Freie Universität Berlin

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

Catalina Martínez-Hernández

School of Business & Economics
Discussion Paper

Economics

2020/18

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

Catalina Martínez-Hernández†‡

Job Market Paper

This version: October 30, 2020
Latest version here

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 the current low-inflation, low-interest-rate scenario. 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. I carry out my analysis based on a high-frequency identification and the estimation of a large Bayesian Vector Autoregression. I find evidence of re-anchored expectations as response to quantitative easing and forward guidance, i.e. forecasters revise their long-run expectations upwards. Consequently, inflation increases, 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

*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 would like to thank Robin Braun, Flora Budianto, Matteo Ciccarelli, Max Diegel, Marc Giannoni, Karel Mertens, Dieter Nautz and 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.

†Freie Universität Berlin, Boltzmannstr. 20, 14195 Berlin

‡DIW Berlin, Mohrenstr. 38, 10117 Berlin,

✉ Email: cmartinezhernandez24@gmail.com

1 Introduction

After the introduction of the euro, the European Central Bank (ECB) is subject to its mandate of price stability for the euro area. Specifically, its current policy objective is to maintain inflation rates "below, but close to 2%" over the medium term. However, for most of the past decade, inflation and inflation expectations have remained low, on average lower than the ECB's target and even reaching deflation episodes.[1] Furthermore, the euro area has faced an era of low interest rates, which has constrained the ECB's policy space. In order to keep on an ample degree of accommodation, the ECB has introduced several non-conventional tools for transmitting its monetary policy stance. Although the nature of such policies may differ, they all share the ultimate goal of achieving price stability and anchoring expectations to the ECB's target.

Since the milestone contribution of Sims (1992), the effects of conventional monetary policy on the macroeconomy are commonly studied through the lenses of Vector Autoregressions (VAR). However, the introduction of the effective-lower bound has risen complications in identifying unconventional monetary policy shocks. While the effects of conventional monetary policy shocks on price stability are well studied, e.g. the price puzzle, (Eichenbaum (1992), Hanson (2004), Bernanke, Boivin, and Eliasz (2005)), the effects of unconventional monetary policy shocks remain a subject of constant debate. Due to the challenges of disentangling the individual policies, a big strand of the literature identifies a unique unconventional monetary policy shock summarising the multidimensionality of the ECB's toolkit in a single shock; therefore assuming that all tools have the same impact, as in Corsetti, Duarte, and Mann (2018) and Hachula, Piffer, and Rieth (2019). Another approach is to narrow the focus to a single or a block of tools and analyse their impact on macroeconomic and financial variables, for instance Campbell et al. (2012), Boeckx, Dossche, and Peersman (2017), Burriel and Galesi (2018), Jarociński and Karadi (2020), Andrade and Ferroni (2020), among many others. The work of Rostagno et al. (2019) and Altavilla et al. (2019) are prominent and recent examples which integrate the multidimensional feature of monetary policy in their analyses. Nevertheless, they do not directly assess the role of inflation expectations for the transmission of monetary policy.

In this paper, I study the effects of conventional and unconventional monetary policy 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 evaluating its implica-

[1] For an outlook, see graphs in appendix A.

tions on price stability and the anchoring of inflation expectations. I propose a novel high-frequency identification of a conventional - interest rate target - and four different types of unconventional monetary policy shocks - information, forward guidance, Longer-Term Refinancing Operations (LTRO) and quantitative easing (QE). Specifically, I carry out my analysis based on a two-step approach which combines a high-frequency identification strategy and the estimation of a large Bayesian VAR; whereas the mixture of macroeconomic and financial variables allows to have a real-world picture of the full dynamics of the euro area economy which includes the possibility of several transmission channels.

I find the following results. Long-term inflation expectations of forecasters anchor after expansionary forward guidance and QE shocks hit the economy. Consequently, for the case of forward guidance, inflation increases and remains significant one year after the shock. This result stresses the importance of inflation expectations as a monetary policy transmission channel since after re-estimating the model without expectations, the response of inflation weakens. Additionally, I find evidence of the ECB's information channel because after an information shock that decreases interest rates and inflation, consumers and forecasters revise their inflation expectations downwards. Moreover, I obtain that consumers and forecasters contemporaneously react in opposite ways to LTRO and QE shocks. In detail, 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. However, consumers learn and mildly revise their expectations upwards a few months after a forward guidance shock. Overall, my results highlight the power of influencing inflation expectations for the transmission of monetary policy and bring 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)).

The outline of this paper is the following. Section 2 reviews the exiting literature and highlights my contributions. In section 3, I explain my identification strategy whereas in section 4 I explain the internal instrument approach and the estimation a large Bayesian VAR. Section 5 gives 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), inter alia). This is due to the availability of asset prices in an intra-daily and daily frequencies, whereby it is possible to exploit the rich information contained in futures and swap rates for identifying a measure of monetary policy shocks over different windows. In this paper, I compute a new set of monetary policy proxies (target, information, forward guidance, LTRO and QE) for the euro area inspired by the trilogy of papers: Gürkaynak, Sack, and Swanson (2005), Swanson (2017) and Altavilla et al. (2019).[2]

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.[3] 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 crisis period and by restricting it to not react to the current level of the fed funds rate. 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 sur-

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

[3]A statement is a press release emitted every six weeks on the last day of an FOMC meeting where the members make a decision regarding monetary policy in the US.

[4]Monetary policy decisions from the Governing Council meeting are communicated in two

prises 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 proxy also includes timing effects. Furthermore, I identify an additional factor that isolates the effects of policies implemented to provide funding and 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

phases. First, a press release is published at 13:45 CET containing policy decisions. Afterwards, 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

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 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 scenario in the euro area, this isolation is crucial for a simultaneous comparison among policies.

function from private-sector agents.

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 identification of the following shocks:

Target. Before the zero-lower-bound period, 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 I tag it as conventional monetary policy shock.

Information. This shock represents the response of the markets to news regarding the view of the central bank about the current and future state of the economy. It is also known as Delphic forward guidance (see Campbell et al. (2012)).

Forward guidance. It corresponds to the reaction of market participants to statements referring the commitment from the central bank 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 with the goal of avoiding a credit crunch, especially in periphery countries. Specifically these policies are the Securities Purchase Programme (SMP), Outright Monetary Transactions (OMT) and Longer-Term Refinancing Operations (LTRO).

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

Given the fact that announcements about changes in the policy rates are delivered in the press release, I define the target factor, F_t^{Target}, as the surprises in the price of the OIS at one month maturity during this window. Similarly, this practice is also carried out by Rogers, Scotti, and Wright (2018) and Altavilla et al. (2019).

The second block of proxies captures some non-standard measures adopted by the ECB. Whereas I construct it based on the surprises of thirty four asset and bond prices over the whole monetary policy event window,[7] spanning form January 2002 to February 2020. Specifically, I consider 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;[8] 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 shocks uniquely using the surprises from the press conference window because from March 2016 onwards information about unconventional policies are included 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 to reassure funding in the aftermath of the Sovereign Debt Crisis, especially in periphery countries. For this reason, Wright (2019) calls it *save the euro* shock.

Defining T^* as the number of Governing Council meetings, I assume that the matrix of $T^* \times 34$ 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 $T^* \times r$, Λ is a $34 \times r$ loading matrix and ξ is the idiosyncratic component with diagonal covariance matrix R. As it is standard 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 $r = 4$.

[7]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)).

[8]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.

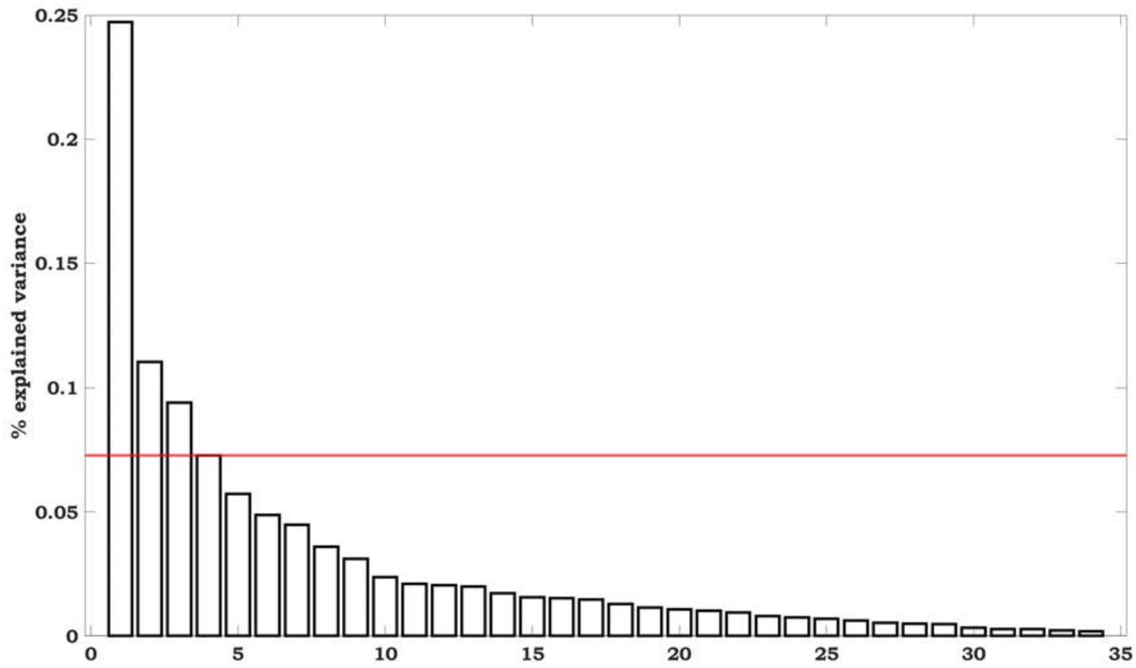


Figure 1: Scree plot (Monetary Policy event window)

The first part of the right-hand-side of equation (1) is called the common component, $\chi = F\Lambda'$ and it suffers from an identification problem. To see this, let us consider a $r \times r$ rotation matrix Q, such that $Q'Q = I_r$. Then, we can define another common component matrix as $\chi^* = F^*\Lambda^{*\prime}$, with $F^* = FQ$ and $\Lambda^* = \Lambda Q$. The model with this new set of factors and loadings is observationally equivalent to equation (1). In order interpret the factors, we must find a unique rotation matrix that fulfils a set of restrictions with an economic meaning. In particular, I want to interpret the five factors in the order: Information, forward guidance, LTRO and QE.

Firstly, I split the factors into two blocks. The first one correspond to the communication factors (information and forward guidance) whereas the second block includes the two balance-sheet factors (LTRO and QE). Without loss of generality I denote the second block as $\mathcal{F}$. The policies covered in the second block 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 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 forward guidance, LTRO and QE 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, whereas the majority of the analyses focuses on horizons larger than six months. I remain agnostic about the impact of all surprises on the information factor.The previous set of restrictions does not guarantee the identification between LTRO and QE factors. Given the fact that QE is aimed at influencing the long end of the yield curve, I additionally restrict the OIS of six months maturity not to load on the QE factor. Moreover, it is important to highlight that the identification among the forward guidance 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.

In order to find a unique rotation, Q^*, that incorporates the restrictions above, I consider the following optimisation problem for the pre-crisis period:

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

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:

$$
\Lambda^* = \begin{bmatrix} \text{Info} & \text{FG} & \text{LTRO} & \text{QE} \\ * & 0 & 0 & 0 \\ * & * & * & 0 \\ * & * & * & * \\ \vdots & \vdots & \vdots & \vdots \\ * & * & * & * \end{bmatrix} \begin{matrix} \\ \text{OIS1M} \\ \text{OIS3M} \\ \text{OIS6M} \\ \vdots \\ \\ \end{matrix}
$$

where the * denotes an unrestricted value.

