the volumes with a moving average defined for cost of borrowing purposes), New business coverage, Non-Financial corporations sector, denominated in Euro	ECB-SWH	Levels

D Robustness Checks

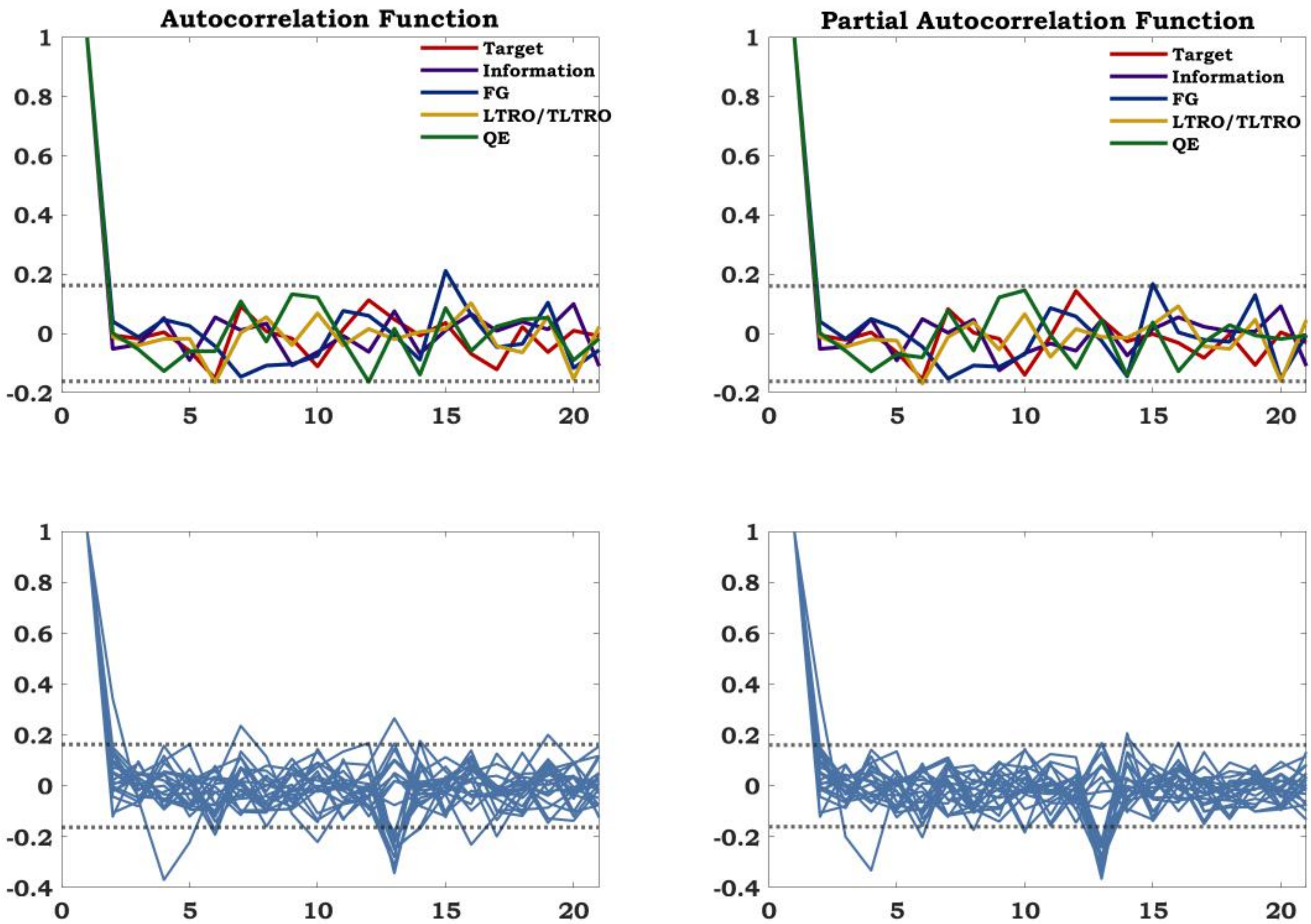


Figure 9: Autocorrelation and partial autocorrelation functions of the reduced-form errors from equation (15)

Note: The upper panel shows the reduced-form corresponding to the shocks of interest whereas the bottom panel depicts the remaining errors.

