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Changes in the euro area interest rate pass-through

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Non-technical summary

Research question

In order to achieve its objectives with regard to economic developments, euro area monetary policy sets key interest rates. For changes in key interest rates to take their effect in the intended way, banks should pass them through quickly and completely. Complete pass-through is achieved once a change in key interest rates results in a roughly equivalent change in bank lending rates. Bank lending rates play an important role for borrowing among households and enterprises. This Discussion Paper examines whether interest rate pass-through in the euro area has changed over time and, if so, whether these changes were associated with the financial crisis or sovereign debt crisis, the use of non-standard monetary policy measures, or the low interest rate environment.

Contribution

A Bayesian vector autoregressive model with time-varying parameters is estimated to describe time-variant economic interrelationships in the euro area. Using this model, it is possible to depict changes in the pass-through of key interest rates to bank lending rates that have occurred over time. To ensure the ability to continue investigating pass-through once key interest rates are at their lower bound and monetary policy resorts to non-standard measures, the key interest rate is approximated by means of the "shadow rate". This represents the key interest rate that would prevail if there were no zero lower bound on interest rates and thus no need to resort to non-standard monetary policy measures. At present, there are only a small number of empirical studies on interest rate pass-through during the period of non-standard measures.

Results

The point estimator indicates that the pass-through of interest rates to bank lending rates is greater and distorted during the financial crisis. In 2016, in the low interest rate environment, there is a weakening of interest rate pass-through. From then until the end of 2019, the point estimator fluctuates at a lower level. However, estimation uncertainty is very high over the entire period under analysis, meaning that constant and complete pass-through of interest rates cannot be ruled out at any point in time. From 2016 to 2018, the explanatory power of changes in monetary policy for changes in bank lending rates also decreases. Furthermore, since the beginning of non-standard measures in 2011, it appears that non-standard changes in monetary policy are the main influencing factor for changes in bank lending rates.

Nichttechnische Zusammenfassung

Fragestellung

Um ihre Ziele in Bezug auf die Wirtschaftsentwicklung zu erreichen, setzt die Geldpolitik im Euroraum die Leitzinsen fest. Damit Änderungen der Leitzinsen ihre Wirkung in der gewünschten Weise entfalten können, sollten sie von den Banken schnell und vollständig weitergegeben werden. Eine vollständige Weitergabe liegt vor, wenn eine Änderung des Leitzinses zu ungefähr der gleichen Änderung des Bankkreditzinses führt. Bankkreditzinsen spielen eine wichtige Rolle für Kreditaufnahmen von Unternehmen und privaten Haushalten. In dieser Arbeit wird untersucht, ob sich die Zinsweitergabe im Euroraum im Laufe der Zeit verändert hat und ob eventuelle Veränderungen verbunden waren mit der Finanz- oder Staatsschuldenkrise, dem Einsatz von unkonventionellen geldpolitischen Instrumenten oder dem Niedrigzinsumfeld.

Beitrag

Um die zeitvariierenden ökonomischen Zusammenhänge im Euroraum zu beschreiben, wird ein bayesianisches vektorautoregressives Modell mit über die Zeit variierenden Parametern geschätzt. Mit diesem Modell können im Laufe der Zeit aufgetretene Veränderungen der Weitergabe des Leitzinses auf den Bankkreditzins abgebildet werden. Um die Weitergabe auch dann untersuchen zu können, wenn die Leitzinsen an ihrer Untergrenze liegen und die Geldpolitik auf unkonventionelle Instrumente zurückgreift, wird der Leitzins über den sogenannten Schattenzins approximiert. Dies ist der Leitzins, der sich ohne Zinsuntergrenze und somit ohne die Notwendigkeit unkonventioneller Maßnahmen ergeben würde. Bisher sind nur wenige empirische Studien zur Zinsweitergabe für den Zeitraum unkonventioneller Maßnahmen verfügbar.

Ergebnisse

Der Punktschätzer legt eine höhere und gestörte Zinsweitergabe auf Bankkreditzinsen während der Finanzkrise nahe. In 2016, im Niedrigzinsumfeld, schwächt sich die Zinsweitergabe ab. Ab dann bis Ende 2019 schwankt der Punktschätzer um ein niedrigeres Niveau. Allerdings ist die Schätzunsicherheit im gesamten betrachteten Zeitraum sehr hoch, so dass eine konstante und vollständige Zinsweitergabe zu keinem Zeitpunkt ausgeschlossen werden kann. Im Zeitraum 2016 bis 2018 verringert sich auch der Erklärungsgehalt einer geldpolitischen Änderung für die Veränderungen im Bankkreditzins. Ferner beeinflussen scheinbar seit dem Beginn von unkonventionellen Maßnahmen in 2011 vor allem unkonventionelle geldpolitische Änderungen die Veränderungen im Bankkreditzins.

Changes in the euro area interest rate pass-through[1]

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Abstract

This paper uses a time-varying vector autoregressive (VAR) model for the euro area to explore the changes in the interest rate pass-through to bank retail rates following conventional and unconventional monetary policy shocks. The median estimate of the impulse responses shows a considerably higher pass-through during crisis periods, especially the financial crisis and the coronavirus pandemic. From mid-2013 to 2015-16, the monetary policy pass-through to the bank lending rate becomes slightly stronger. In the remainder of 2016, the pass-through weakens. From then until the end of 2019, it hovers at a lower level. However, the credible intervals reveal a large uncertainty concerning the pass-through over the entire sample. Therefore, a constant and complete pass-through is clearly within the realms of possibility. Since the standard deviation of monetary policy shocks grows substantially since the onset of unconventional measures in 2011, changes in bank retail rates seem to be driven mainly by such shocks in this period.

Keywords: Euro area, interest rate pass-through, time-varying vector autoregressive model, sign restrictions

JEL-Classification: C11, E40, E43, E52, G21

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1 Introduction

Central banks exert significant control over the conditions of the money market, thereby influencing money market interest rates. Subsequently, fluctuations in these interest rates have repercussions on retail bank interest rates for instance, and thus expenditure and investment behaviour and finally real economic activity. Therefore, a rapid and complete pass-through of central bank interest rates to retail bank rates strengthens monetary policy transmission. A complete pass-through exists when an increase in the policy rate leads to roughly the same increase in the bank rate. Retail bank interest rates are particularly crucial in the transmission of monetary policy. Borrowing by firms and households predominantly takes place via this channel. More specifically, between 2014 and 2021, bank financing accounted for roughly 55 % of lending to the private non-financial sector in the euro area (BIS, 2022). Thus, the pass-through of interest rate is a key component in monetary policy transmission. Consequently, it is crucial for central banks to know about their ability of influencing bank retail rates and thus eventually affect aggregate demand.

The renewed focus on how market rates transfer to bank retail rates emerged when the financial system was impaired following the financial crisis and in the course of the European sovereign debt crisis. Since then, the European Central Bank (ECB) has repeatedly stated its concerns about distortions to euro area monetary policy transmission (Draghi, 2012; ECB, 2010a, b, 2014). Influenced by these developments, the ECB, like other major central banks, cut its policy rates to virtually zero and simultaneously engaged in massive unconventional monetary policy measures to restore the effectiveness of monetary policy. In light of these various measures as well as crises which modified the transmission of a monetary policy impulse, it is important to allow for a substantial degree of time variation in the econometric model used here. By using a time-varying parameter vector autoregression (TVP-VAR) model with stochastic volatility, I allow for both: time-varying parameters and covariance matrices. The time horizon for exploring the interest rate pass-through in response to a monetary policy shock ranges from 2004:Q3 until 2022:Q2. In addition to the monetary policy shock, two business cycle shocks are identified by means of sign restrictions: an aggregate demand shock and an aggregate supply shock. Using this approach, I intend to analyse the varying effectiveness and characteristics of the monetary policy transmission mechanism across the ECB's different monetary policy stances.

Many studies to date employ money market rates to approximate the monetary policy stance, thereby merely reflecting changes in the key central bank interest rates and their level. However, these short-term money market rates cannot map the impact of unconventional monetary policy measures. The latter have increasingly flanked the ECB's interest rate measures, especially since 2011 (in order to safeguard the effectiveness of monetary policy transmission). Therefore, the literature increasingly refers to what is known as the shadow rate (SR) for approximating the monetary policy stance. Besides the interest rate policy (conventional monetary policy), it also reflects announcements and implementations of unconventional monetary policy measures as well as forward guidance. The SR is also described as the hypothetical short-term interest rate in absence of physical currency and has the potential to fall below zero at the zero lower bound (ZLB). In the euro area, unconventional measures gained especially in importance since mid-2011.[2] Furthermore, estimations reveal an increase in the impact of unconventional measures on the SR since mid-2011 for the euro area (De Rezende and Ristiniemi, 2023).[3] I therefore choose to approximate monetary policy changes since then using the SR. Before that, the ECB's key policy instruments are mirrored by means of the EONIA.