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. Therefore, as a next step I sample the rotated factors and loadings through Bayesian methods based on two blocks. First, I denote the orthogonalised factors as $\tilde{F}_{k,t}$, for $k = \{$information, forward guidance, LTRO, QE$\}$. I obtain draws of the orthogonalised factors through the following linear regressions:

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

based on a Normal - inverse Gamma prior. I obtain the g-th draw of the orthogonalised factors by defining them as the residual of each regression, i.e. $\tilde{F}_{k,t}^{(g)} = F_{k,t} - \beta_k^{(g)} F_t^{Target} - \sum_{j=1}^{k-1} \gamma_j^{(g)} \tilde{F}_{j,t}^{(g)}$. In the second block, I sample 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 $i = 1, \cdots, 34$. Similarly as for the factors, I also consider a Normal-inverse Gamma prior.

After the estimation, I normalise the loadings of the target, information, forward guidance and QE factors to unity for the one-month, one-year, five- and ten-year OIS, respectively. Moreover, I normalise the LTRO factor such that the five-year German bond yield equals one.

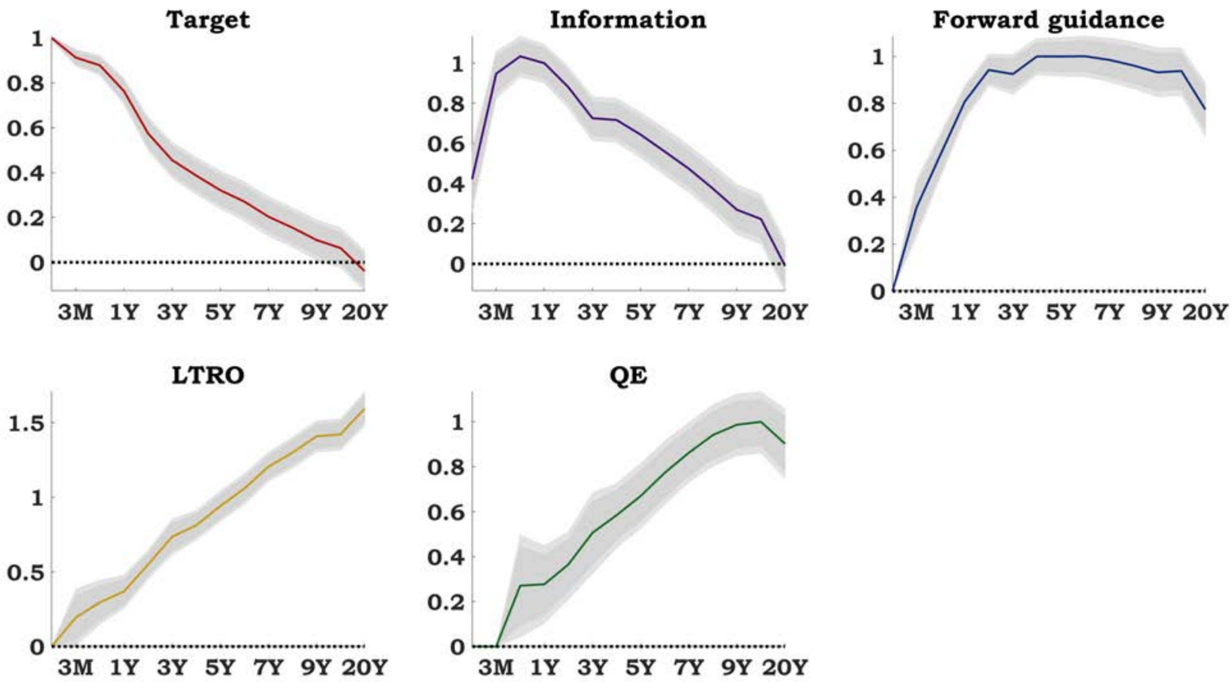


Figure 2: Loadings and the OIS term structure

Note: The shaded areas correspond to the 68% and 90% percentiles of the posterior distribution of the normalised loadings whereas 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 peak at the six-month maturity and the importance of long-end maturities decreases fast such that the effect on the 20-year OIS rate is not significant. Contrary, the relevance of medium- to long-term maturities reach a plateau for the loadings associated to the forward guidance factor. Moreover, the power of longer-term maturities is greater for the loadings linked to the LTRO and QE factors.

In Table 1 I show the full set of orthogonalised and normalised loadings. As expected from macroeconomic theory, in the presence of a conventional monetary policy shock, here measured by the target factor, short-term interest rates and stock market prices react in the opposite direction. When the shock is contractionary (expansionary), sovereign bond yields increase (decrease) and the euro appreciates (depreciates).

In contrast to Kerssenfischer (2019), Jarociński and Karadi (2020) and Andrade and Ferroni (2020), I find a negative relationship between the stock market and interest rates for the information loadings; and a positive relation for the forward guidance loadings. I would like to stress three points regarding these results. First, as stressed by Kerssenfischer (2019), the impact of information shocks on the stock market is a priori ambiguous. Therefore, my results may be governed by the surprise window considered in the EA-MPD, which deviates from the papers previously described. Second, identification of information shocks furthermore hinges on the relationship between expectations and interest rates, as in Andrade and Ferroni (2020). My results however are in line with the literature as they move expectations and interest rates in the same direction (see section 5.2). Third, my results shed light on a signalling effect in the forward guidance factor. The normalisation of the loadings is linked to contractionary forward guidance, i.e. long term interest rates are expected to increase. Therefore, the positive reaction of stock prices signifies that market participants buy now given that they expect even higher rates in the future.

Table 1: Orthogonalised and normalised factor loadings

		Target	Information	FG	LTRO	QE
OIS	OIS1M	1.00	0.42	0.00	0.00	0.00
	OIS3M	0.91	0.95	0.36	0.19	0.00
	OIS6M	0.88	1.03	0.58	0.30	0.27
	OIS1Y	0.76	1.00	0.81	0.37	0.28
	OIS2Y	0.58	0.88	0.94	0.55	0.37
	OIS3Y	0.46	0.73	0.92	0.74	0.51
	OIS4Y	0.39	0.72	1.00	0.81	0.58
	OIS5Y	0.32	0.64	1.00	0.94	0.67
	OIS6Y	0.27	0.56	1.00	1.06	0.77
	OIS7Y	0.20	0.47	0.99	1.21	0.86
	OIS8Y	0.15	0.38	0.96	1.30	0.94
	OIS9Y	0.10	0.27	0.93	1.41	0.99
	OIS10Y	0.06	0.22	0.94	1.42	1.00
	OIS20Y	-0.04	-0.01	0.77	1.60	0.90
Government Bond Yields	DE3M	0.60	0.35	-0.03	-0.20	0.22
	DE6M	0.67	1.10	0.38	0.09	0.29
	DE1Y	0.70	0.98	0.71	0.33	0.33
	DE2Y	0.44	0.87	0.92	0.55	0.47
	DE5Y	0.24	0.64	0.95	1.00	0.72
	DE10Y	0.02	0.22	0.83	1.53	1.26
	FR2Y	0.44	0.86	0.89	0.57	0.46
	FR5Y	0.30	0.59	0.92	0.84	0.97
	FR10Y	0.03	0.15	0.79	1.22	1.73
	IT2Y	0.28	0.47	0.73	**-0.46**	1.58
	IT5Y	0.19	0.23	0.67	**-0.49**	2.04
	IT10Y	0.03	0.04	0.48	**-0.25**	2.57
	ES2Y	0.37	0.57	0.83	**-0.42**	1.37
	ES5Y	0.20	0.31	0.80	**-0.38**	1.89
	ES10Y	0.15	0.05	0.57	**-0.27**	2.32
Stock Market	STOXX50	-0.25	-0.32	0.45	0.40	-2.12
	SX7E	-0.11	-0.28	0.31	1.02	-1.57
Exchange Rates	EURUSD	0.16	0.70	-0.22	1.33	1.14
	EURGBP	0.21	0.67	-0.14	1.31	1.14
	EURJPY	0.18	0.67	-0.02	1.55	0.96

Followed by the terminology in the Economic Bulletin ECB (2015), our LTRO and QE factors are considered proxies for active balance sheet shocks.[9] 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 distinguished 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 like Italy and Spain in opposite directions. I find evidence of this characteristic depicted by the bold numbers in Table 1. This means that the LTRO factor increases the OIS and the five-year German and French Government bonds yields. At the same time, it declines the Government bond yields of Italy and Spain. Therefore, our 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 complete 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 the different large-asset purchasing programmes introduced by the ECB.

[9] A passive balance sheet is considered as the transactions the ECB conduct in order 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.

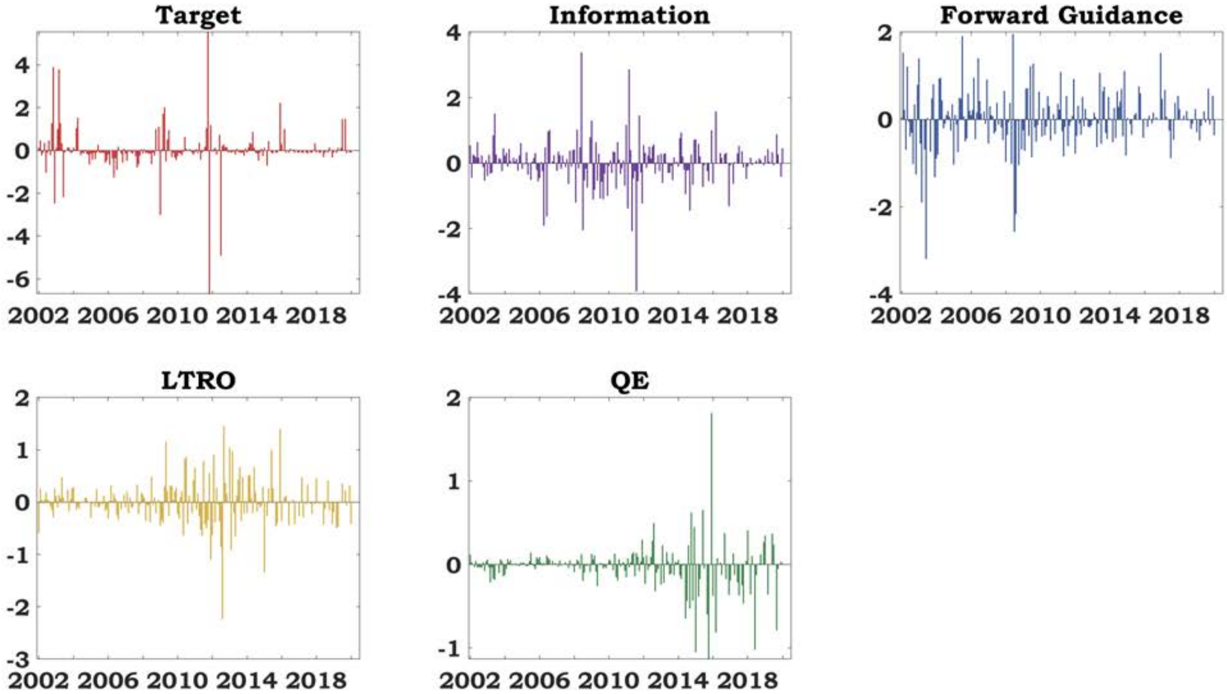


Figure 3: Proxies for conventional and unconventional monetary policy shocks

Note: The bars represent the median posterior distribution of the orthogonalized, normalized 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 closer real-world picture of the full dynamics of the economy, I consider a wide range of macroeconomic and financial variables. Therefore, I concentrate my study based on a large Bayesian VAR and explain its estimation in the next subsection.

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.

Due to a high degree of parametrisation in large systems, the estimation of VARs is not feasible under conventional methods and therefore we must apply a dimension reduction (sparse) or a shrinkage (dense) technique.[10] 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 summarize 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 VAR where the econometrician relies on the implementation of Bayesian shrinkage. In this paper, I consider the second approach since it neither depends on stationary transformations of the variables nor in normalisation of the factors for analysing the results of the model.[11]

The literature on large Bayesian VARs can be tracked back to the articles of Litterman (1980, 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. However, the selection of the degree of shrinkage for larger models was formally introduced 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. In more detail, they estimate a large Bayesian VAR based

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

[11] 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.