E Convergence test

The estimation of the hybrid Bayesian VAR (15) is based on 50000 draws, whereby I use the last 25000 draws for inference. In detail, I compute the χ^2-test proposed by Geweke (1992). The idea of this test is to carry out a text of equal mean between the initial 20% and the last 60% of the draws. Given the fact that we have a total of twenty six variables (including the proxies in the VAR), three lags and an intercept, it sums up a total of 2730 parameters (2054 from the reduced-form matrices and 676 from the covariance matrix).

As standard in Bayesian estimation, I consider every fourth draw for inference in order to reduce the chances that our draws are autocorrelated. In Figure 10, I show the histogram of the χ^2 test p-value, where I highlight in red the proportion of parameters that do not converge based on a 5% significance level. Since this group only corresponds to 3% of the total parameters, we accept the results.

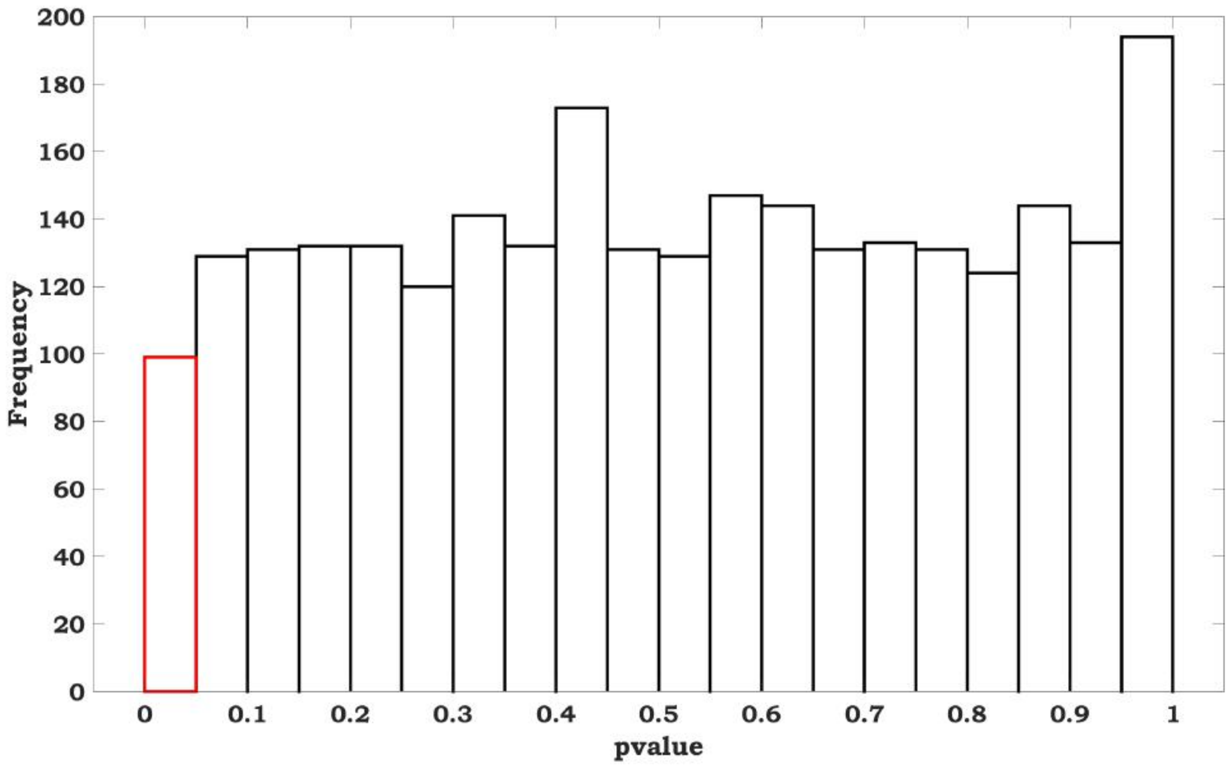


Figure 10: Geweke convergence test (p-values)

Note: This figure shows the histogram of the p-values from the χ^2-test of Geweke (1992).