The impulse response analysis reveals time-varying effects following a monetary policy shock on the bank lending rate for non-financial corporations: During the financial crisis, the median pass-through estimate of a conventional monetary policy shock to the bank rate seems to be larger. While this point estimate would suggest a substantial degree of distortion to the pass-through mechanism, the estimation uncertainty is high and a complete pass-through lies well within the credible intervals. From mid-2011, the ECB increasingly resorts to unconventional monetary measures. From mid-2013 until 2015-16, the monetary policy pass-through to the bank rate becomes slightly stronger. Afterwards in 2016, the pass-through decreases somewhat and thus suggests a slight weakening of the transmission mechanism. Since then until the end of 2019, it varies less and develops at a lower level. However, it hovers around a level that still indicates a more or less complete pass-through. From 2020 onward, however, the pass-through to the bank rate seems to increase considerably again. This period is largely influenced by the coronavirus pandemic and the decisive monetary and fiscal measures implemented in

[2] Examples of unconventional measures which the ECB has announced since mid-2011 are: the longer-term refinancing operations (LTRO) in June 2011, the outright monetary transactions (OMT) in August 2012 and the expanded asset purchase programme (EAPP) in January 2015.
[3] The SR mirrors both conventional and unconventional monetary impulses. Although conventional impulses have also influenced the shadow rate since mid-2011, the dominant influence stems from unconventional impulses (De Rezende and Ristiniemi, 2023).

response to it.[4] It should be noted that the credible intervals are relatively wide for the entire sample, such that a constant and complete pass-through cannot be ruled out.

The explanatory power of a monetary policy shock on the bank rate also supports these findings: that is, it decreases substantially in 2016 and increases decisively again in 2020. Furthermore, the standard deviation of a monetary policy shock changes considerably over time as well. Since unconventional measures began in 2011, it has grown steadily. Thus, in addition to conventional monetary policy, unconventional monetary policy impulses also help to influence lending rates, whereas the movements in lending rates seem to be mainly driven by large monetary policy shocks since 2011. In addition, (unconventional) monetary policy shocks still seem effective in influencing real economic variables, in particular inflation.

The remainding structure of the paper is as follows: Section 2 provides a summary of related literature on the euro area; Section 3 delineates the empirical framework and its structural identification and Section 4 presents the results. Section 5 details the robustness checks and Section 6 offers concluding remarks.

2 Survey of Related Literature

While there is a large literature branch on monetary policy transmission to key economic variables in the euro area, the literature on the interest rate pass-through process to euro area retail rates is smaller but growing. Studies analysing this pass-through are often based on error-correction models (ECM) (see e.g. Cottarelli and Kourelis, 1994; Toolsema et al., 2001; Sander and Kleimeier, 2004; de Bondt, 2005; Kok Sørensen and Werner, 2006; Kleimeier and Sander, 2006; Kwapil and Scharler, 2010; van Leuvensteijn et al., 2013; Belke et al., 2013; Holton and Rodriguez d'Acri, 2018). They widely indicate a sluggish reaction of euro area retail bank interest rates to changes in money market rates.

In recent years, research has increasingly started analysing whether the financial crisis influenced the degree of interest rate pass-through in the euro area. By means of an ECM, authors as Karagiannis et al. (2010) and Hansen and Welz (2011) trace changes in the speed retail bank interest rates respond to fluctuations in money market rates. They find

[4] Note that the corona pandemic has led to large data movements that affect parameter estimates in BVARs as well (Carriero et. al, 2022). The model's assumption of a random walk behaviour for volatility implies that huge changes in a variable like growth at the beginning of the pandemic are regarded as extreme increases in shock volatilities, which are supposed to persist, but growth volatility decreased strongly at the end of 2020 already. These large movements in estimated shock volatilities, in turn, might lead to a very large estimate for the variance of the shock to volatility itself, which could be problematic especially regarding inference. Moreover, the model does not contain variables, which describe the evolution of fiscal measures, such that the causal relationships identified by the model during the pandemic are especially difficult to interpret.

a less complete pass-through since the crisis. Similar results are provided by Avouyi-Dovi et al. (2017). They use an ECM with time-varying parameters and stochastic volatility to handle the time-varying long-run relationship between banks' lending rates and banks' marginal costs. They estimate that the long-run relationship between lending rates and marginal costs is not stable: after the sovereign debt crisis (after January 2010), the pass-through became slower.

Yet, ECMs may suffer from inappropriately imposed cointegration relations, which can lead to biased estimates. VAR models avoid this possibility of misspecification (de Bondt, 2005; von Borstel et al., 2016). Aristei and Gallo (2014), for example, use a Markov-switching VAR model and Hristov et al. (2014) apply a panel VAR to two sub-periods, namely before the financial crisis (2003-2007) and the crisis period (2008-2011). They confirm the results of a more sluggish pass-through to retail bank rates following the financial crisis.

However, most studies rely exclusively on money market rates to trace the pass-through mechanism. These rates are close to the zero lower bound (ZLB) during the low/negative interest rate period from about mid-2012 to 2022 in the euro area. By neglecting the unconventional measures which complemented the interest rate tools, most of these studies do not account for the effects of unconventional monetary policy. They were undertaken to safeguard conventional measures and may have affected bank retail rates as well. One exception is the study by von Borstel et al. (2016). The authors use a factor-augmented VAR and investigate the roles of both conventional and unconventional monetary policy.[5] They estimate a weaker pass-through of unconventional policies during the sovereign debt crisis (2010 to 2013) compared to conventional shocks during the pre-crisis (2000 to mid-2007). The global financial crisis period is excluded from their estimation.

However, the large changes in money market rates during the crises periods as well as the various unconventional measures implemented underline the importance of allowing for a substantial degree of time variation in the estimation framework. To the best of my knowledge, only one other paper (Filardo and Nakajima (2018)) uses a TVP-VAR to analyse the pass-through to retail bank interest rates. The authors analyse the transmission mechanism of unconventional monetary policy shocks for the euro area from 1995 until 2016 Q2. Based on an event study, they identify the monetary policy shock as a change in sovereign bond yields at the time of significant unconventional monetary policy announcements. For the euro area, they estimate no change in the pass-through of

[5] von Borstel et al. (2016) capture unconventional monetary policy shocks in different ways. However, the shadow rate plays a very important role in their analysis.

unconventional monetary policy shocks to the bank rate from 2014 until 2016. However, they restrict their analyses to two points in time (2014 and 2016) and do not trace the development of monetary policy shocks across time in more detail. Furthermore, their analysis stops in 2016. Given the relatively limited empirical evidence on the influence of unconventional measures, it is essential to provide more additional insights on their transmission mechanism.

I use a relatively agnostic framework to analyse monetary policy shocks. Additionally, two types of economic disturbances, specifically a demand and a supply shock are identified for dual purpose: firstly, to inhibit the infiltration of economic disturbances into the isolated monetary shock, and secondly, to assess the quantitative importance of the monetary policy shock in comparison to the other two shocks, as well as to observe their evolution over time.

3 Empirical Model

I employ a Bayesian TVP-VAR model with stochastic volatility to track the response of the bank rate as well as other key economic variables to a monetary policy shock across time.[6] My empirical approach closely follows Primiceri (2005) and Michaelis and Watzka (2017).[7] The benefit of this approach lies in its adaptability to deal with the evolving characteristics of the monetary transmission mechanism over time. This appears especially critical for the euro area, where the ECB has repeatedly expressed its concerns about distortions to the euro area's monetary policy transmission and in circumstances where there were substantial changes in the array of monetary policy instruments.

The TVP-VAR model features matrices of coefficients and covariance that both change over time.[8] The time-varying coefficients account for potential non-linear behaviours or time variation in the model's lagged relationships, while the dynamic variance–covariance matrices capture potential heteroscedasticity in the shocks and non-linear simultaneous relationships within the variable set.

I calculate the ensuing VAR model:

$$y_t = c_t + B_{1,t} y_{t-1} + \cdots + B_{n,t} y_t + u_t \qquad t = 1, \dots, T \tag{3.1}$$

where y_t represents a $n \times 1$ vector comprising the endogenous variables; c_t denotes a $n \times 1$ vector of intercepts that vary over time; $B_{i,t}$ depicts a $n \times n$ matrix of coefficients

[6] The code used for the estimation comes from Korobilis (2018). The code has been amended to take account of the corrigendum of Del Negro and Primiceri (2015).
[7] A further related study is Hristov et al. (2014).
[8] The TVP-VAR model description closely follows Michaelis and Watzka (2017).

that also vary over time and are associated with lag length $i = 1, \dots, l$; and u_t, is a $n \times 1$ vector of error terms. The time-varying covariance matrix of u_t is represented by Ω_t, which can be broken down as follows:

$$Var(u_t) = \Omega_t = A_t^{-1}\Sigma_t\Sigma_t'(A_t^{-1})', \tag{3.2}$$

where A_t is defined as a lower triangular matrix with elements that change over time, and Σ_t is a diagonal matrix whose covariance values are also time-varying:

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \cdots & 0 \\ \vdots & \cdots & \ddots & 0 \\ a_{n1,t} & \cdots & a_{n(n-1),t} & 1 \end{bmatrix} \Sigma = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \cdots & 0 \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix} \tag{3.3}$$

The time-varying VAR can subsequently be reformulated as:

$$y_t = X_t'B_t + A_t^{-1}\Sigma_t\varepsilon_t, \tag{3.4}$$

$$X_t' = \mathrm{I_n} \otimes [1, y_{t-1}', \dots, y_{t-l}'],$$

where B_t is a consolidated vector encompassing all coefficients from the right hand side of equation 3.1, and I_n represents the identity matrix of dimension $n \times n$. $VAR(\varepsilon_t) = \mathrm{I}_n$ and the operator $\otimes$ indicates the Kronecker product.