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 $\alpha = \text{vec}(A'_+)$ and the inverse Wishart distribution is parametrised with degrees of freedom $d = N + 2$ such that the mean of Σ exists.[12] The authors also set the scale matrix to be a diagonal matrix, i.e. $\Psi = \text{diag}(\psi_1, \cdots, \psi_N)$. 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 $a = \text{vec}(\underline{A})$ 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, they 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

[12]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:

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

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

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 draws converge to Least Squares estimates. For lags $\ell > 1$, the hyperparameter θ_2 penalises the more distant lags.

The last two priors are extensions of the Minnesota prior and both are implemented by adding artificial or dummy observations to the original data.[13] 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 and therefore there are no cointegration relationships among the variables. On the contrary 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 sample T_0, $\bar{y}_{0,i}$, is a good model to forecast y_i. The tightness of the prior is

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

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^* which 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 equal $\tilde{T} = T + T_d$. 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 prior and its refinements 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 close-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. Secondly, given the hyperparameters they draw the parameters of the VAR based on (13) and (14).

4.2 The *internal* instrument approach

The literature studying large Bayesian structural VARs has relied on identifying macroeconomic shocks through a recursive approach.[14] 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.[15] 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.[16] The main idea of this model is to augment the VAR by additional equations representing the relationship between instruments and the shocks of interest.

Let us denote the $N \times 1$ vector of structural shocks as $\varepsilon_t \sim \mathcal{N}(0, I_N)$ which I split into two blocks

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

without loss of generality, I denote $\varepsilon_{1,t}$ as the $k \times 1$ block of shocks of interest. In a similar fashion, $\varepsilon_{2,t}$ corresponds to the $(N-k) \times 1$ vector of remaining shocks. As showed by Stock and Watson (2018), under invertibility,[17] we can bridge the reduced-form errors from model (5) with the structural shocks as follows:

$$\begin{aligned} u_t &= H\varepsilon_t \\ &= H_1\varepsilon_{1,t} + H_2\varepsilon_{2,t}. \end{aligned} \tag{15}$$

Where the nonsingular matrix $H = [H_1 \quad H_2]$ captures the impact effects of structural shocks on the endogenous variables, y_t. The dimensions of the blocks H_1 and H_2 are $N \times k$ and $N \times (N-k)$, respectively. The impact matrix is obtained by decomposing the reduced-form covariance matrix as $\Sigma = HH'$. Thus, the identification of the shocks of interest $\varepsilon_{1,t}$ is achieved through the identification of the columns of matrix H_1.

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

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

[16] 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).

[17] A VAR is invertible when the structural shocks can be written as a linear combination of the reduced-form errors (see Kilian and Lütkepohl (2017), Chapter 17), in other words, the shocks can be recovered by current and past values of the data.

Now, we denote the $k \times 1$ vector of proxies as m_t and focus on its relationship between the shocks of interest which is represented by the following equation:

$$m_t = \Phi\varepsilon_{1,t} + \nu_t, \quad \nu_t \sim \mathcal{N}(0, \Omega). \tag{16}$$

The $k \times k$ matrix Φ is nonsingular and $\varepsilon_{1,t}$ and ν_t are uncorrelated. As explained by Stock and Watson (2012) and Mertens and Ravn (2012), valid instruments must fulfil the following conditions:

$$\mathbb{E}[m_t\varepsilon_{1,t}] = \Phi \tag{17}$$

$$\mathbb{E}[m_t\varepsilon_{2,t}] = 0. \tag{18}$$

Equation (17) corresponds to the *relevance* condition which means that the instruments need to be correlated with the shocks of interest. On the other hand, the remaining shocks ($\varepsilon_{2,t}$) must be uncorrelated to the instruments, this condition is called *orthogonality* and is summarised by equation (18). In addition to these conditions, it is typically assumed that the proxy is not serially autocorrelated.

Stock and Watson (2018) stress the relevance of invertibility for obtaining consistent impulse response functions. Consequently, they provide a Hausman-type test of invertibility by comparing the results from a Proxy-VAR and a model based on local projections after controlling for the same endogenous variables. Thus, we would find evidence for invertibility when we cannot reject the null that these two models yield the same impulse responses. Alternatively, Noh (2017) tests invertibility of the Proxy-VAR by assuring that the proxies have no forecasting power on the endogenous variables, in similar lines as Forni and Gambetti (2014) for VARs and also highlighted by Stock and Watson (2018).[18]

Noh (2017) and Plagborg-Møller and Wolf (2019a) independently show that forward guidance shocks are not invertible. The main reason is that we can conceive forward guidance shocks as a type of news shocks, since the central bank releases “news” about the future path of interest rates. In fact, as showed by Leeper, Walker, and Yang (2013) for the case of anticipated fiscal shocks, there is a mismatch of information between agents and econometricians. When news are released, agents make decisions taking into consideration the latest incoming information. On the other hand, the macroeconomic variables available to the econometrician does not necessarily incorporate the

[18]For a further discussion of problems related to partial identification and invertibility see Giacomini and Kitagawa (2018), Giacomini, Kitagawa, and Read (2019) and Miranda-Agrippino and Ricco (2019).

news released by the central bank in that particular month. The authors also clarify that under this scenario, consumers discount recent news more heavily in comparison to older news. In contrast, the econometrician discounts older news relative to the latest available information. As a consequence, the econometrician would not be able to recover the news shock with current and past values of the data. In our framework, with the exception of the target shock, all shocks of interest can be interpreted as news shocks. As a consequence, the use of a Proxy-VAR in our context is not feasible due to the nature of the shocks we want to analyse. For this reason, we rely on an alternative methodology known as the "internal" instrument approach.

Following Noh (2017) and Paul (2019), the idea of this technique is to augment the VAR in equation (5) with the proxies as exogenous variables. Therefore, they individually consider the following VARX model:[19]

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \Gamma_0 m_t + \cdots + \Gamma_q m_{t-q} + u_t, \quad u_t \sim \mathcal{N}(0, \Sigma) \tag{19}$$

For $q \leq p$, the matrices $\Gamma_0, \cdots, \Gamma_q$ contain the parameters governing the effect of present and lag values of the proxies into the endogenous variables. Therefore, in this framework, the matrix Γ_0 gives the contemporary response of the endogenous variables to a change in the proxies. For the general case of more than one instrument, additional restrictions need to be imposed on Γ_0 in order to achieve identification. Noh (2017) and Paul (2019) develop the conditions under which the VARX 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) $\Gamma_j = 0$, for $j = 1, \ldots, q$.

Prior to estimating equation (19), Paul (2019) orthogonalise the proxies to lags of the endogenous variables. Hence, we can generally assume that the proxies evolve as follows:

$$m_t = \kappa + B_1 m_{t-1} + \cdots + B_s m_{t-s} + C_1 y_{t-1} + \cdots C_l y_{t-l} + w_t, \quad w_t \sim \mathcal{N}(0, \Omega) \tag{20}$$

with $s, l \leq p$. When the proxies are serially uncorrelated and orthogonal to each other and to the lags of the endogenous variables, the parameters $\kappa = 0$, $B_i = 0$ and $C_j = 0$, for $i = 1, \cdots, s$ and $j = 1, \cdots, l$. This case would correspond to the "observable shock" case described by Stock and Watson (2018). A prominent example of this model is the recent paper by Jarociński and Karadi (2020). Taking stock, one can write the most general internal instru-

[19]For an overview of VARX models see Lütkepohl (2005), Chapter 10.

ment approach model in the following equation:[20]

$$\begin{bmatrix} m_t \\ y_t \end{bmatrix} = \begin{bmatrix} \kappa^* \\ c^* \end{bmatrix} + \begin{bmatrix} B_1^* & C_1^* \\ \Gamma_1^* & A_1^* \end{bmatrix} \begin{bmatrix} m_{t-1} \\ y_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} B_p^* & C_p^* \\ \Gamma_p^* & A_p^* \end{bmatrix} \begin{bmatrix} m_{t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} w_t \\ u_t \end{bmatrix} \tag{21}$$

$$\text{with} \quad \begin{bmatrix} w_t \\ u_t \end{bmatrix} \sim \mathcal{N}(0, \zeta)$$

The matrices of parameters are defined as follows:

$$\begin{bmatrix} B_i^* & C_i^* \\ \Gamma_i^* & A_i^* \end{bmatrix} = \begin{bmatrix} I_k & 0 \\ -\Gamma_0 & I_N \end{bmatrix} \begin{bmatrix} B_i & C_i \\ \Gamma_i & A_i \end{bmatrix}, \tag{22}$$

where matrices B_i^*, C_i^* and Γ_i^* equal zero for i larger than s, l and q, respectively. In this most general case of the internal instrument approach, the proxies are embedded in the VAR and for this reason it is also known as hybrid VAR. In this setup, the computation of the impulse response function relies on the Choleski decomposition of the covariance matrix ζ. As pointed out by Plagborg-Møller and Wolf (2019b), this technique yields valid impulse responses regardless of the invertibility of the shocks.

I treat equation (19) 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.[21] 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, 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.[22] For

[20]For further details about equation (21) see appendix C

[21]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).

[22]For detailed information about the data set see appendix D.

capturing the 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.[23] 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)) using monthly expectations at one year horizon and monthly perceptions from EB as bridge variables.[24]

The selection of these variables activates several transmission channels, for instance the exchange rate, the interest rate channels among others.

5.2 Specification and results from the hybrid BVAR

This section presents results from the estimation of the hybrid Bayesian VAR from equation (21) with three lags.[25] As robustness checks, I estimated the model using one through thirteen lags, however our parsimonious selection already eliminates the serial correlation among the block of reduced-form errors linked to the structural shocks (see top panel of graph 8 from Appendix E). The estimation is based on 50000 draws and I keep the last 25000 for inference.[26] 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

[23] 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.

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

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

[26] Appendix F presents a convergence test of the MCMC algorithm.

area. Furthermore, Figures 10 through 14 from appendix G 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. Consumers' expectations decrease contemporaneously but pick up three months after the shock. On the other hand, my results suggest evidence in favour of the central bank's information channel since 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 negative private information or news regarding their current and future view on the state of the economy, professional forecasters become more pessimistic and revise their short- and long-term expectations downwards. The previous results stress the importance of inflation expectations as a key component for transmitting monetary policy to prices.

In 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 12 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, it is not clear the direct effect of such policies for increasing inflation and expectations.[27] This paper sheds new light about the impact of such policies summarised in the LTRO shock. As shown in the forth 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

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

the shock which introduces risks for the anchoring of inflation expectations. These results have strong policy implications, given the fact that LTROs were not implemented with the goal of having a direct impact inflation and expectations. On the other hand, QE shocks are effective in increasing long-term inflation expectations of forecasters. This is a positive piece of news because it can get interpreted as a re-anchoring of inflation expectations.