F Further Impulse Responses

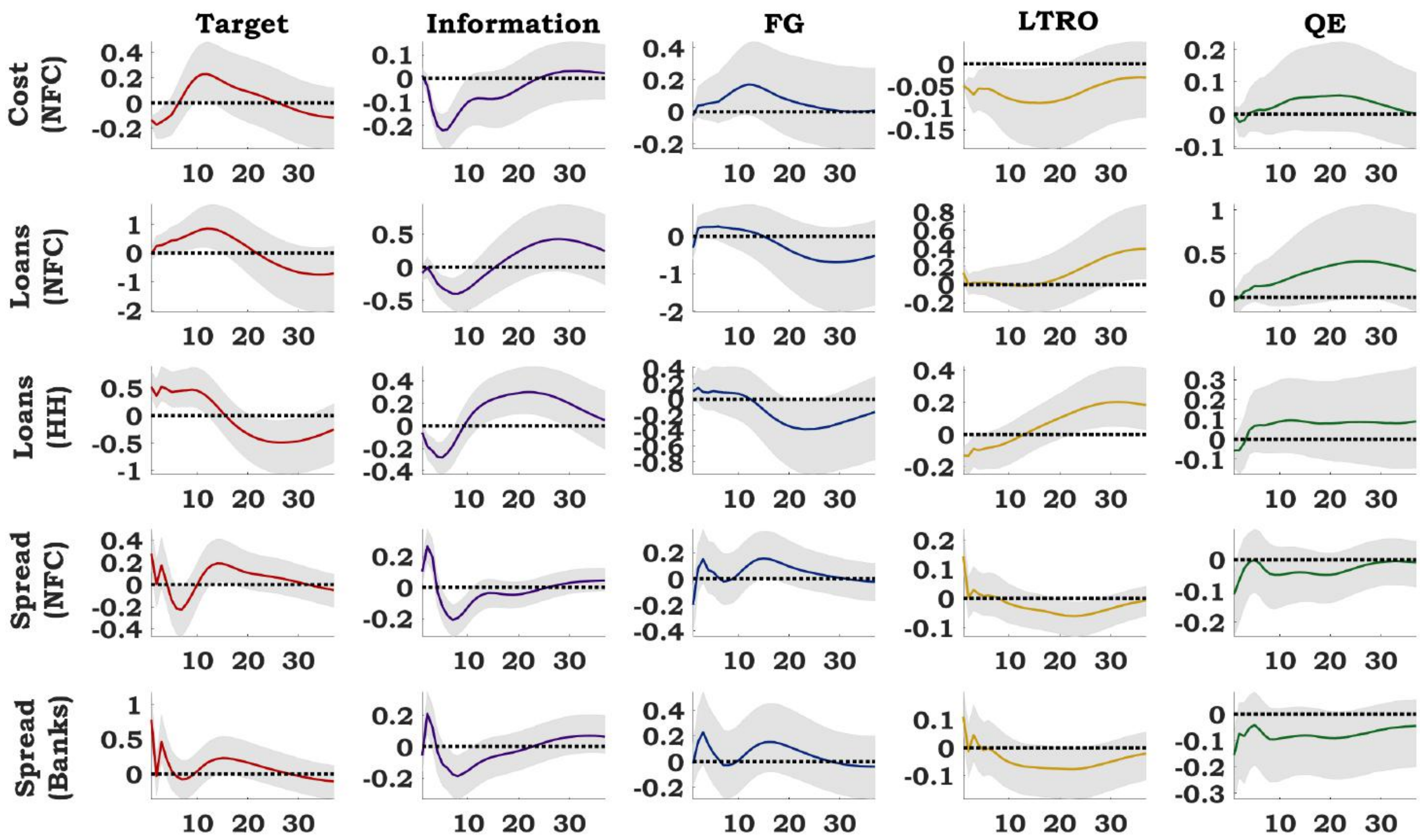


Figure 11: Responses of euro area inflation and expectations to multi-dimensional monetary policy