The changing parameters over time (B_t and A_t) follow a random walk without drift, while the evolution of the covariance matrix (Σ_t) is a geometric random walk also without drift:

$$B_t = B_{t-1} + \nu_t, \tag{3.5}$$

$$a_t = a_{t-1} + \xi_t, \tag{3.6}$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t, \tag{3.7}$$

where a_t is a composite vector consisting of the coefficients from the lower triangular part of matrix A_t. σ_t is the vector containing the diagonal elements' standard deviations from matrix Σ_t. The innovation vector $[\varepsilon_t', \nu_t', \xi_t', \eta_t']$ is presumed to follow a joint normal distribution with the following covariance matrix:

$$Var(\varepsilon_t', \nu_t', \xi_t', \eta_t') = \begin{bmatrix} \mathrm{I}_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}. \tag{3.8}$$

I_n denotes an identity matrix with n dimensions, while Q, S and W are matrices that are positive definite. A block diagonal structure is assumed for S.[9]

3.1 Priors

To evaluate posteriors, it is necessary to define prior distributions. The calibration of these priors uses a training sample that spans from 1998:Q1 to 2004:Q2 and runs an OLS estimation on a VAR model with fixed-coefficients. The prior specifications are largely in line with those presented in Primiceri (2005). A summary of these is provided below. Diverging from Primiceri's approach, I exclude explosive draws of the VAR coefficients, B_t, during the initial phase of the Gibbs sampling process.[10]

The prior mean and variance for the initial values of B_0 and A_0 are calculated by the OLS point estimates $\left(\hat{B}_{OLS}, \hat{A}_{OLS}\right)$ and four times their variance, respectively. The log standard errors' prior mean is the log of the OLS point estimates ($\hat{\sigma}_{OLS}$), and the prior covariance is being set at $4 \cdot I_n$. The priors for the initial starting conditions of the time-varying parameters of the VAR (B_0, A_0, $\log \sigma_0$) are assumed to be normally distributed. The hyperparameters Q, S and W, which are the innovations' covariance matrices (detailed in equations 3.5, 3.6 and 3.7), follow independent inverse-Wishart distributions:

$$B_0 \sim N\left(\hat{B}_{OLS}, 4 \cdot V\left(\hat{B}_{OLS}\right)\right),$$

$$A_0 \sim N\left(\hat{A}_{OLS}, 4 \cdot V\left(\hat{A}_{OLS}\right)\right),$$

$$log\hat{\sigma}_0 \sim N(\hat{\sigma}_{OLS}, 4 \cdot I_n),$$

$$Q \sim IW\left(k_Q^2 \cdot \tau \cdot V\left(\hat{B}_{OLS}\right), \tau\right),$$

$$W \sim IW\left(k_W^2 \cdot \left(1 + dim(W)\right) \cdot \mathrm{I}_n, \left(1 + dim(W)\right)\right),$$

$$S_b \sim IW\left(k_S^2 \cdot \left(1 + dim(S_b)\right) \cdot V\left(\hat{A}_{b,OLS}\right), \left(1 + dim(S_b)\right)\right),$$

where τ represents the size of the training sample. S_b, indexed by b, pertains to the specific blocks associated with a given equation and $\hat{A}_{b,OLS}$ indicates the corresponding blocks of $\hat{A}_{OLS}$.[11] The degrees of freedom for matrices W and S_b are set to one plus its respective dimensions. The training sample size also determines the degrees of freedom for matrix Q. The parameters $k_Q = 0.1$; $k_W = 0.1$ and $k_S = 0.01$ are used to express prior

[9] Please refer to Primiceri (2005) for further details.
[10] Since the work of Cogley and Sargent (2005), it has become standard to assume that the roots of the matrix polynomial defined by B_t are located outside the unit circle.
[11] The system is composed of four blocks, each with sizes: 2, 3, 4 and 5, corresponding to the five endogenous variables employed.

beliefs regarding the extent of time variation in the coefficients, covariances and volatilities. For instance, in the OLS estimation for the VAR coefficients' covariance matrix, 10 % ($k_Q = 0.1$) of time variation in the variance surrounding the $V(\hat{B}_{OLS})$ estimates is permitted, as suggested by Kirchner et al. (2010).[12]

I undertake a systematic model selection process because there is no economic rationale to prefer one specific combination of (k_Q, k_W, k_S) over another. To estimate the posterior probabilities for a collection of 18 models, I utilize the reversible jump Markov chain Monte Carlo (RJMCMC) technique as detailed in Primiceri (2005).[13] This process results in one combination of k_Q, k_W and k_S that yields a posterior probability close to unity.

3.2 Identification and estimation

Up to this point, I have described the calculation for a reduced-form VAR, employing Bayesian techniques, for the data sample spanning from 2004:Q3 to 2022:Q2. The vector y_t consists of five variables: real GDP, HICP, EONIA[14] or the SR[15] as the short-term nominal reference rate, the bank rate on new loans for non-financial corporations[16] as well as a government bond yield spread[17].

The SR reflects conventional and unconventional monetary policy announcements and measures as well as forward guidance in an artificial short-term interest rate. Since the short-term interest rates have reached the ZLB, the literature increasingly refers to the SR for measuring the monetary policy stance (Krippner, 2013; Lombardi and Zhu, 2014; von Borstel et al., 2016; Wu and Xia, 2016; Potjagailo, 2017; Filardo and Nakajima, 2018). For this analysis, I use the SR instead of the EONIA from 2011:Q2 onwards. Before the sovereign debt crisis, the SR basically equals the policy rate (Figure 1). Since then, it takes on negative values to reflect that unconventional monetary policy measures

[12] To verify the robustness of the results, I conducted a sensitivity check by testing other combinations of these coefficients' values. The responses remained consistent with those reported.

[13] The collection of 18 models is created by taking into account every possible combinations of $k_Q = \{0.01, 0.05, 0.1\}, k_W = \{0.001, 0.01\}$ and $k_S = \{0.01, 0.025, 0.1\}$.

[14] The ECB's policy instrument can be mirrored by means of the EONIA. Many studies use this money market rate to approximate the ECB's monetary policy e.g. Hristov et al. (2014) and von Borstel et al. (2016).

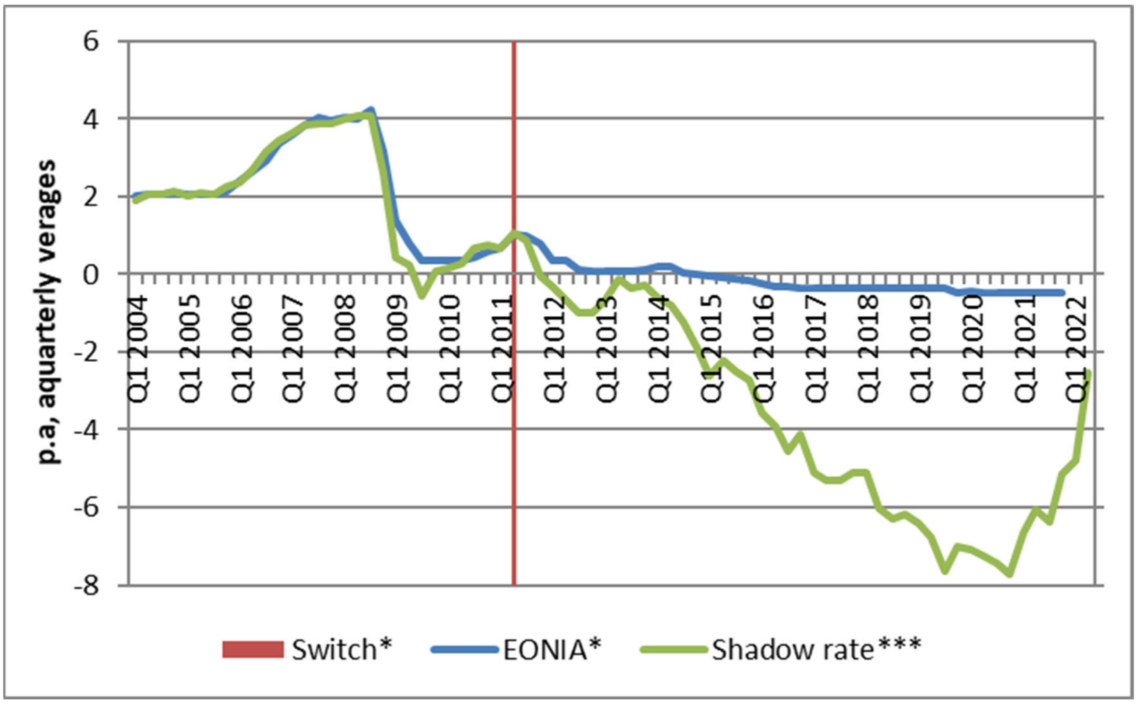
[15] The SR measures the pressure on longer-term interest rates (from unconventional measures and forward guidance) by means of a hypothetical short-term rate. This rate would be the result in the absence of a nominal ZLB for interest rates. The SR is based on estimates by Wu and Xia (2022) for the euro area.