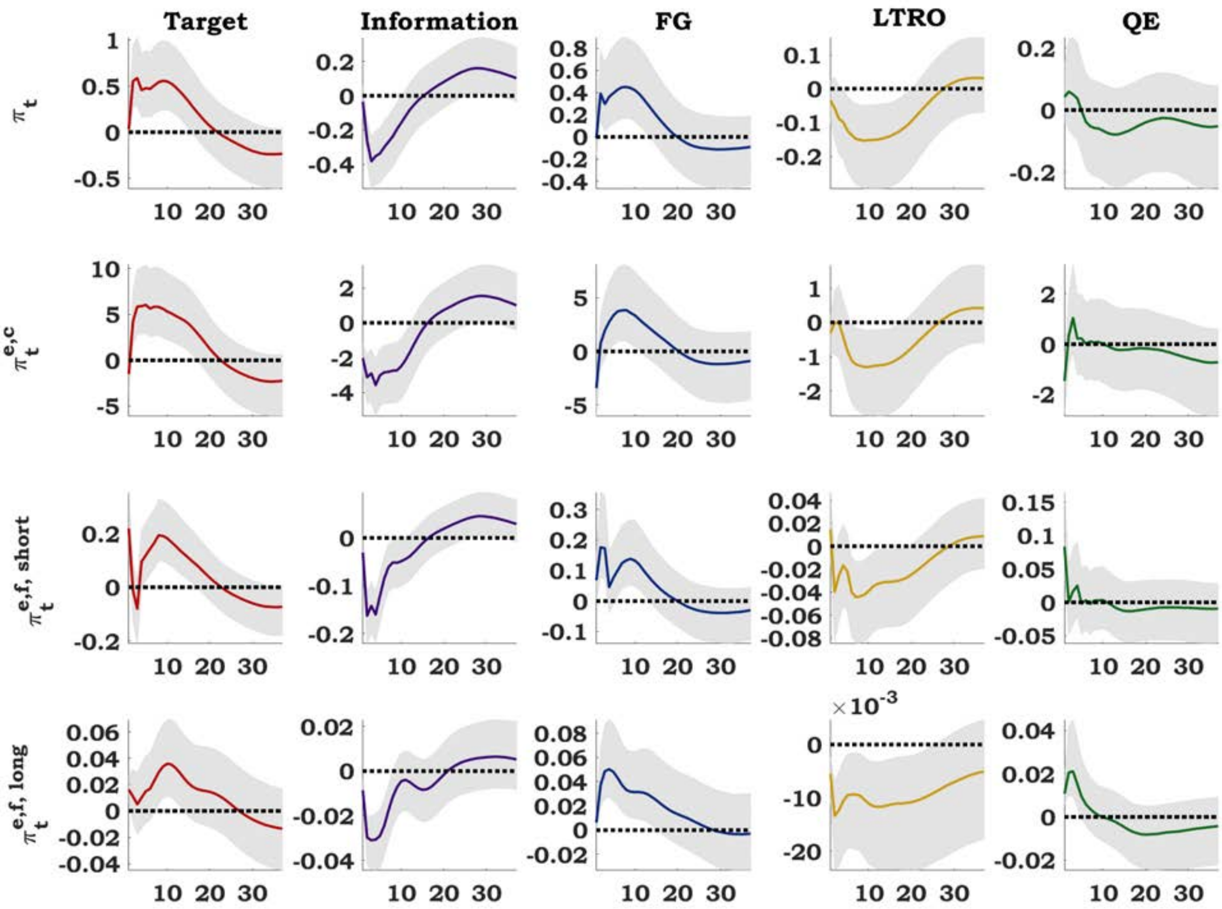


Figure 4: Responses of euro area inflation and expectations to multi-dimensional monetary policy

Note: This figure shows the impulse responses of expansionary target (red), information (purple), Forward guidance (blue) and QE (green) shocks, normalized to a decrease of 25 basis points in the one month rate, 15 basis points in the one and two year rate and 10 basis points in the 10 year rate, respectively. The LTRO/TLRTO 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

5.3 Policy implications

As a response to the Great Recession and the Sovereign Debt Crisis, the ECB has conducted a series of unconventional monetary policy tools in order to provide economic stimulus for addressing the undershooting of inflation and inflation expectations. In spite of the high degree of policy accommodation, inflation has 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.

As shown in the previous section, 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. The policy implication of this result is strong because we can think of long-term inflation expectations as a successful monetary policy transmission channel.

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

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)). The fact that consumers and forecasters react in contrary directions urge for a reform in the communication strategy of the ECB.

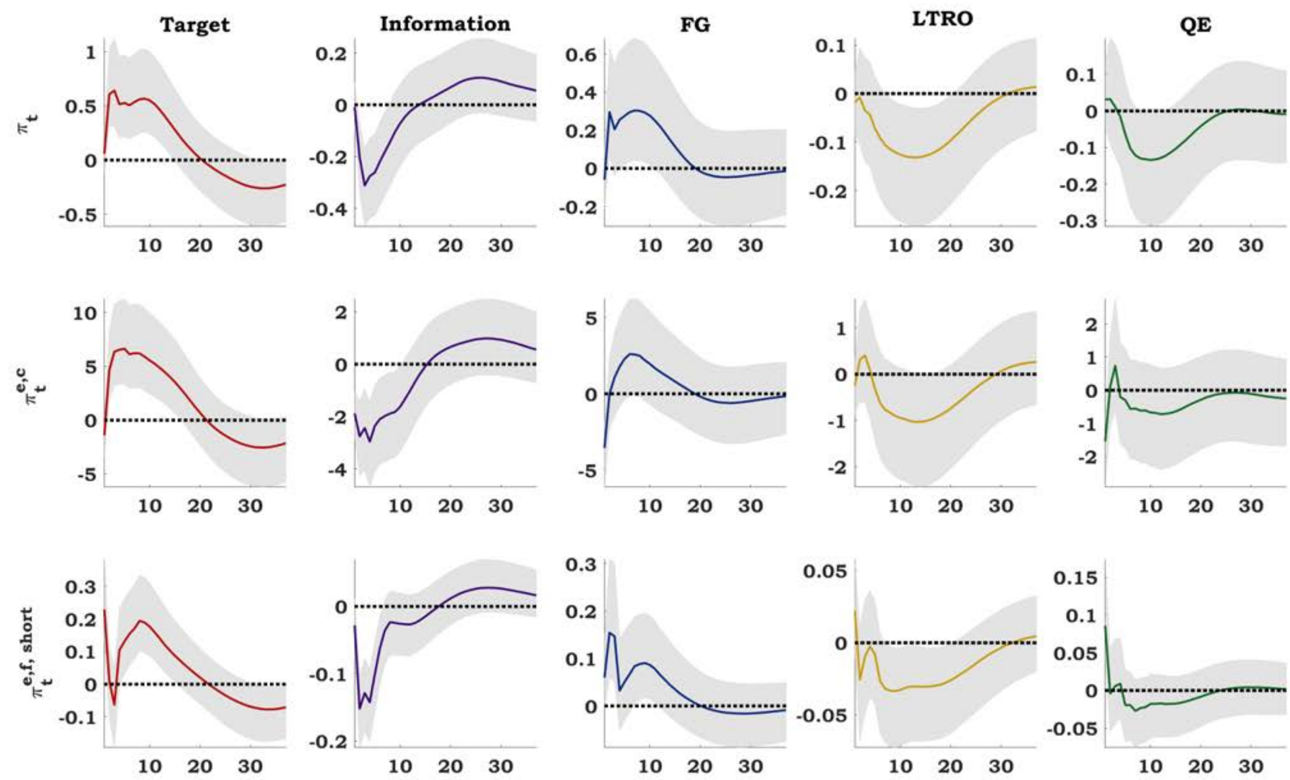


Figure 5: Responses of euro area inflation and short-term expectations of consumers and forecasters to multi-dimensional monetary policy.

6 Conclusions

In this paper, I study the reaction of inflation and inflation expectations to a conventional and four types of unconventional monetary policy shocks (information, forward guidance, policies to ease lending conditions and quantitative easing). Given the current low-inflation-low-expectations scenario combined with the effective lower bound, this study is crucial for analysing 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 long-term inflation expectations of forecasters re-anchor as a response to forward guidance and quantitative easing shocks. Moreover, inflation increases and remain significant one year after a forward guidance shock hit 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, the way how the ECB communicates its view on current economic conditions is significant for the transmission of monetary policy through the expectations channel. This rules in favour to the recent paper by Candia, Coibion, and Gorodnichenko (2020) who urge for more transparent communication strategies in order to avoid misinterpretation of information.

Whilst this paper disseminates among several types of unconventional monetary policies, there is still space for an even deeper analysis, for instance by 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 isolates 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. This topic is however left for future research.

References

ALTAVILLA, C., ET AL. (2019): "Measuring euro area monetary policy," *Journal of Monetary Economics*, 108, 162 – 179.

ALTAVILLA, C., D. GIANNONE, AND M. LENZA (2016): "The Financial and Macroeconomic Effects of the OMT Announcements," *International Journal of Central Banking*.

ANDRADE, P., AND F. FERRONI (2020): "Delphic and Odyssean monetary policy shocks: Evidence from the euro area," *Journal of Monetary Economics*.

ARIAS, J., J. RUBIO-RAMÍREZ, AND D. F. WAGGONER (2020): "Inference in Bayesian Proxy-SVARs," Working paper.

ARIOLI, R., C. BATES, H. DIEDEN, ET AL. (2017): "EU consumers' quantitative inflation perceptions and expectations: An evaluation," Discussion paper, ECB Occasional Paper.

Bańbura, M., D. Giannone, and L. Reichlin (2010): "Large Bayesian vector auto regressions," *Journal of Applied Econometrics*, 25(1), 71–92.

Bauer, M. D., and E. T. Swanson (2020): "The Fed's Response to Economic News Explains the" Fed Information Effect"," Discussion paper, National Bureau of Economic Research.

Bernanke, B. S., and J. Boivin (2003): "Monetary policy in a data-rich environment," *Journal of Monetary Economics*, 50(3), 525–546.

Bernanke, B. S., J. Boivin, and P. Eliasz (2005): "Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach," *The Quarterly journal of economics*, 120(1), 387–422.

Boeckx, J., M. Dossche, and G. Peersman (2017): "Effectiveness and Transmission of the ECB's Balance Sheet Policies," *International Journal of Central Banking*.

Burriel, P., and A. Galesi (2018): "Uncovering the heterogeneous effects of ECB unconventional monetary policies across euro area countries," *European Economic Review*, 101, 210–229.

Caldara, D., and E. Herbst (2019): "Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs," *American Economic Journal: Macroeconomics*, 11(1), 157–92.

Campbell, J. R., et al. (2012): "Macroeconomic effects of federal reserve forward guidance [with comments and discussion]," *Brookings Papers on Economic Activity*, pp. 1–80.

Candia, B., O. Coibion, and Y. Gorodnichenko (2020): "Communication and the beliefs of economic agents," Working paper.

Canova, F., and M. Ciccarelli (2013): *Panel Vector Autoregressive Models: A Survey*. Emerald Group Publishing Limited.

Chow, G. C., and A.-l. Lin (1971): "Best linear unbiased interpolation, distribution, and extrapolation of time series by related series," *The review of Economics and Statistics*, pp. 372–375.

Chow, G. C., and A.-L. Lin (1976): "Best linear unbiased estimation of missing observations in an economic time series," *Journal of the American Statistical Association*, 71(355), 719–721.

CICCARELLI, M., AND C. E. A. OSBAT (2017): “Low inflation in the euro area: Causes and consequences,” *ECB occasional paper*, (181).

COCHRANE, J. H., AND M. PIAZZESI (2002): “The fed and interest rates-a high-frequency identification,” *American Economic Review*, 92(2), 90–95.

COIBION, O., ET AL. (2020): “Inflation expectations as a policy tool?,” *Journal of International Economics*, p. 103297.

COOK, T., AND T. HAHN (1989): “The effect of changes in the federal funds rate target on market interest rates in the 1970s,” *Journal of Monetary Economics*, 24(3), 331–351.

CORSETTI, G., J. B. DUARTE, AND S. MANN (2018): “One Money, Many Markets,” Discussion paper.

DEES, S., F. D. MAURO, M. H. PESARAN, AND L. V. SMITH (2007): “Exploring the international linkages of the euro area: a global VAR analysis,” *Journal of applied econometrics*, 22(1), 1–38.

DEL NEGRO, M., AND F. SCHORFHEIDE (2011): “Bayesian Macroeconometrics,” in *Handbook of Bayesian Econometrics*, ed. by H. van Dijk, G. Koop, and J. Geweke.

DOAN, T., R. LITTERMAN, AND C. SIMS (1984): “Forecasting and conditional projection using realistic prior distributions,” *Econometric reviews*, 3(1), 1–100.

DRAUTZBURG, T. (2020): “A narrative approach to a fiscal DSGE model,” *Quantitative Economics*, 11(2), 801–837.

ECB (2010): “Monthly Bulletin—June 2010,” .

——— (2015): “The Role of the Central Bank Balance Sheet in Monetary Policy,” *European Central Bank, Economic Bulletin*, 4, 61–77.

EICHENBAUM, M. (1992): “‘Interpreting the macroeconomic time series facts: The effects of monetary policy’: by Christopher Sims,” *European Economic Review*, 36(5), 1001 – 1011.

FINANCIAL TIMES, . (2020): “Lagarde’s deflation dilemma: virus piles stimulus pressure on ECB,” *Financial Times*.