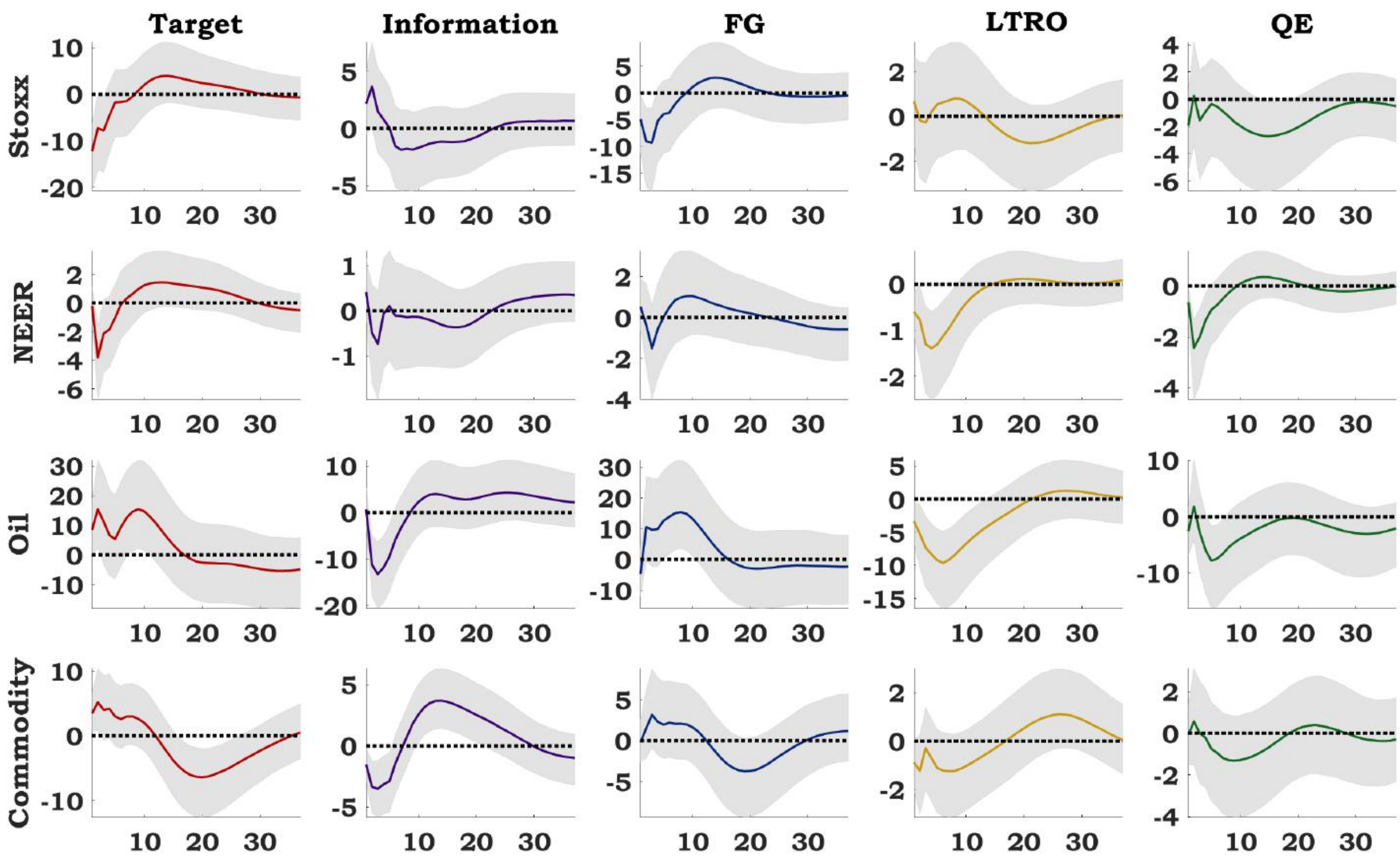


Figure 12: Responses of euro area inflation and expectations to multi-dimensional monetary policy