[16] The bank rate refers to new loans (other than revolving loans and overdrafts) with an initial interest rate fixation period.

[17] The spread is based on the difference between the synthetic euro area 10-year bond yield and the German 10-year government bond yield. It reflects the development of risk premiums in euro area government bonds. Large movements (such as during the financial- or sovereign debt crisis) may influence the interest rate pass-through. This underlines the necessity to control for this influence in order to accurately estimate the monetary policy transmission.

extended the degree of accommodation by more than the ZLB-constrained policy rate alone allowed for.

Figure 1: EONIA and shadow rate



*From 2011:Q2 onwards, the shadow rate is employed instead of the EONIA in the TVP-VAR; **EONIA: Euro Over Night Index Average; ***Shadow rate is based on Wu and Xia (2022).

Real GDP and the price level are expressed as quarterly growth rates, whereas the interest rates are represented by their first differences.[18] The model is based on one lag.[19] To estimate the posterior distribution, I utilize 800,000 iterations of the Gibbs sampling method, discarding the initial 20,000 iterations to allow for convergence. To breake the autocorrelation among the sampled iterations, I retain only every 10th iteration. Consequently, the final estimates are derived from a total of 78,000 iterations.[20]

[18] Real GDP and HICP are seasonally adjusted. For further information on the data, please refer to Appendix 7.1.
[19] The lag length is determined based on a marginal likelihood calculation. More specifically, I employ Geweke's (1999) modified harmonic mean method to estimate the marginal likelihood. The model with the highest log likelihood estimate is considered the best fit for the data: for the TVP-VAR with a single lag, log marginal likelihood value is –100.7, while for the TVP-VAR with two lags, it is –114.5. Thus, the model with one lag fits the data best.
[20] To assess the convergence of the Markov chain Monte Carlo (MCMC) algorithm, I adhere to Primiceri (2005). This involves examining the autocorrelation function of the sampled draws to determine the effectiveness of the chain's mixing. For the algorithm to be deemed efficient, the draws should exhibit independence. The autocorrelation estimates and the inefficiency factors, which are based on the relative numerical efficiency measures introduced by Geweke (1992), yield satisfactory outcomes. Additionally, I perform the Raftery and Lewis (1992) diagnostics to estimate the total number of iterations necessary to

Sign restrictions are used to identify the monetary policy shock as in Canova and de Nicolo (2002), Peersman (2005) and Uhlig (2005). The restrictions used are standard in the literature (Galí et al., 2003; Peersman, 2005; Straub and Peersman, 2006; Canova and Paustian, 2010; Hristov et al., 2014). Essentially, the concept is to leave the variable of primary interest, the retail bank rate, unrestricted, while applying comparatively gentile sign restrictions on the other variables. Next to the bank rate, the bond spread is also unrestricted. More specifically, I assume that a monetary tightening shock has a negative effect on output and prices and affects the EONIA/SR positively. In addition to a monetary policy shock, I identify two business cycle disturbances: a positive aggregate demand and an adverse aggregate supply shock. The demand shock is assumed to increase output, prices and the EONIA/SR. The supply shock decreases output and increases prices as well as the EONIA/SR. All sign restrictions remain in effect for two quarters following the shock. Table 1 summarizes the restrictions.

Table 1: Sign restrictions

Shock	Real GDP	HICP	EONIA/SR	Bank rate	Bond spread
Monetary policy	↓	↓	↑	?	?
Supply (aggregate)	↓	↑	↑	?	?
Demand (aggregate)	↑	↑	↑	?	?

↑ denotes a positive impact, ↓ a negative and ? refers to an unrestricted variable.

To implement the restrictions, I make minor adjustments to the model as defined by equations (3.4), (3.5), (3.6) and (3.7), which was originally based on recursive identification. Furthermore, I define an orthonormal rotation matrix G_t, i.e. $G_t' G_t = \mathrm{I}_n$. Consequently, equation 3.4 can be reformulated as follows:

$$y_t = X_t' \tilde{B}_t + A_t^{-1} G_t' G_t \varepsilon_t = X_t' \tilde{B}_t + A_t^{-1} \Sigma_t G_t' \tilde{\varepsilon}_t. \tag{3.9}$$

The new shocks are represented by $\tilde{\varepsilon}_t = G_t \varepsilon_t$. The corresponding variance is given by $Var(\tilde{\varepsilon}_t) = G_t \mathrm{I}_n G_t'$. To determine G_t, I employ the QR decomposition method. Given that the VAR includes five variables, G_t is a matrix of dimension 5×5:

$$G_t = \begin{bmatrix} QR(\theta[1,1]) & \cdots & QR(\theta[1,5]) \\ \vdots & \ddots & \vdots \\ QR(\theta[5,1]) & \cdots & QR(\theta[5,5]) \end{bmatrix} \tag{3.10}$$

attain a certain precision. The findings indicate that the actual number of iterations conducted is far above the required threshold. Detailed results are available upon request.

Initially, I draw a 5×5 matrix, denoted as θ, from the $N(0, \mathrm{I}_5)$ distribution. Subsequently, I apply the QR decomposition on θ to form the G_t matrix, which serves as a potential structural impact matrix. Next, I verify whether G_t complies with the predetermined sign restrictions. If it meets these restrictions, it is stored; if not, I draw a new θ from the standard normal distribution etc.

4 Results of the TVP-VAR

Subsequently, Section 4.1 details the estimated median impulse responses to the monetary policy shock over time. Section 4.2 focuses primarily on the varying impacts of an identical monetary policy shock under different monetary policy stances taken by the ECB. In Section 4.3, to gauge the monetary policy shock's quantitative importance in comparison to the two business cycle disturbances, a forecast error variance decomposition (FEVD) is provided. Appendix 7.2 presents the time-varying posterior estimates of the covariance matrix.

4.1 Impulse responses to monetary policy shocks

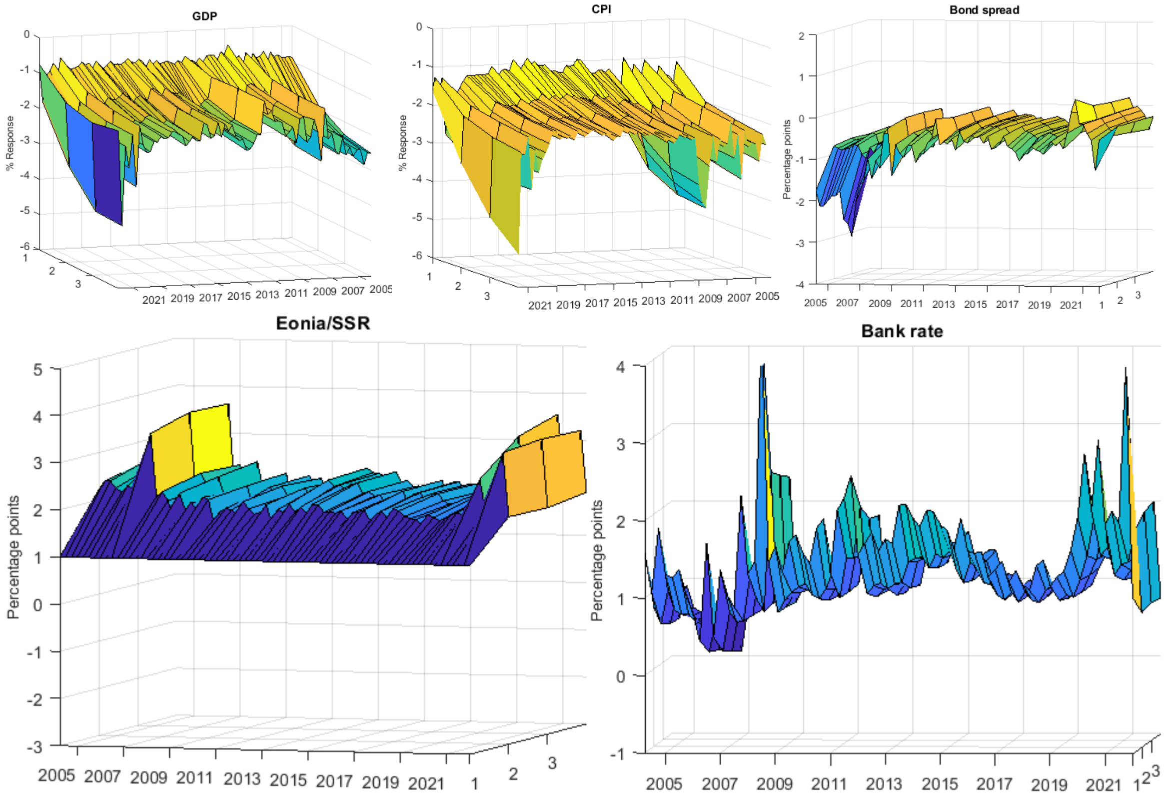
Figure 2 displays the cumulative median impulse responses (for the time period: 2004:Q3–2022:Q2, over four quarters) to a one-percentage-point rise in the EONIA/SR. The impulse response functions to the monetary policy shock verify clear variations across time.