FORNI, M., ET AL. (2009): “Opening the black box: Structural factor models with large cross sections,” *Econometric Theory*, 25(5), 1319–1347.

Forni, M., and L. Gambetti (2014): "Sufficient information in structural VARs," *Journal of Monetary Economics*, 66, 124–136.

Gambetti, L., and A. Musso (2017): "The macroeconomic impact of the ECB's expanded asset purchase programme (APP)," .

George, E. I., and R. E. McCulloch (1995): "Stochastic search variable selection," *Markov chain Monte Carlo in practice*, 68, 203–214.

Geweke, J. (1992): "Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments," in *Bayesian Statistics*.

Giacomini, R., and T. Kitagawa (2018): "Robust Bayesian inference for set-identified models," Discussion paper, Cemmap working paper.

Giacomini, R., T. Kitagawa, and M. Read (2019): "Robust Bayesian Inference in Proxy SVARs," Discussion paper, Centre for Microdata Methods and Practice, Institute for Fiscal Studies.

Giannone, D., M. Lenza, and G. E. Primiceri (2015): "Prior selection for vector autoregressions," *Review of Economics and Statistics*, 97(2), 436–451.

——— (2018): "Economic predictions with big data: The illusion of sparsity," CEPR Discussion Paper No. DP12256.

Gilchrist, S., and B. Mojon (2018): "Credit risk in the euro area," *The Economic Journal*, 128(608), 118–158.

Gürkaynak, R. S., B. Sack, and E. T. Swanson (2005): "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*.

Gürkaynak, R. S., B. P. Sack, and E. T. Swanson (2007): "Market-based measures of monetary policy expectations," *Journal of Business & Economic Statistics*, 25(2), 201–212.

Hachula, M., M. Piffer, and M. Rieth (2019): "Unconventional Monetary Policy, Fiscal Side Effects, and Euro Area (Im)balances," .

Hanson, M. S. (2004): "The "price puzzle" reconsidered," *Journal of Monetary Economics*, 51(7), 1385–1413.

Jarociński, M., and P. Karadi (2020): "Deconstructing Monetary Policy Surprises—The Role of Information Shocks," *American Economic Journal: Macroeconomics*, 12(2), 1–43.

KADIYALA, K. R., AND S. KARLSSON (1997): "Numerical methods for estimation and inference in Bayesian VAR-models," *Journal of Applied Econometrics*, 12(2), 99–132.

KERSSENFISCHER, M. (2019): "Information effects of euro area monetary policy: New evidence from high-frequency futures data," .

KILIAN, L., AND H. LÜTKEPOHL (2017): *Structural vector autoregressive analysis*. Cambridge University Press.

KOROBILIS, D. (2020): "Sign restrictions in high-dimensional vector autoregressions," *Available at SSRN*.

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.

LEEPER, E. M., T. B. WALKER, AND S.-C. S. YANG (2013): "Fiscal foresight and information flows," *Econometrica*, 81(3), 1115–1145.

LENZA, M., AND G. E. PRIMICERI (2020): "How to Estimate a VAR after March 2020," Discussion paper, National Bureau of Economic Research.

LITTERMAN, R. B. (1980): *A Bayesian procedure for forecasting with vector autoregressions*. MIT.

——— (1986): "Forecasting with Bayesian vector autoregressions-five years of experience," *Journal of Business & Economic Statistics*, 4(1), 25–38.

LÜTKEPOHL, H. (2005): *New introduction to multiple time series analysis*. Springer Science & Business Media.

MERTENS, K., AND M. O. RAVN (2012): "Empirical evidence on the aggregate effects of anticipated and unanticipated US tax policy shocks," *American Economic Journal: Economic Policy*, 4(2), 145–81.

——— (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 (2019): "Identification with external instruments in structural vars under partial invertibility," CEPR Discussion Paper No. DP13853.

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.

NOH, E. (2017): "Impulse-response analysis with proxy variables," *Available at SSRN 3070401*.

PARK, T., AND G. CASELLA (2008): "The bayesian lasso," *Journal of the American Statistical Association*, 103(482), 681–686.

PAUL, P. (2019): "The time-varying effect of monetary policy on asset prices," *Review of Economics and Statistics*, pp. 1–44.

PESARAN, M. H., AND R. SMITH (2006): "Macroeconometric modelling with a global perspective," *The Manchester School*, 74, 24–49.

PLAGBORG-MØLLER, M., AND C. K. WOLF (2019a): "Instrumental Variable Identification of Dynamic Variance Decompositions," *Unpublished paper: Department of Economics, Princeton University*.

PLAGBORG-MØLLER, M., AND C. K. WOLF (2019b): "Local projections and VARs estimate the same impulse responses," *Unpublished paper: Department of Economics, Princeton University*.

ROGERS, J. H., C. SCOTTI, AND J. H. WRIGHT (2014): "Evaluating asset-market effects of unconventional monetary policy: a multi-country review," *Economic Policy*, 80(29), 749–799.

——— (2018): "Unconventional monetary policy and international risk premia," *Journal of Money, Credit and Banking*, 50(8), 1827–1850.

ROSTAGNO, M., ET AL. (2019): "A Tale of Two Decades: The Ecb's Monetary Policy at 20," .

SIMS, C. A. (1992): "Interpreting the macroeconomic time series facts: The effects of monetary policy," *European economic review*, 36(5), 975–1000.

——— (1993): "A nine-variable probabilistic macroeconomic forecasting model," in *Business Cycles, Indicators and Forecasting*, pp. 179–212. University of Chicago Press.

SIMS, C. A., AND T. ZHA (1998): "Bayesian methods for dynamic multivariate models," *International Economic Review*, pp. 949–968.

STOCK, J. H., AND M. W. WATSON (2012): “Disentangling the Channels of the 2007-2009 Recession,” Discussion paper, National Bureau of Economic Research.

——— (2018): “Identification and estimation of dynamic causal effects in macroeconomics using external instruments,” *The Economic Journal*, 128(610), 917–948.

SWANSON, E. T. (2017): “Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets,” Discussion paper, National Bureau of Economic Research.

TIBSHIRANI, R. (1996): “Regression shrinkage and selection via the lasso,” *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1), 267–288.

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.

A Inflation and Inflation expectations in the euro area

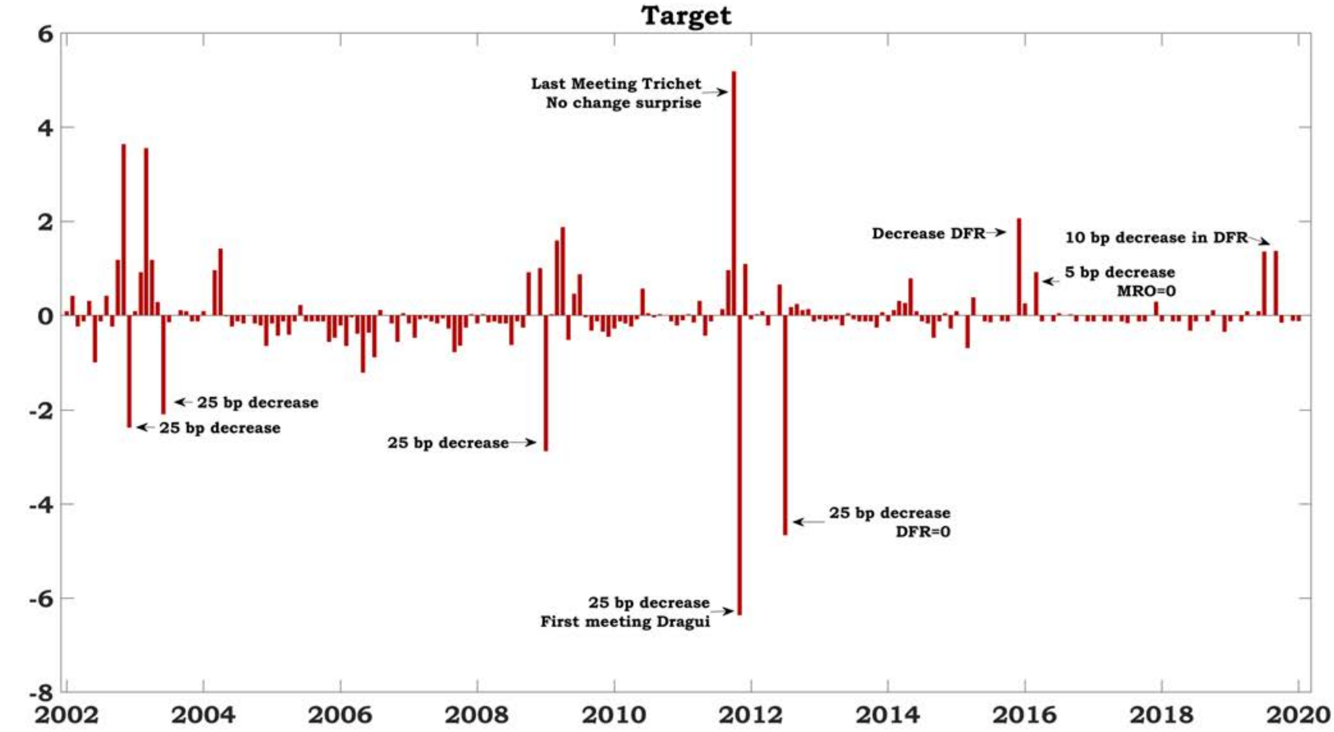
Figure 6: Inflation and inflation expectations of professional forecasters in the euro area

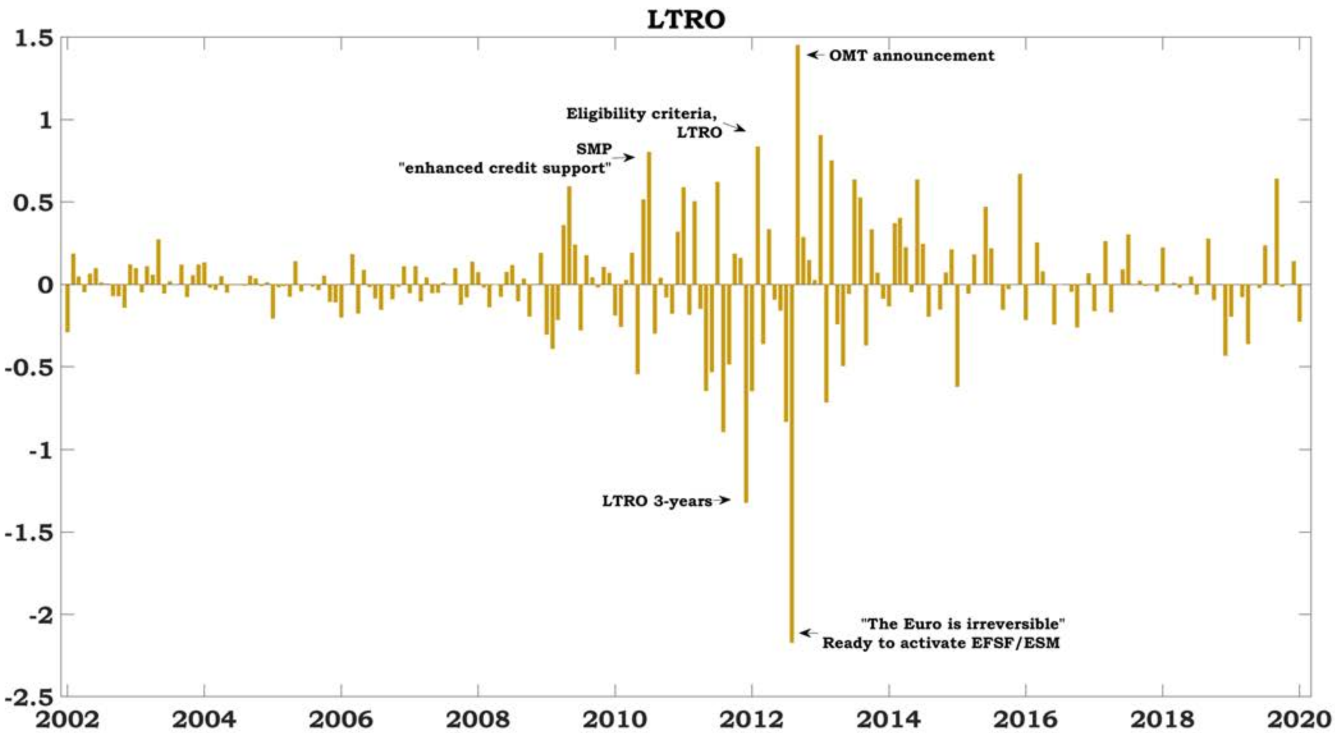
Note: The upper panel presents the year-on-year inflation in the euro area. The bottom panel shows the short-term (one-year-ahead) inflation expectations of forecasters from the EuroZone Barometer of MjEconomics in the blue, continuous line. The time series of long-term inflation expectations from the 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.