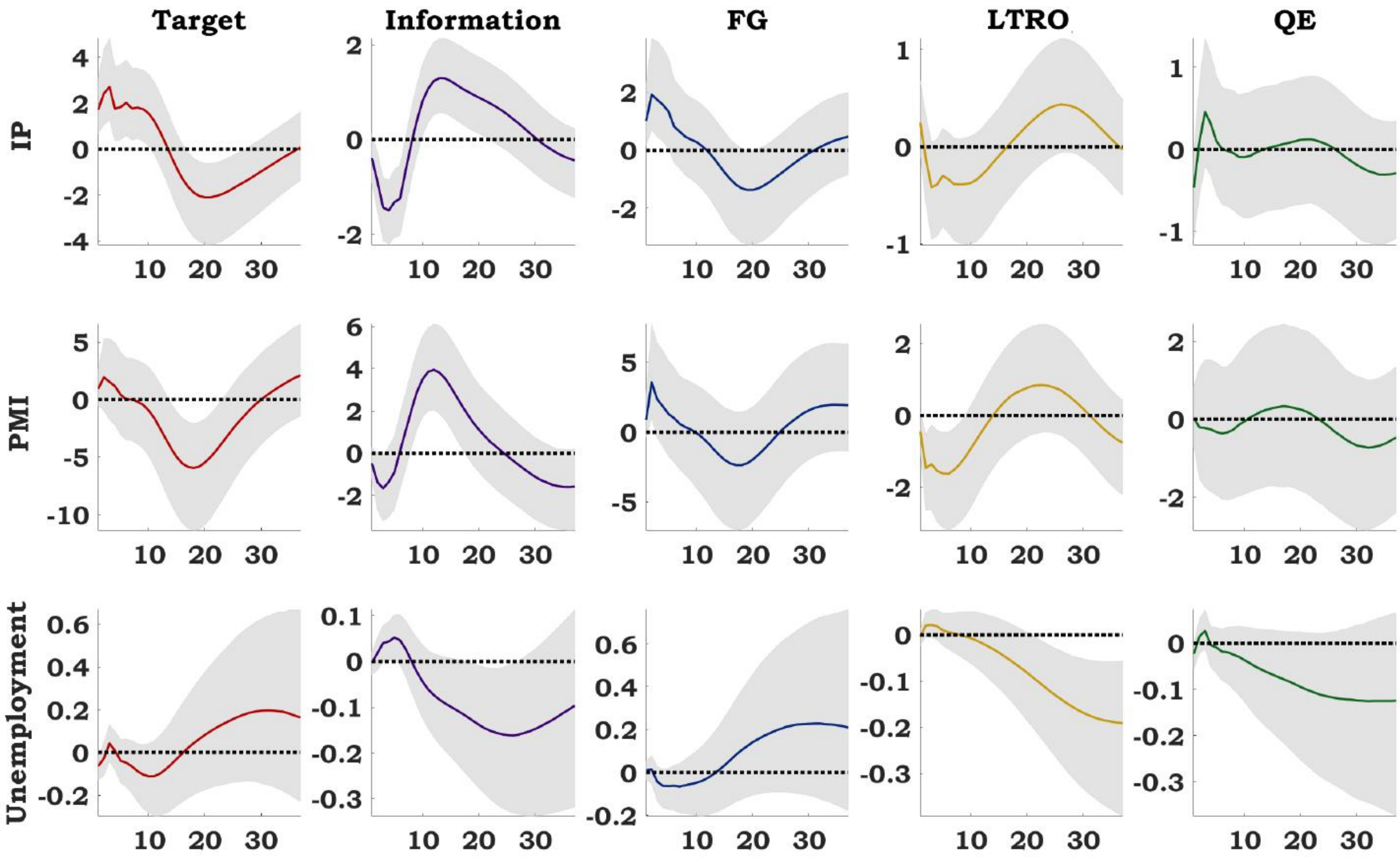


Figure 13: Responses of euro area inflation and expectations to multi-dimensional monetary policy