The responses of GDP and prices are restricted to decrease for two quarters after the monetary policy shock. Thus, the immediate decrease occurs by construction (Figure 2). However, credible intervals suggest that a monetary policy shock also implies negative effects on the price level until about one year after the shock following the financial crisis (Figure A.3).[21] In contrast, the decrease in GDP is less pronounced.

The immediate pass-through of a monetary policy shock to the bank lending rate for non-financial corporations changes considerably over time. In the years before the financial crisis the point-estimate of the median impulse response following a conventional monetary policy shock seems incomplete: a one percentage point increase in the EONIA increases the bank rate by roughly 0.8 percentage point. During the financial crisis, the median bank rate responds more strongly to a conventional monetary policy shock than before or afterwards.[22] However, the median bank rate responses during the European

[21] Figure 3 shows the respective credible intervals. The credible intervals refer to the 16th and 84th percentile of the posterior distribution.
[22] Please note that the employed estimation mechanism does not prove that a certain episode like the financial crisis is responsible for the observed changes in the monetary transmission mechanism. However,

Figure 2: Time-varying impulse responses to a monetary policy shock



Accumulated median impulse responses to a 1 PP monetary policy shock. Length of the impulse responses is four quarters, whereas quarter one denotes the shock period. The impulse response of the bank rate and the bond spread is in relation to the EONIA/SR impulse response. From 2011:Q2 onwards, the SR is used instead of the EONIA.

sovereign debt crisis (2011/12) do not show comparable anomalies: the bank rate responses are only somewhat larger than before in 2010. Yet, the estimation uncertainty is relatively high. This is reflected by the relatively large credible intervals. They reveal non-distinguishable responses from zero from 2004 until mid-2013 (Figure 3.1).[23] From mid-2011 onwards, the shadow rate approximates monetary policy. A non-zero response is estimated from mid-2013 until 2015-16 (Figure 3.1). Thus, the monetary pass-through to the bank rate seems slightly stronger during this period. However, the credible intervals are still quite large. They lie roughly between 0.5 and 3.5 percentage points at the shock period. From 2016 until the end of 2019, the credible intervals instead reveal a non-distinguishable response from zero (Figure 3.1). This is due to the decreasing pass-

it appears likely that in periods like the financial crisis, European debt crisis or coronavirus crisis, changes to the transmission mechanism occurred. Moreover, during these times, besides monetary policy measures, other measures such as fiscal policy measures were also introduced. These may have influenced the effectiveness of the monetary policy transmission mechanism as well.

[23] The credible intervals refer to the 16^{th} and 84^{th} percentile of the posterior distribution. The interval ranges roughly between -0.4 and 3.7 percentage points.

Figure 3: IRFs to a monetary policy shock at selected quarters

Figure 3.1: IRF at 1st quarter (shock period)

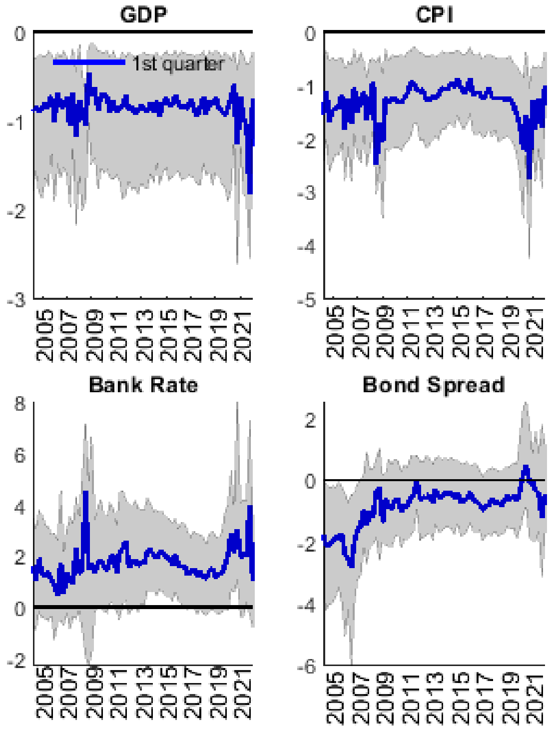
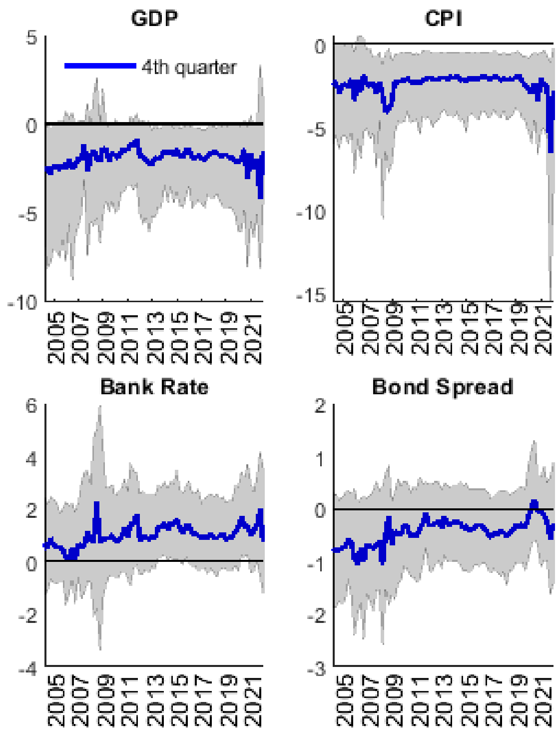


Figure 3.2: IRF at 4th quarter



Solid lines depict the accumulated median impulse responses to a 1PP monetary policy shock, grey area the 16th and 84th percentiles of the posterior distribution of the responses. RiR denotes the reference interest rate which is the EONIA/SR.

through in 2016. After this, until the end of 2019, it develops at a lower level compared to the years before. This signals a somewhat weaker pass-through of a monetary policy shock during this period. Nevertheless, the point-estimate still hovers around a level indicating a more or less complete pass-through. However, from 2020 onwards, the pass-through to the bank rate increases considerably again. But the credible intervals are also wider and only suggest a non-distinguishable response from zero for 2020. This period is largely influenced by the coronavirus pandemic and the decisive monetary and fiscal measures implemented in response to it. Please note that the BVAR estimates during the coronavirus pandemic might be less reliable due to the large and uncommon data movements during this period (Carriero et. al, 2022).

In addition, the variance of a monetary policy shock changes considerably over time (Figure A2.1). For instance, during the financial crisis, the standard deviation of a monetary policy shock is about 3 times higher than before or ultimately afterwards. After the introduction of unconventional monetary policy in 2011, the standard deviation of a monetary policy shock rises steadily. In 2019, it is about 2.5 times higher than at the beginning of unconventional measures in 2011. Thus, it seems that in addition to conventional monetary policy also unconventional monetary policy impulses contribute to this increase and eventually help in influencing lending rates, whereas the unconventional pass-through seems to be mainly driven by large unconventional monetary policy shocks. In 2020, during the coronavirus pandemic, a further temporary pronounced increase occurs in the standard deviation of a monetary policy shock (by about 1.4 times).

4.2 Analysis of differences between monetary policy shocks over time

My findings are further confirmed by the posterior probability for the difference in impulse responses. To be more precise, I evaluate the statistical difference in impulse responses to a monetary policy shock across different time periods by computing the ratio of the Markov Chain Monte Carlo (MCMC) draws for the responses at two separate points in time. I calculate the posterior probability that the response at a specific point in time (initial response considered) is less than at another time (subsequent response considered). Table 2 shows the posterior differences in these responses. Posterior probability values nearing 50 % suggest a negligible difference between the two points in time. Probabilities greater than (or less than) 50 % suggest that the initial response is smaller (or larger) than the subsequent response.

I consider the following points in time[24]: 2005:Q2 and 2010:Q2 reflect the environment before and after the financial crisis and 2008:Q4 the financial crisis period. The period of the sovereign debt crisis is reflected by 2011:Q4 and the beginning of unconventional measures by 2012:Q4. 2013:Q4 and 2014:Q2 denote the period before the introduction of the negative interest rate policy. 2015:Q2, 2016:Q1, 2017:Q2, 2018:Q2 and 2019:Q2 represent the negative interest rate period as well as the period under massive unconventional easing. The most recent coronavirus pandemic period is reflected by 2020:Q1 and 2021:Q3.