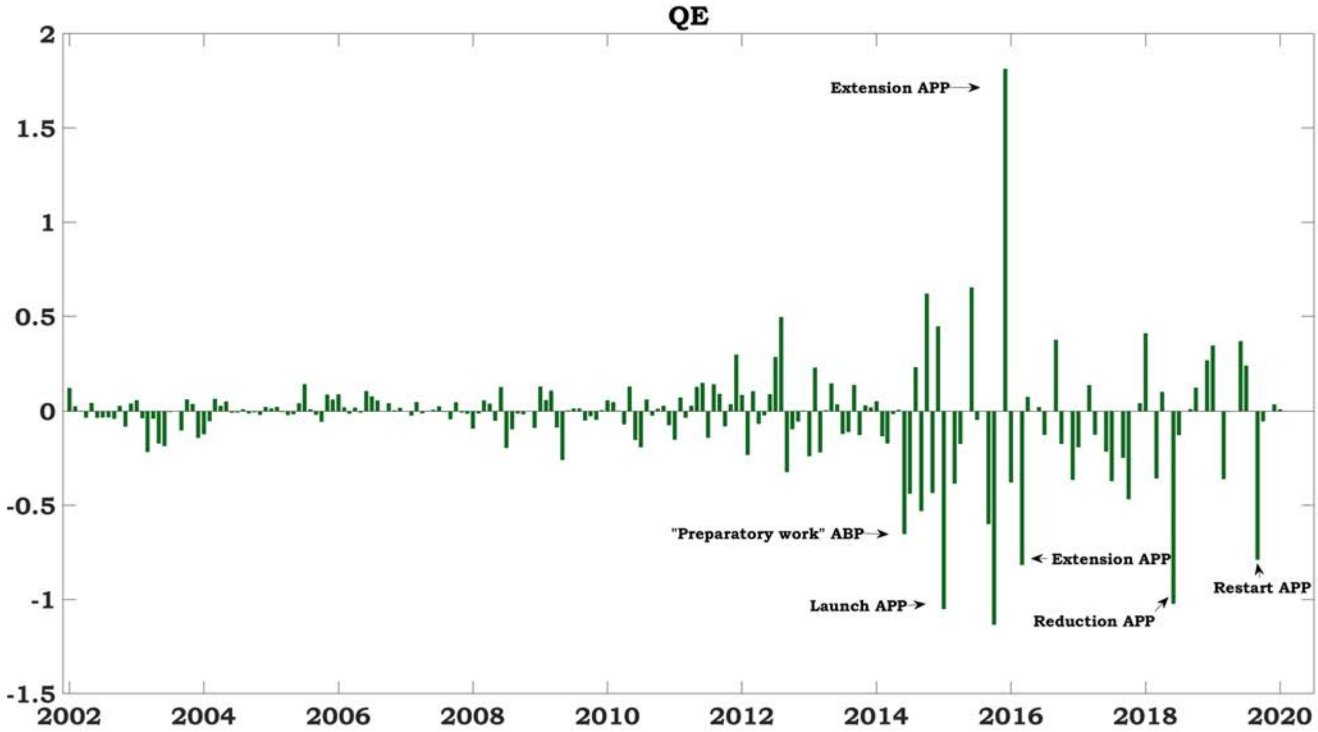
Figure 7: Inflation expectations of consumers in the euro area

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

B Monetary Policy Proxies and selected Governing Council Meetings







C The internal instrument approach

The joint process of the proxies and the data can be written by merging equations (19) and (20) as follows:

$$\underbrace{\begin{bmatrix} I_k & 0 \\ \Gamma_0 & I_N \end{bmatrix}}_{D} \begin{bmatrix} m_t \\ y_t \end{bmatrix} = \begin{bmatrix} \kappa \\ c \end{bmatrix} + \begin{bmatrix} B_1 & C_1 \\ \Gamma_1 & A_1 \end{bmatrix} \begin{bmatrix} m_{t-1} \\ y_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} B_p & C_p \\ \Gamma_p & A_p \end{bmatrix} \begin{bmatrix} m_{t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} w_t \\ u_t \end{bmatrix}$$

Premultiplying the previous equation by the inverse of matrix D yields to the hybrid VAR described by equation (21). The covariance matrix ζ has the following form:

$$\begin{aligned} \zeta &= \begin{bmatrix} I_k & 0 \\ -\Gamma_0 & I_N \end{bmatrix} \mathbb{E} \begin{bmatrix} w_t w_t' & w_t u_t' \\ u_t w_t' & u_t u_t' \end{bmatrix} \begin{bmatrix} I_k & -\Gamma_0' \\ 0 & I_N \end{bmatrix} \\ &= \begin{bmatrix} I_k & 0 \\ -\Gamma_0 & I_N \end{bmatrix} \begin{bmatrix} \zeta_{1,1} & \zeta_{1,2} \\ \zeta_{1,2}' & \zeta_{2,2} \end{bmatrix} \begin{bmatrix} I_k & -\Gamma_0' \\ 0 & I_N \end{bmatrix} \end{aligned}$$

with $\zeta_{1,1} = \Omega$ and $\zeta_{2,2} = \Sigma$, therefore

$$\zeta = \begin{bmatrix} \Omega & -\Omega\Gamma_0' + \zeta_{1,2} \\ -\Gamma_0\Omega + \zeta_{1,2}' & (\Gamma_0\Omega + \Sigma)\Gamma_0' - \Gamma_0\zeta_{1,2} + \Sigma \end{bmatrix} \tag{23}$$

The impulse responses are thus computed by a recursive identification which relies on a Choleski decomposition of the covariance matrix $\zeta = H^* H^{*\prime}$. Consequently, the matrix H^* contains the contemporaneous responses of the endogenous variables to changes in the proxies.

I experimented with different orderings of the proxies block. However, due to the orthogonal nature of the proxies, results were robust.

D Data description

Table (2) shows the description of the macroeconomic and financial data used in the large hybrid VAR (21) 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 2: 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

E Robustness Checks

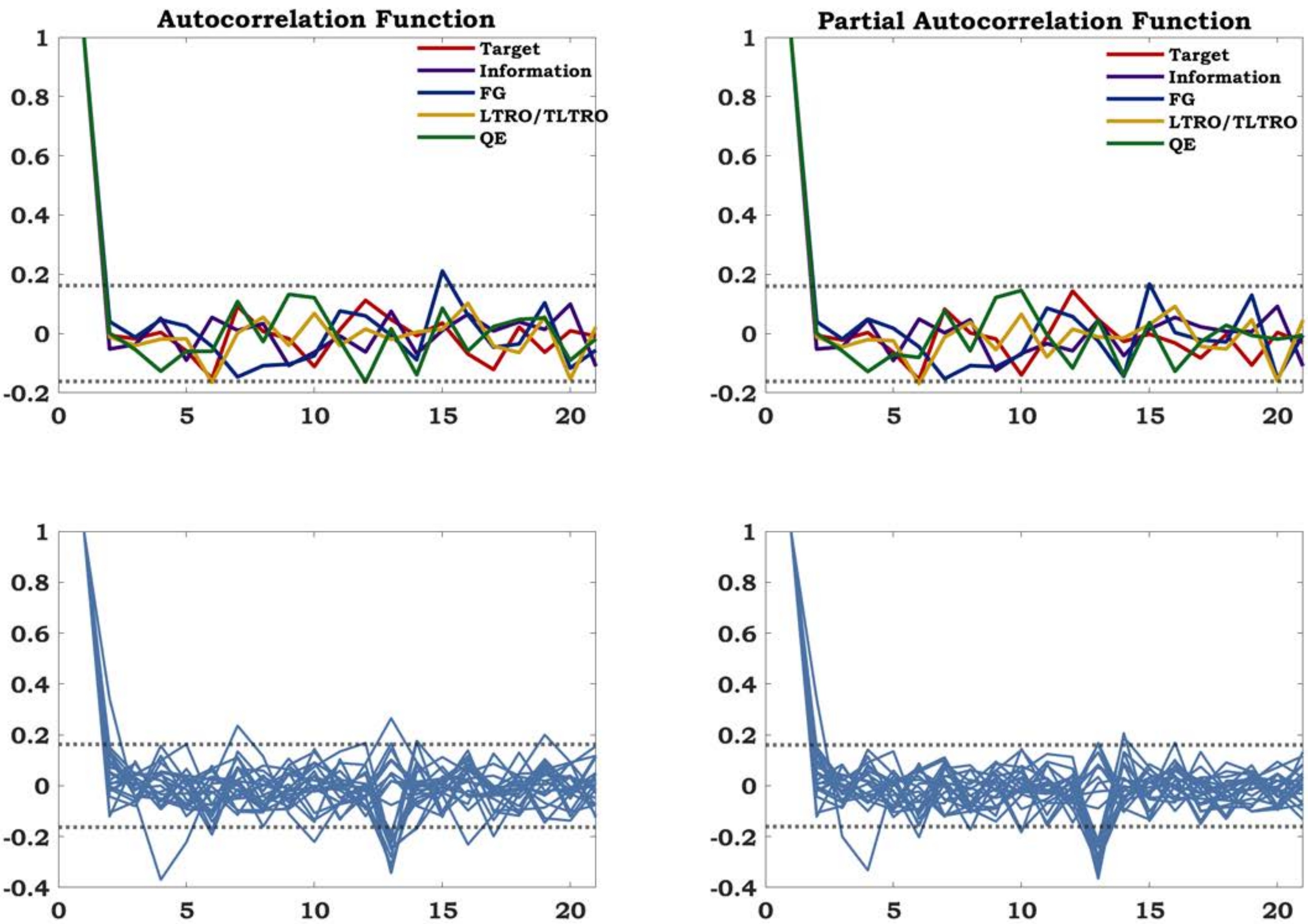


Figure 8: Autocorrelation and partial autocorrelation functions of the reduced-form errors from equation (21)

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

F Convergence test

The estimation of the hybrid Bayesian VAR (21) 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 9, 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.