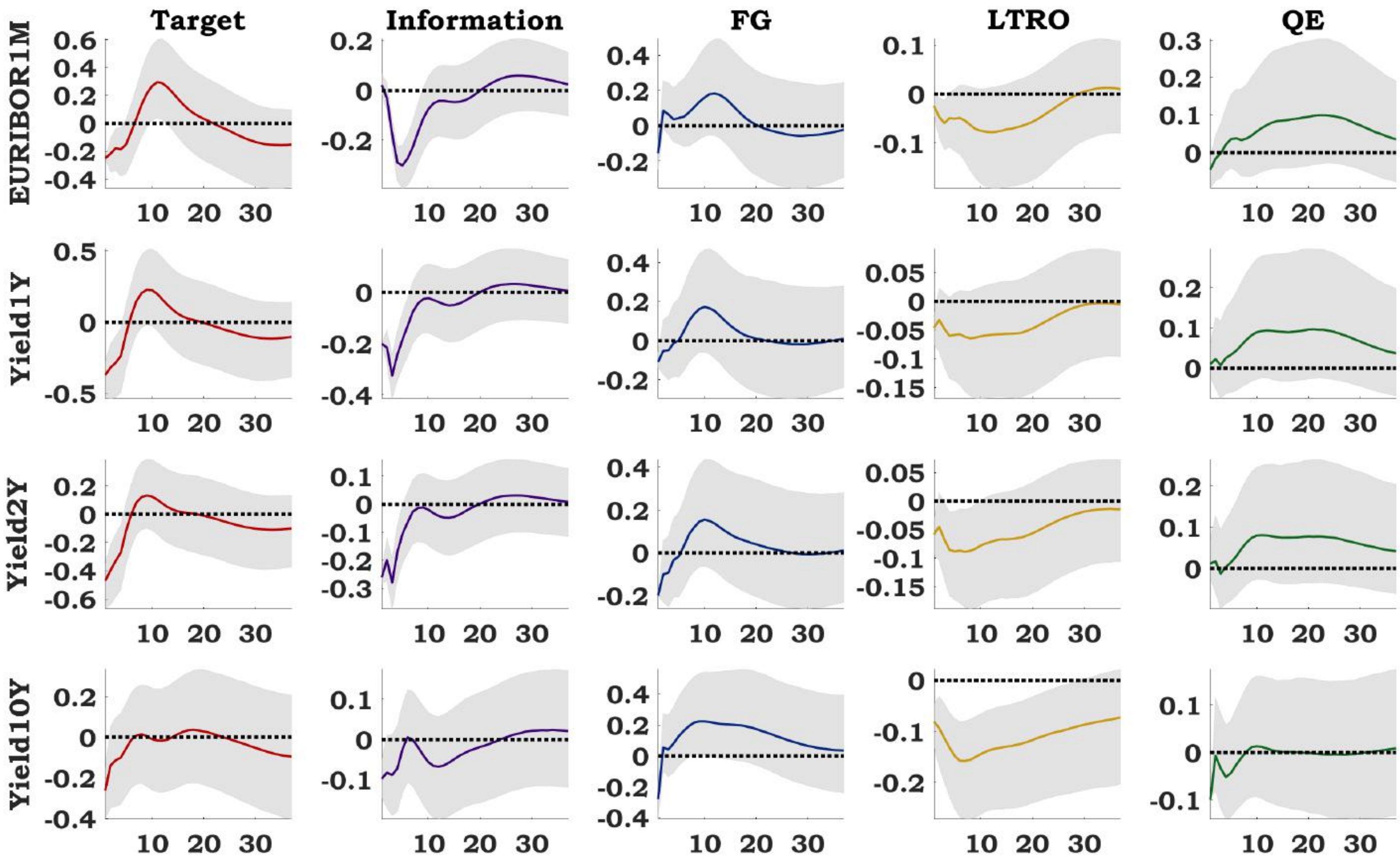


Figure 14: Responses of euro area inflation and expectations to multi-dimensional monetary policy