Table 2: Posterior probability for the difference in bank rate impulse responses following a monetary policy shock

Horizon	0Q (%)	1Q (%)	2Q (%)	3Q (%)
2005Q2 vs 2008Q4	77	54	46	54
2010Q2 vs 2008Q4	76	52	54	54
2010Q2 vs 2011Q4	59	63	61	58
2012Q4 vs 2011Q4	58	61	57	57
2012Q4 vs 2016Q1	56	63	64	67
2013Q4 vs 2016Q1	47	54	55	60
2015Q2 vs 2016Q1	49	50	51	56
2012Q4 vs 2018Q2	43	52	55	60
2013Q4 vs 2018Q2	30	34	40	47
2014Q2 vs 2018Q2	38	42	46	49
2015Q2 vs 2018Q2	37	40	45	51
2016Q1 vs 2018Q2	40	43	43	45
2017Q1 vs 2018Q2	50	50	52	51
2019Q2 vs 2018Q2	49	51	49	48
2020Q3 vs 2018Q2	35	38	36	37
2021Q3 vs 2018Q2	44	46	48	43

Difference in bank rate impulse responses evaluated at different points in time, e.g. 2005Q2 vs 2008Q4. The impulse response length starts at 0 (shock period) until 3 quarters ahead. Posterior probability values nearing 50 % suggest a negligible difference between the two compared time points. Probabilities exceeding (falling below) 50 % indicate that the initial response is lesser (greater) than the subsequent response.

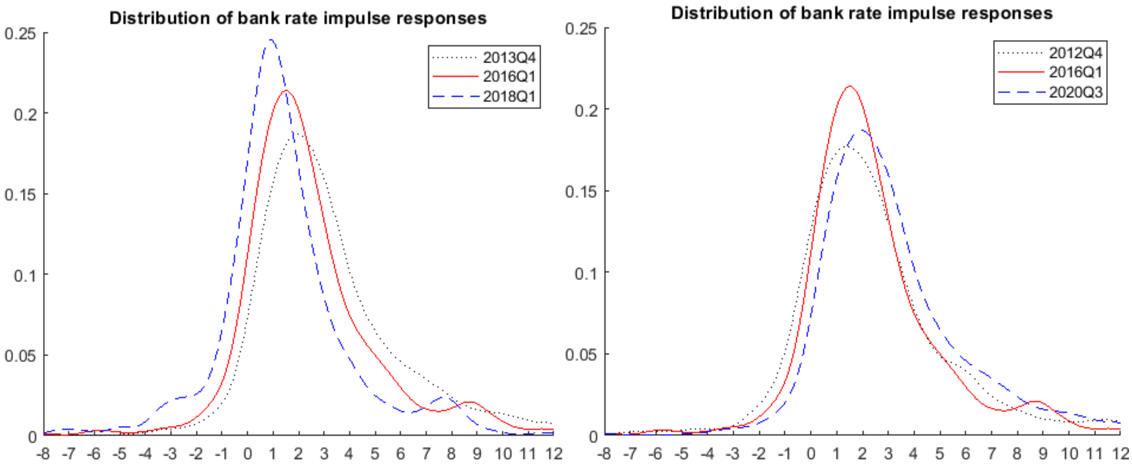
The analysis shows that, compared to the financial crisis, the initial responses before 2008:Q4 and afterwards are considerably smaller as the values are well above 50 %. A fairly similar picture emerges during the sovereign debt crisis: the response in 2011:Q4 seems larger than before and afterwards as the values are again larger than 50 %. During the first years of unconventional easing, the pass-through to the bank rate seems to get stronger. More specifically, at the beginning of unconventional measures (end 2012), the responses are smaller compared to 2016 since the values are well above 50 %. In the

[24] The selection of time points is made at random. I also compute the mean effects across the various monetary policy stances. They reveal the same findings as the periods chosen at random. Results can be obtained upon request.

following years from end-2013 up to the beginning of 2016, the responses are quite similar as the values are close to 50 %. During 2016, the pass-through to the bank rate possibly weakens. This can be seen by means of a two-step comparison: firstly, comparing 2017:Q1 with 2018:Q2 reveals values close to 50 % and thus indicates similar responses between them. Secondly, the previous values of the comparison (2013:Q4 until 2016:Q1) with 2018:Q2 are clearly below 50 % and thus reflect larger responses until the beginning of 2016 than afterwards. During the coronavirus pandemic, the bank rate responses seem larger again as the values are below 50 %. Summing up, these results support my previous findings from Section 4.1.

Figure 4: Distribution of bank rate impulse responses

(a) **(b)**



Kernel distribution of the bank rate impulse responses to a 1 PP monetary policy shock. The impulse response at the time of the shock is shown.

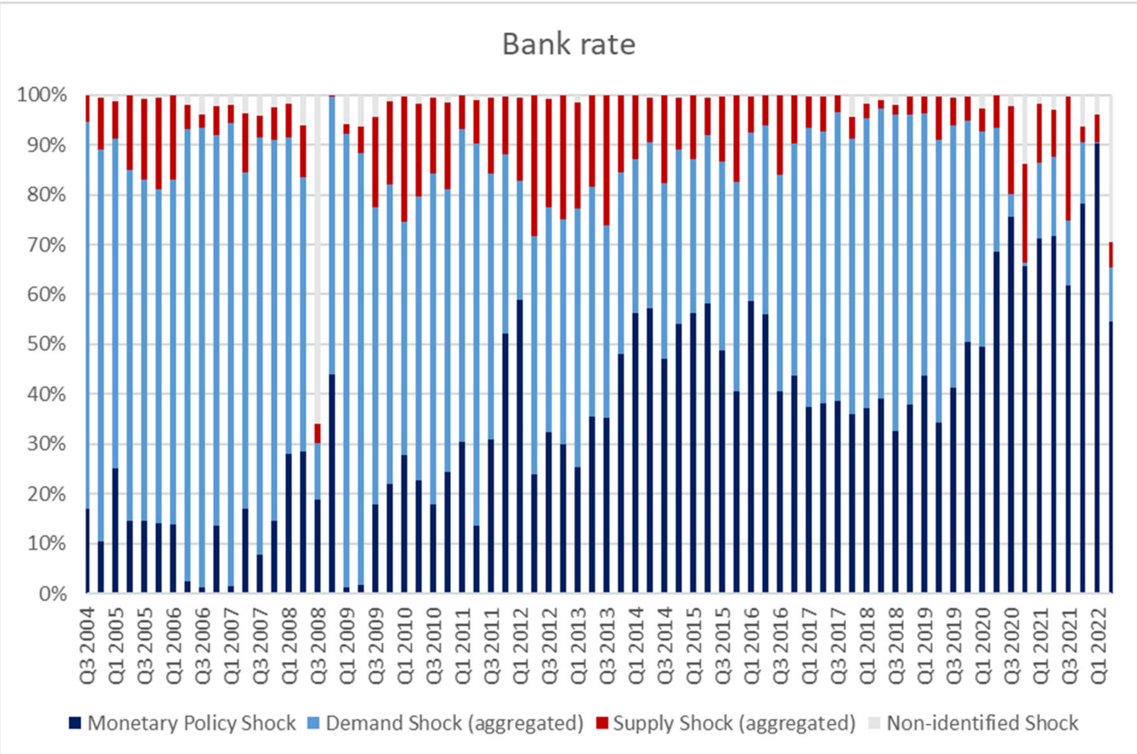
To ensure that these findings are not driven by differences in the scattering width of the impulse response distributions, I show the distribution of the bank rate impulse responses in Figure 4 at the time of the shock. The figure reveals that the scattering width (x-axis) of the distribution functions are about the same. Thus, the above posterior probability results seem not to be driven by scattering differences. Furthermore, the distribution functions indicate a possible weakening of the 2018:Q1 response (Figure 3a) as well: compared to the 2016:Q1-response, the distribution mass in 2018:Q1 seems more skewed to the left.

4.3 Results of the forecast error variance decomposition

The forecast error variance decomposition (FEVD) analyses the extent to which the monetary policy shock accounts for the variance in the forecast errors in comparison to the other structural shocks. This analysis considers, in contrast to the impulse responses, the estimated standard deviations of the shocks. Figure 5 and Figure A.3 (Appendix 7.3) presents the calculated proportions of the forecast error variance for each of the three identified shocks. They focus on the shock period and show the development of the explanatory power between 2004 and 2022. The non-identified shock is calculated as 100 % subtracted by the total variance shares of all three identified shocks of every variable for the respective period.