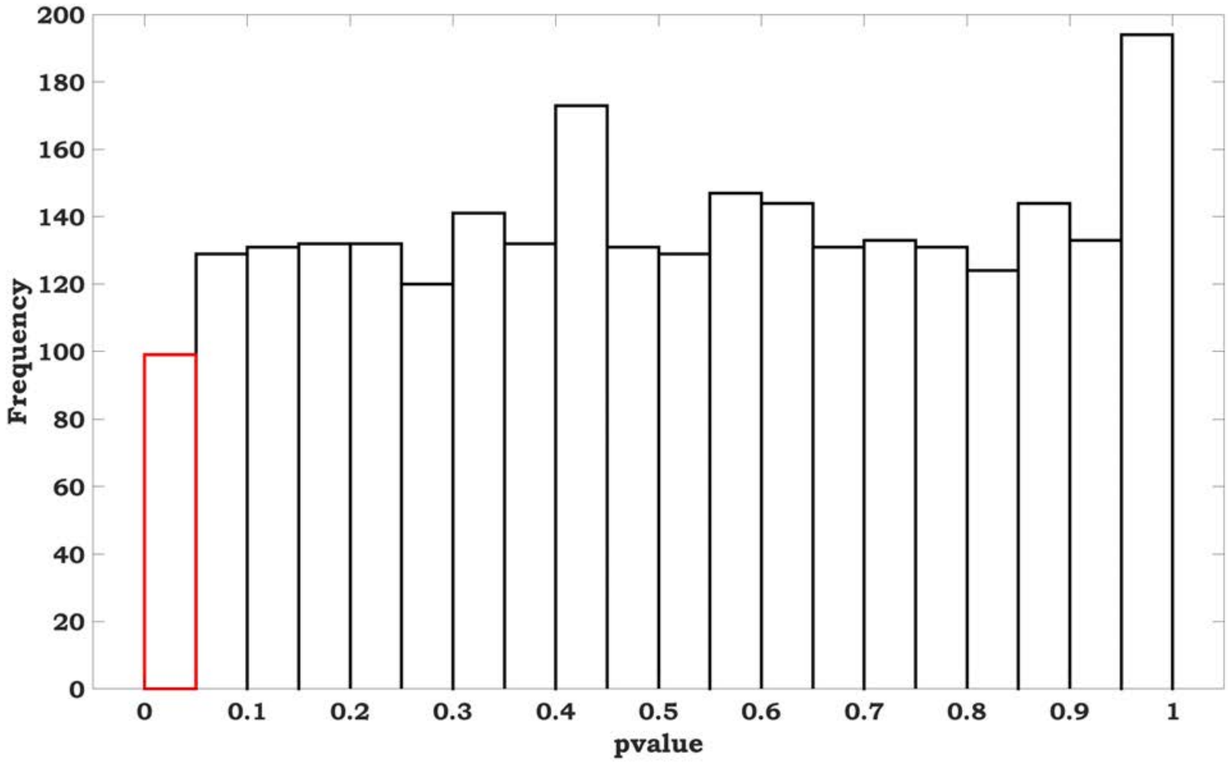


Figure 9: Geweke convergence test (p-values)

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

G Further Impulse Responses

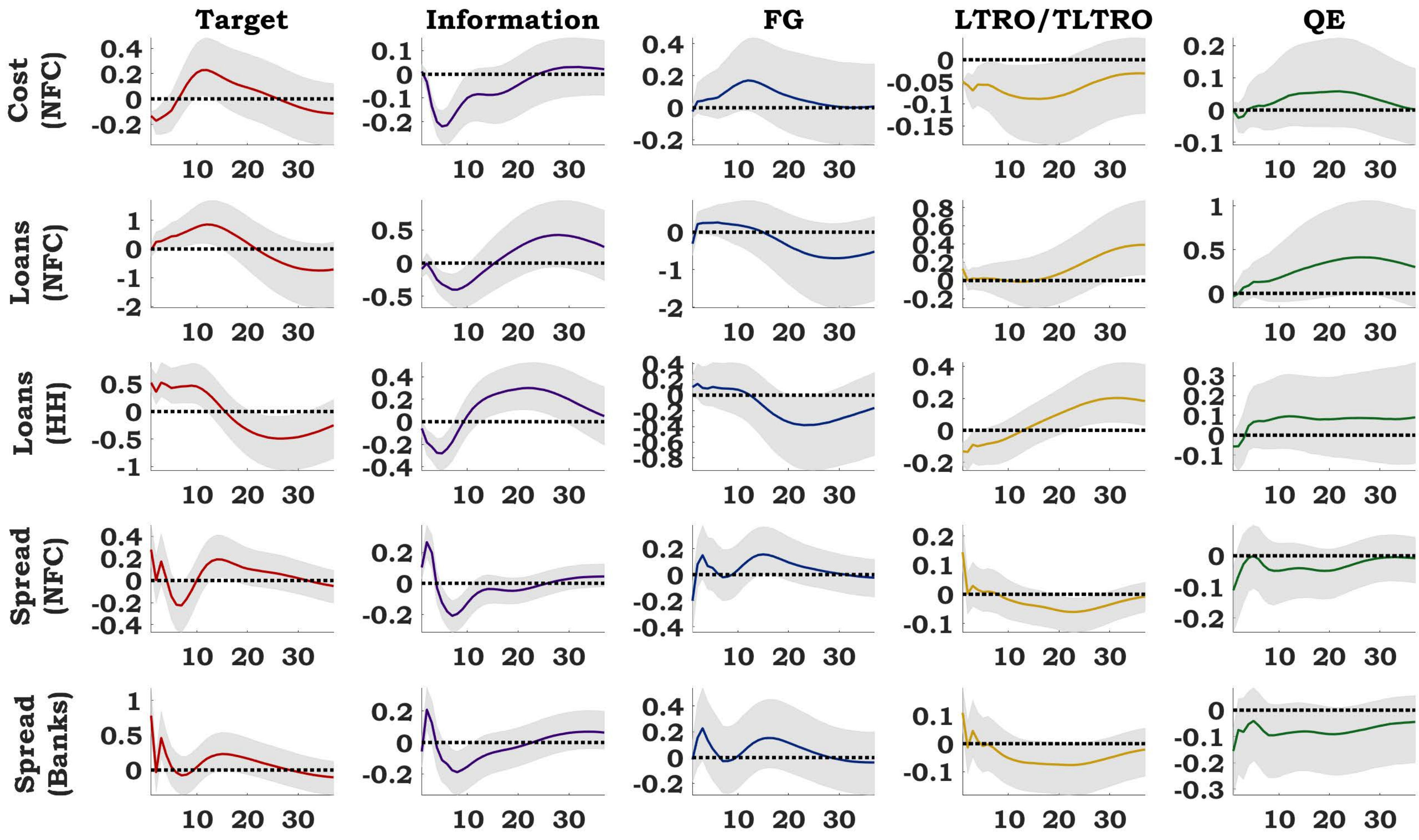


Figure 10: Responses of euro area inflation and expectations to multi-dimensional monetary policy

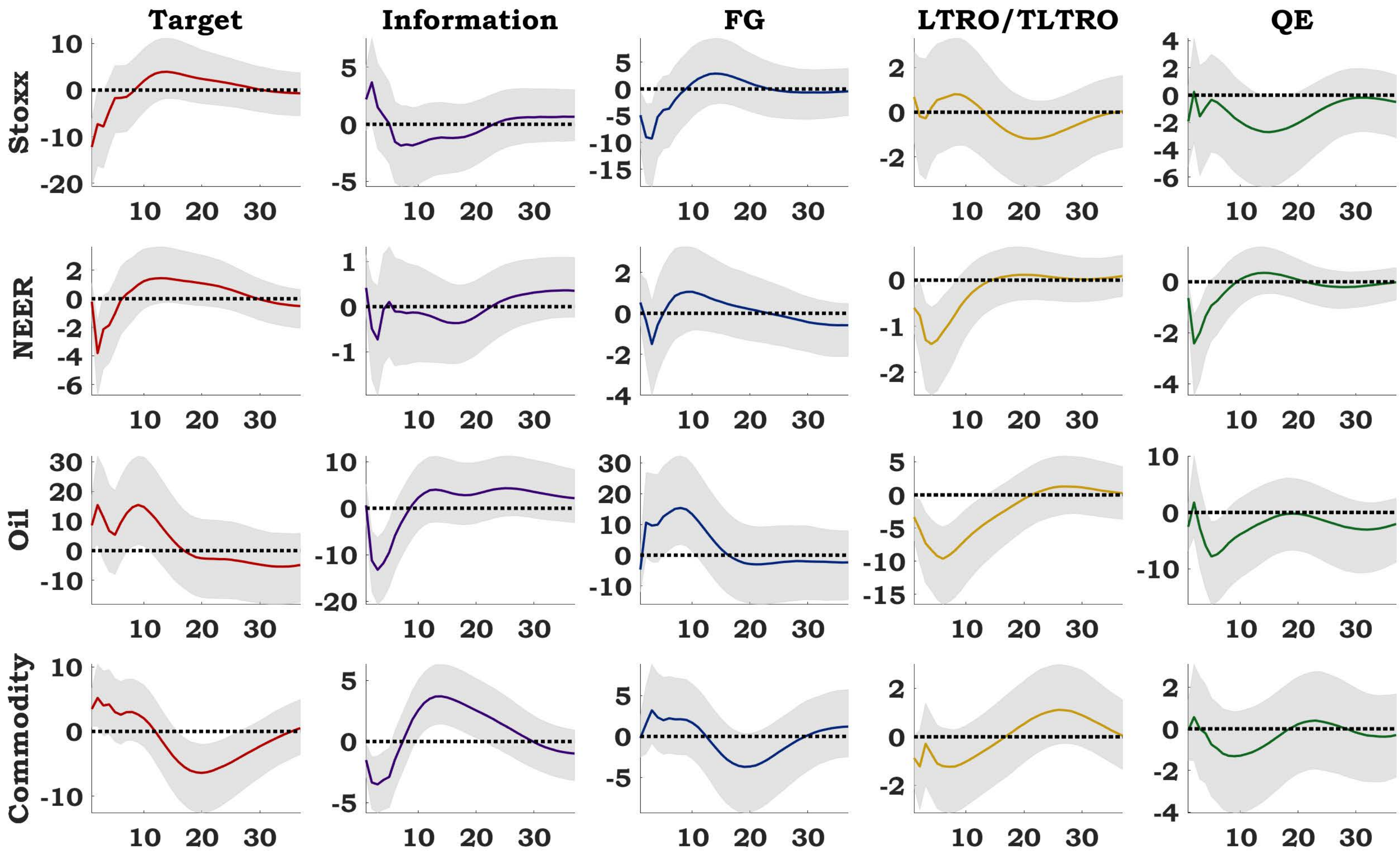


Figure 11: Responses of euro area inflation and expectations to multi-dimensional monetary policy

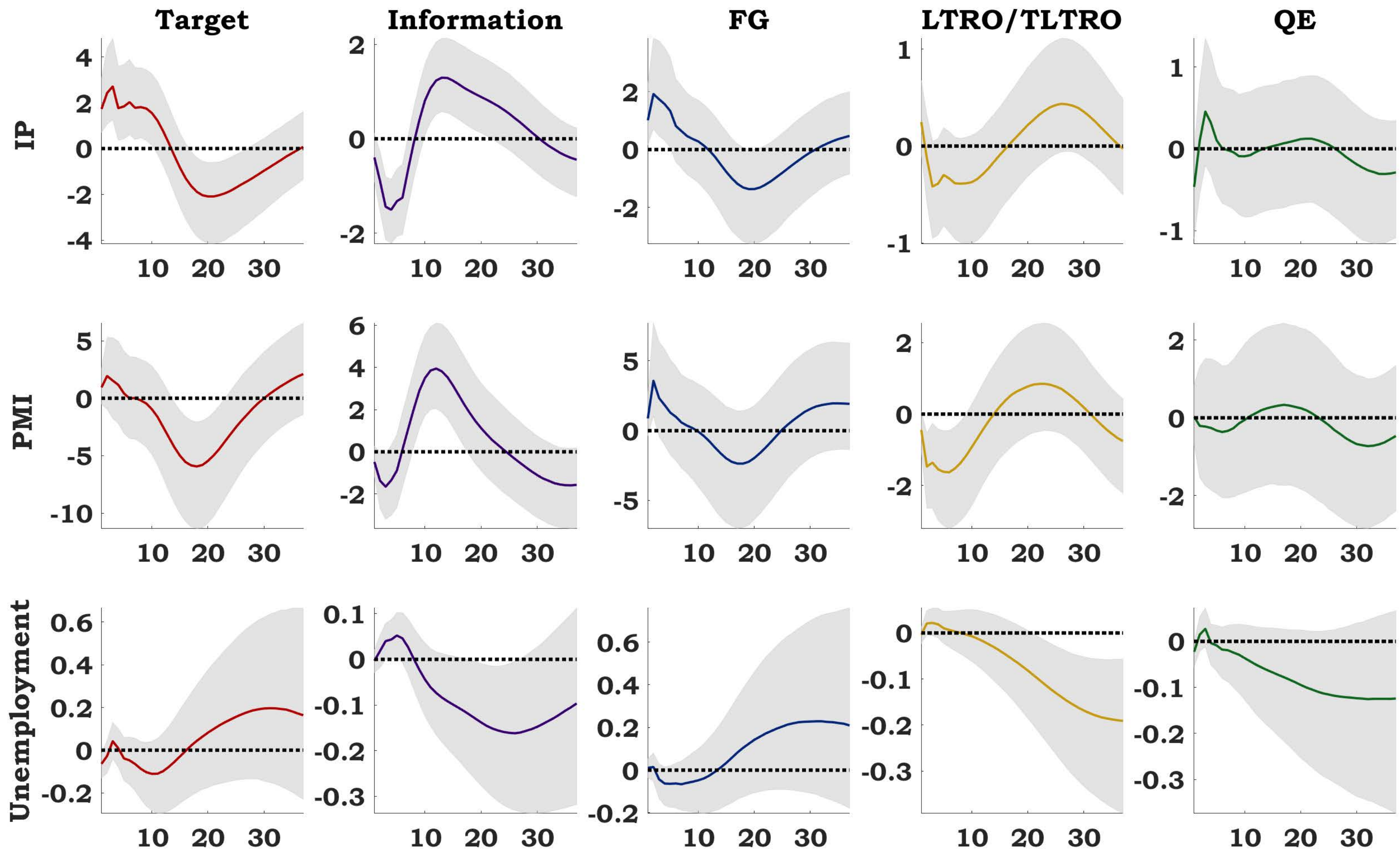


Figure 12: Responses of euro area inflation and expectations to multi-dimensional monetary policy