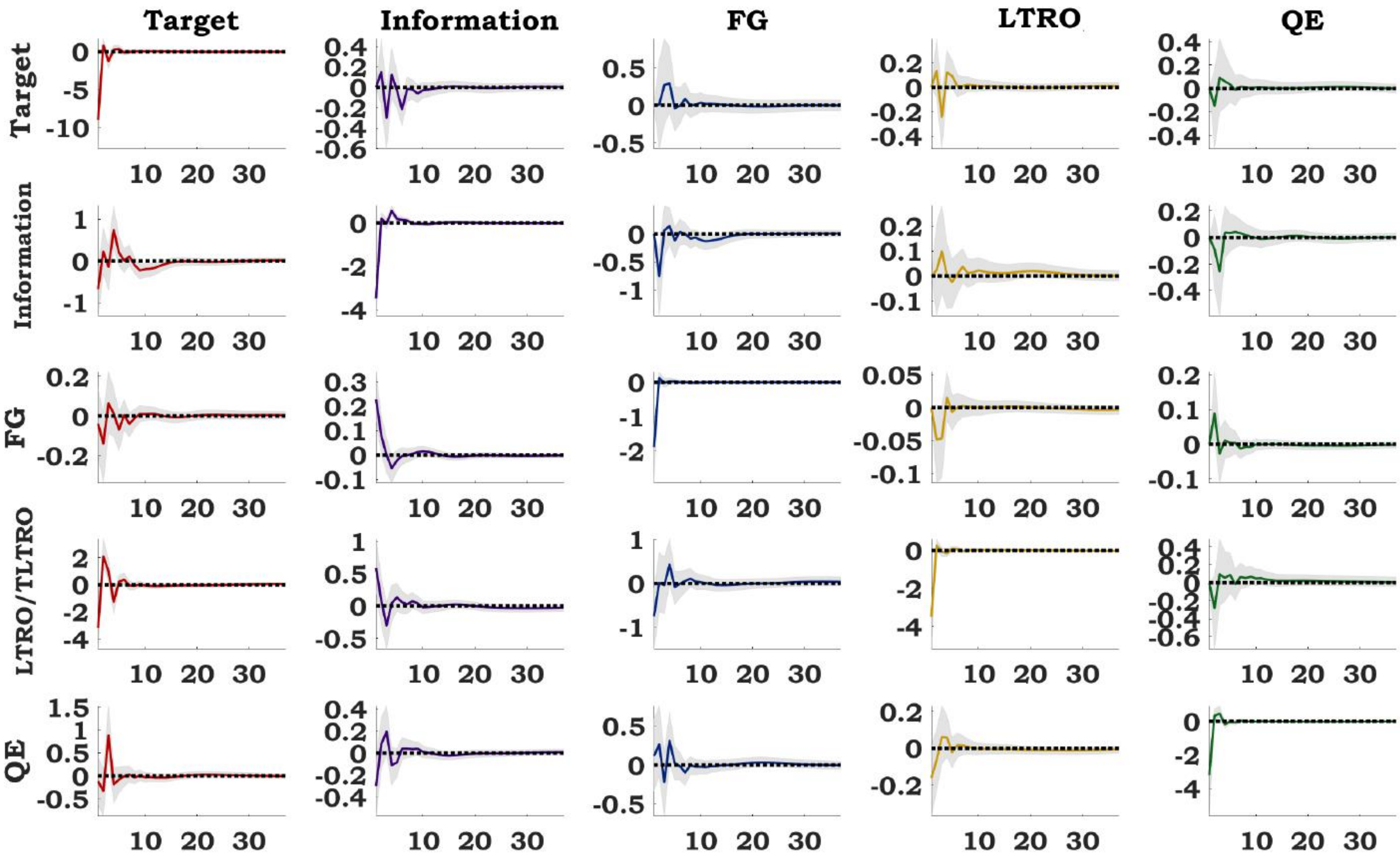


Figure 15: Responses of euro area inflation and expectations to multi-dimensional monetary policy