Looking at GDP, demand shocks explain the lion's share of the variation, whereas for price fluctuations, supply and monetary policy shocks seem to be most relevant factor (Figure A.4, Appendix 7.4). The driving forces behind the bank rate are on average demand and monetary policy shocks (Figure 5). Their importance for the bank rate, however, varies across time with an increasing share of the monetary policy shock during the last ten years: For example, between 2004 and 2007, this shock explains roughly 10 % of the bank rate variation. During the financial crisis, the explanatory power seems to increase somewhat compared to the period before. Moreover, the non-identified shock gains in importance in 2008. This shock summarises all remaining structural shocks, e.g. a risk premium shock. It results from the difference to the sum of all identified shocks.

Figure 5: Forecast error variance decomposition of the bank rate



Variance shares of the monetary policy, demand and supply shock on the bank lending rate.

During the sovereign debt crisis in 2011-12, too, the explanatory power of the monetary policy shock seems higher, explaining about 50 % of the bank rate variations. Before and afterwards, the explanatory power is smaller and hoovers between 20 % and 30 %. The importance of the monetary policy shock for the bank rate increases again at the end of 2013 and hovers around 50 % until the beginning of 2016. Inter alia, this period is characterised by sizeable unconventional monetary policy easing by the ECB. For instance, the expaned asset purchase programme (EAPP) of the ECB was launched at the beginning of 2015. These measures likely also contribute to a larger explanatory power of monetary policy shocks.[25] However, the explanatory power decreases from mid-2016 onward and stays at around 35 % until the end of 2019. In response to the outbreak of the coronavirus pandemic, the ECB set up new unconventional easing measures. Inter alia, these might contribute to the substantial increase in the explanatory power of monetary policy shocks to around 70 % in 2020-21 as well. In addition, the non-identified shock gains somewhat in importance from 2020. Demand shocks are less important compared to the years before 2020.

5 Robustness checks

This paper primarily explores the effects of a monetary policy shock across time. Hence, the subsequent sections focus particularly on this shock. To maintain clarity, the main figures and tables to my robustness checks are included in Appendix 7.4. Comprehensive details on the robustness checks are available upon request.

5.1 Close-to-median model

The posterior median of impulse responses, determined through sign restrictions, pools responses from various models. As an initial step in verifying robustness, I examine the stability of my findings against the close-to-median presentation. This approach identifies the impulse response that most closely approximates the median response. Figure A4.1, located in Appendix 7.4, illustrates both the median and the close-to-median responses for the quarters 2005:Q2, 2010:Q2, 2015:Q2, 2017:Q1, 2019:Q2 and 2020:Q2 to a monetary policy shock. The close-to-median responses frequently exhibit quite similar response to those based on the median. However, this does not hold for the responses of the bank rate in 2017:Q1 and in 2020:Q2.

[25] Please note that the same comment applies as in footnote 24: the estimation mechanism used does not prove that a certain episode or policy measure is responsible for a certain observation. But it is very likely that crisis periods or large monetary policy measures, for example, led to changes in the transmission mechanism.

5.2 Robustness checks on priors

To perform a robustness check, I extend the training sample from 2004:Q2 to 2005:Q3. The results confirm those presented in this paper: the transmission mechanism to the bank rate seems to show some anomalies during the financial- and sovereign debt crisis period as well as during the coronavirus pandemic. Furthermore, the responses again reveal a slight increase in the pass-through to the bank rate from 2013 to 2015-16 and a somewhat weaker pass-through from 2017 up to the end of 2019.

Given the potential for over-parameterisation with the TVP-prior, I employ a hierarchical prior for B_o as an extra robustness check. This approach merges the Minnesota prior, which promotes shrinkage and mitigates over-parameterization risks, with the TVP-prior. The outcomes further support the findings of this paper.[26]

5.3 Robustness checks on identification

According to Paustian (2007), all acceptable sign restrictions should be imposed on the shock of interest to uniquely recover the correct sign of the impulse responses. Therefore, I impose an additional restriction on the bank rate as it is plausible to assume that it increases (or responds at least non-negatively) following a monetary policy tightening – at least during non-crisis times. The results for this robustness check resemble the findings presented above.[27]That is, increased responses during the three crisis periods (financial-, sovereign debt- and coronavirus crisis), larger pass-through from late 2013 to 2015 and a weaker pass-through between 2016 and the end of 2019.

5.4 Robustness check on shadow rate

Since SR estimates are subject to uncertainty and vary widely depending on the underlying model, I also use the average over different SRs for the euro area.[28] More specifically, I replace the Wu and Xia (2022) SR by the average of the respective estimates from Geiger and Schupp (2018), Krippner (2022) and Wu and Xia (2022). The overall effects are similar to those presented above. Just as above, following a monetary policy shock, the bank rate responses exhibit some anomalies during 2009 and 2011-12 (the financial crisis and European sovereign debt crisis periods). Furthermore, the estimates confirmed again a slightly weaker pass-through of unconventional measures from mid-2016 to 2019 and considerably higher bank rate responses from 2020 onwards (Figure A4.2).

[26] The robustness results for the priors can be obtained upon request.
[27] The robustness results for the additional imposed sign restrictions can be obtained upon request.
[28] See Appendix Figure A1 for the development of the different SRs.

Looking at the FEVD, it is very similar to the previous results as well. The explanatory power of a monetary policy shock on the bank rate increases at the end of 2013 and varies between 50 % and 60 % until 2016 (Figure A4.3). As in the benchmark findings, the explanatory power of monetary policy shocks starts to decrease from mid-2016 and stays between 30 % and 40 % until 2019. With the outbreak of the coronavirus pandemic in 2020-21, the explanatory power increases to more than 80 %.

For a further robustness check, I test whether my results are sensitive to a different starting point of the shadow rate. More specifically, I check whether an earlier (2009Q1, 2010Q1) or later (2011Q4) switch from the EONIA to the shadow rate of Wu and Xia (2022) alters my benchmark results. The overall effects are again similar to those presented above.[29]

5.5 Alternative bank rate: lending rate for house purchase

To gain a broader view of changes in the euro area interest rate pass-through, the analysis is extended to another bank retail rate. More specifically, in addition to the bank rate on loans to non-financial corporations analysed above, I consider here the bank rate to households for house purchases.[30] The results resemble the previous findings. Just as above, the bank rate responses exhibited some anomalies during 2009, but to a lesser extent during 2011-12 following a monetary policy shock (Figure A4.4). Furthermore, the pass-through to the bank lending rate seems to weaken again throughout 2016 and stays at a lower level until 2019. From 2020, the pass-through to the bank rate increases considerably again. The FEVD confirms the previously stated findings: e.g., the explanatory power of a monetary policy shock on the bank rate weakens in 2016 and increases again in around 2020 (Figure A4.5).

6 Conclusion

The transmission from market rates to bank retail rates attracted a renewed focus when the financial system was impaired following the financial crisis and in the course of the European sovereign debt crisis. Alerted by these developments, the ECB, in addition to other major central banks, cut its policy rates to virtually zero and simultaneously engaged in massive unconventional monetary policy measures to restore the effectiveness of monetary policy. In light of these various measures as well as the crises that modified the transmission of monetary policy, for a model-based analysis of the pass-through of

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[29] The robustness results on the different starting points of the shadow rate can be obtained upon request.

[30] Lending rate for house purchase (excluding loans other than revolving loans and overdrafts, convenience and extended credit card debt) to households and non-profit institutions serving households, annualized agreed rate, euro area (changing composition), and monthly series transformed into a quarterly series (by averaging across the corresponding three months), Source: ECB, MIR.

monetary policy is important to allow for a substantial degree of time variation. Therefore, this paper applies a TVP-VAR with sign restrictions to trace the impact of a monetary policy shock across the ECB's different monetary policy stances. More specifically, until mid-2011 the effect of a conventional monetary policy shock is analysed. Afterwards, unconventional measures increasingly complemented the ECB's interest rate measures. Against this background, I use the shadow rate (SR) to trace the changing impacts of mostly unconventional shocks since mid-2011.

My results show that the reaction of macroeconomic variables as well as the bank rate on loans to non-financial corporations to a monetary policy shock varies across time. More specifically, the median impulse response following a monetary policy shock reveals a distorted pass-through during 2008-09 (the financial crisis period) to the bank rate. From mid-2013 until 2015-16, the model estimates a slight improvement in the pass-through of a monetary policy shock to the bank rate. In 2016, the pass-through seems to weaken. Afterwards, until the end of 2019, the median response seems to develop at a lower level. Nevertheless, it varies around a level still indicating a more or less complete pass-through. In 2020, however, the pass-through to the bank rate increases considerably again. This period is largely influenced by the coronavirus pandemic and the decisive monetary and fiscal measures implemented in response to it.[31] During the entire sample period, the credible intervals suggest large estimation uncertainty. While the median impulse response exhibits the dynamics described above, the credible intervals are so wide that a constant and complete pass-through over the entire sample is undoubtedly within the realms of possibility.