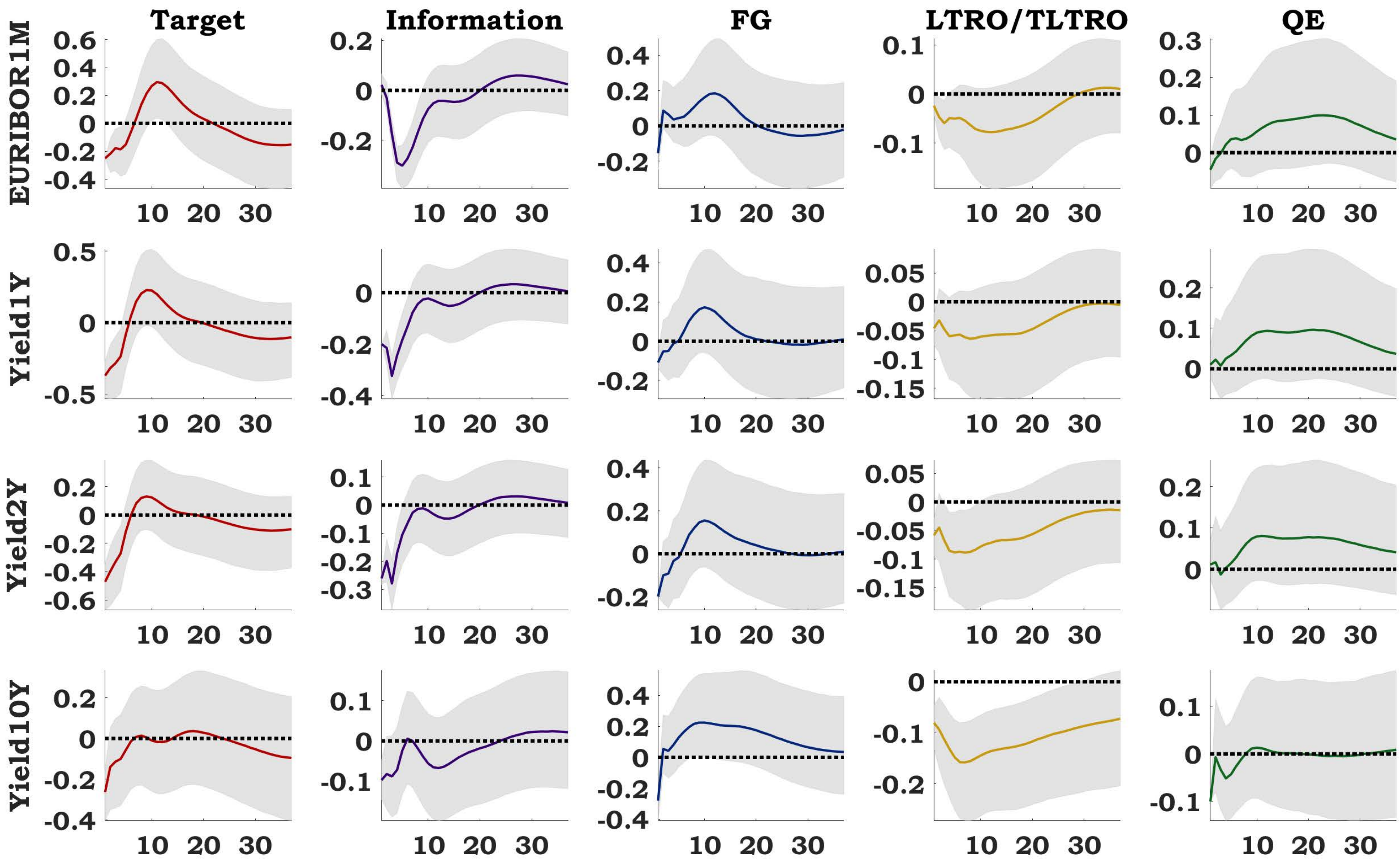


Figure 13: Responses of euro area inflation and expectations to multi-dimensional monetary policy

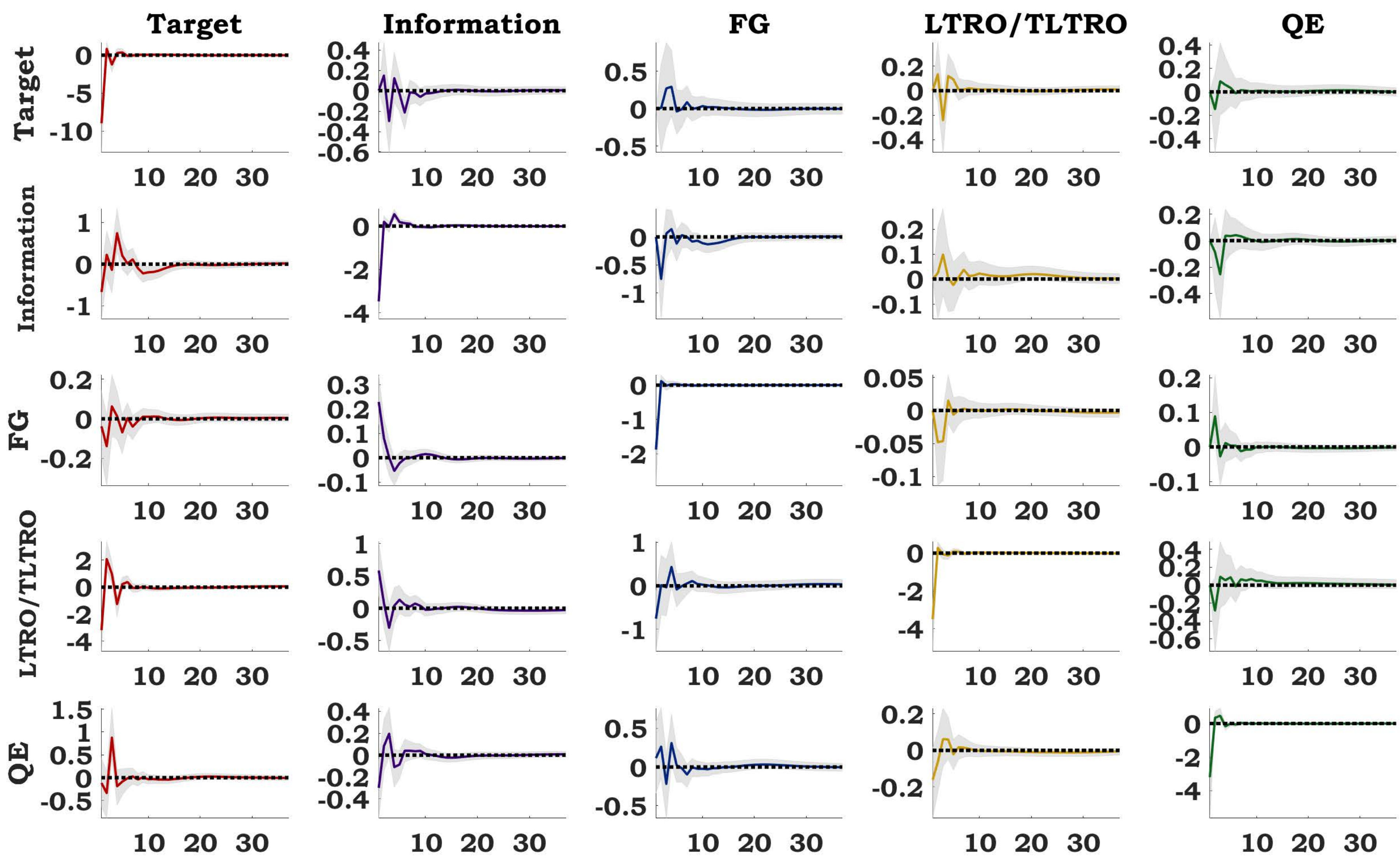


Figure 14: Responses of euro area inflation and expectations to multi-dimensional monetary policy

Diskussionsbeiträge - Fachbereich Wirtschaftswissenschaft - Freie Universität Berlin
Discussion Paper - School of Business & Economics - Freie Universität Berlin

2020 erschienen:

2020/1	ASSEYER, Andreas: Wholesale price discrimination with regulatory asymmetry *Economics*
2020/2	JESSEN, Robin und Johannes KÖNIG: Hours Risk and Wage Risk: Repercussions over the Life-Cycle *Economics*
2020/3	ASSEYER, Andreas: Collusion and Delegation under Information Control *Economics*
2020/4	ADAM, Marc Christopher: Liquidating Bankers' Acceptances: International Crisis, Doctrinal Conflict and American Exceptionalism in the Federal Reserve 1913-1932 *Economics*
2020/5	BÖNKE, Timm; Rick GLAUBITZ; Konstantin GÖBLER; Astrid HARNACK; Astrid PAPE und Miriam WETTER: Die Entwicklung und Prognose von Lebenserwerbseinkommen in Deutschland *Economics*
2020/6	HUNDSDOERFER, Jochen und Eva MATTHAEI: Gender Discriminatory Taxes, Fairness Perception, and Labor Supply *FACTS*
2020/7	ZHU, Junbing und Theocharis GRIGORIADIS: Chinese Dialects, Revolutionary War & Economic Performance *Economics*
2020/8	POLUGODINA, Maria und Theocharis GRIGORIADIS: East Prussia 2.0: Persistent Regions, Rising Nations *Economics*
2020/9	DOMBI, Akos; Theocharis GRIGORIADIS und Junbing ZHU: Antiquity and capitalism: the finance-growth perspective *Economics*
2020/10	AHMED LAHSEN, Amina; Alan T. PIPER und Ida-Anna THIELE: Kim Jiyoung, Born 1982, and the Labour Market: Overeducation, Gender, Income and Life Satisfaction. Panel evidence from Korea *Economics*

2020/11 COLEMAN, Winnie und Dieter NAUTZ: The Credibility of the ECB's Inflation Target in times of Corona: New Evidence from an Online Survey
Economics

2020/12 SYDOW, Jörg; Georg SCHREYÖGG und Jochen KOCH: Current interest in the theory of organizational path dependence. a short update on the occasion of the 2019 AMR Decade Award
Management

2020/13 DIECKELMANN, Daniel: Cross-Border Lending and the International Transmission of Banking Crises
Economics

2020/14 WOLF, Tobias: Welfare while working: How does the life satisfaction approach help to explain job search behavior?
Economics

2020/15 PIPER, Alan: Temps dip deeper: temporary employment and the midlife nadir in human well-being
Economics

2020/16 OLSEN, Nils: A Literature Overview on Scheduling Electric Vehicles in Public Transport and Location Planning of the Charging Infrastructure
Information Systems

2020/17 WINKELMANN, Lars und Wenying YAO: Cojump Anchoring
Economics