The variance decomposition supports the previous findings. That is, the relative explanatory power of a monetary policy shock on the bank rate seems to increase from the end of 2013 until the beginning of 2016. Inter alia, this period is likely characterised by the ECB's new and comprehensive unconventional monetary policy easing measures. However, the explanatory power of monetary policy shocks decreases afterwards and stays at a lower level until the end of 2019. In 2020-21, the explanatory power of monetary policy shocks substantially increases again. Most likely, this reflects the new unconventional easing measures the ECB set up in response to the outbreak of the coronavirus pandemic. However, it cannot be ruled out that the transmission of monetary

[31] Please note that the estimation mechanism used does not prove that a certain episode or policy measure is responsible for a certain observation. But it is very likely that crisis periods or large monetary policy measures, for example, led to changes in the transmission mechanism. Moreover, during crisis periods, besides monetary policy measures, other measures such as fiscal policy measures were also introduced. These may have influenced the effectiveness of the monetary policy transmission mechanism as well.

policy is to some extent also influenced by other sources, e.g. decisive fiscal policy measures during crisis periods.

Further, the growing standard deviation of a monetary policy shock since the onset of unconventional measures in 2011 shows that, besides to conventional monetary policy, unconventional impulses also influence lending rates, whereas the unconventional pass-through seems to be mainly driven by large monetary policy shocks. In addition, (unconventional) monetary policy shocks still seem effective in influencing real economic variables and in particular inflation.

7 Appendix

7.1 Data sources

This paper employs quarterly data on the euro area and covers a time horizon between 1998:Q1 and 2022:Q2 using the following variables:

Gross domestic product (GDP): real gross domestic product in 2010 chained prices, in logs and first differences, seasonally adjusted, euro area (19), quarterly series. Source: Eurostat.

Consumer prices (HICP): HICP in logs and first differences, all items, seasonally and calendar adjusted, monthly index 2015 =100, euro area, transformed into a quarterly series (by averaging across the corresponding three months). Source: ECB.

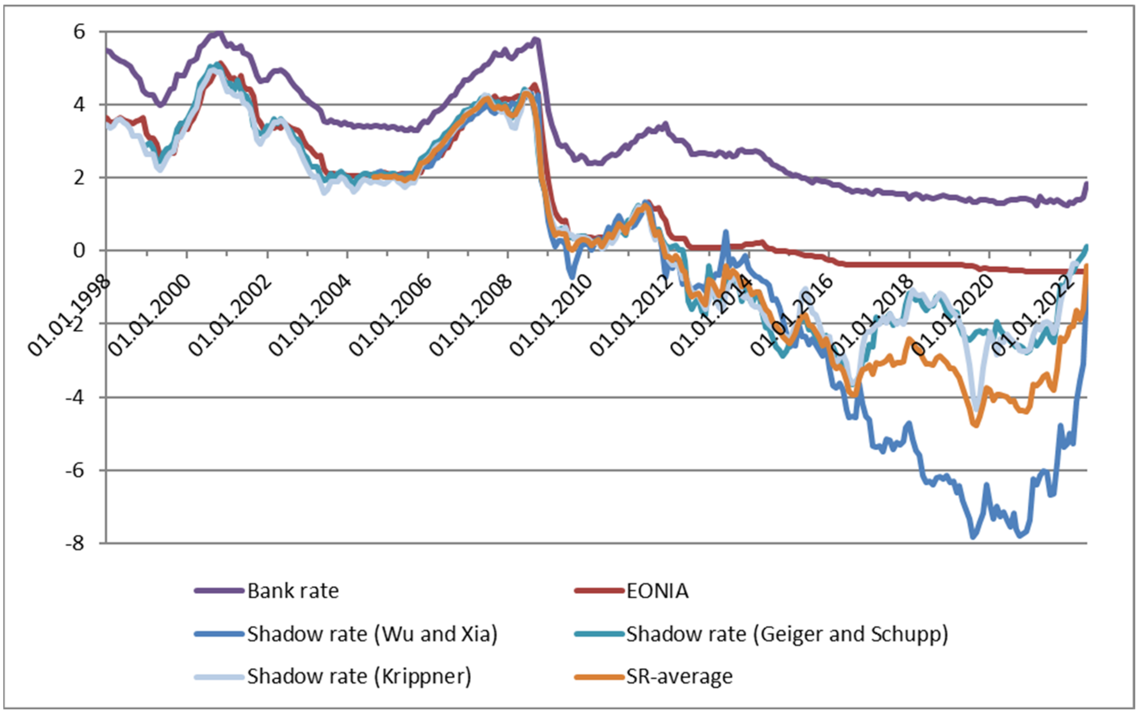
EONIA: in first differences, euro area, monthly series transformed into a quarterly series (by averaging across the corresponding three months), series is extended by the three month FIBOR from 1998Q1 – 1998Q4. Source: Deutsche Bundesbank.

Shadow rate (SR): in first differences, euro area, monthly series transformed into a quarterly series (by averaging across the corresponding three months). Source: Wu and Xia (2022).

Bank rate: in first differences, MFIs excluding MMFs and central banks, loans other than revolving loans and overdrafts, convenience and extended credit card debt to non-financial corporations, new business, annualised agreed rate, euro area (changing composition), monthly series transformed into a quarterly series (by averaging across the corresponding three months), series is extended by euro area retail bank lending rates to enterprises (with maturity over one year) in Germany based on Deutsche Bundesbank from 1998:Q1 – 1999Q4. Source: ECB, MIR; Deutsche Bundesbank.

Bond spread (BS): in first differences, the spread is based on the difference between the synthetic euro area 10-year bond yield and the German 10-year government bond yield, transformed into a quarterly series (by averaging across the corresponding three months). Source: Thomson Reuters.

Figure A1: Interest rates, euro area



Bank rate: MFIs excluding MMFs and central banks, loans other than revolving loans and overdrafts, convenience and extended credit card debt to non-financial corporations, new business. SR-Average: average over the shadow rates from Geiger and Schupp (2018), Krippner (2022) and Wu and Xia (2022).

7.2 Time-varying posterior estimates of the stochastic covariance

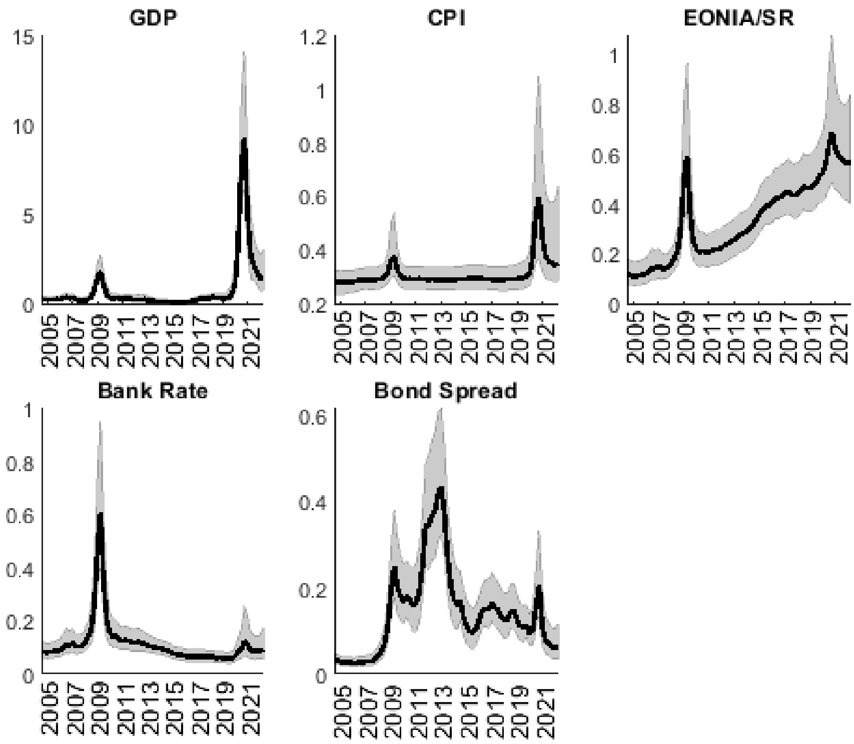
The variance-covariance matrix of the residuals, which changes over time, is broken down into $A_t^{-1}\Sigma_t\Sigma_t'(A_t^{-1})'$ and consists of two matrices: (1) matrix Σ_t, which varies with time and represents the diagonal matrix containing the variances of the structural shocks ε_t, and (2) the matrix A_t, also time-varying and lower triangular, which defines the simultaneous relations. The structure of the latter is as follows:

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{y\pi,t} & 1 & 0 & 0 & 0 \\ \alpha_{yr,t} & \alpha_{\pi r,t} & 1 & 0 & 0 \\ \alpha_{yb,t} & \alpha_{\pi b,t} & \alpha_{rb,t} & 1 & 0 \\ \alpha_{ys,t} & \alpha_{\pi s,t} & \alpha_{rs,t} & \alpha_{bs,t} & 1 \end{bmatrix}$$

where π_t is real GDP, π_t prices, r_t EONIA/SR, b_t the bank rate and s_t the bond spread. More specifically, $\alpha_{y\pi,t}$ captures the simultaneous impact of a GDP shock on inflation.

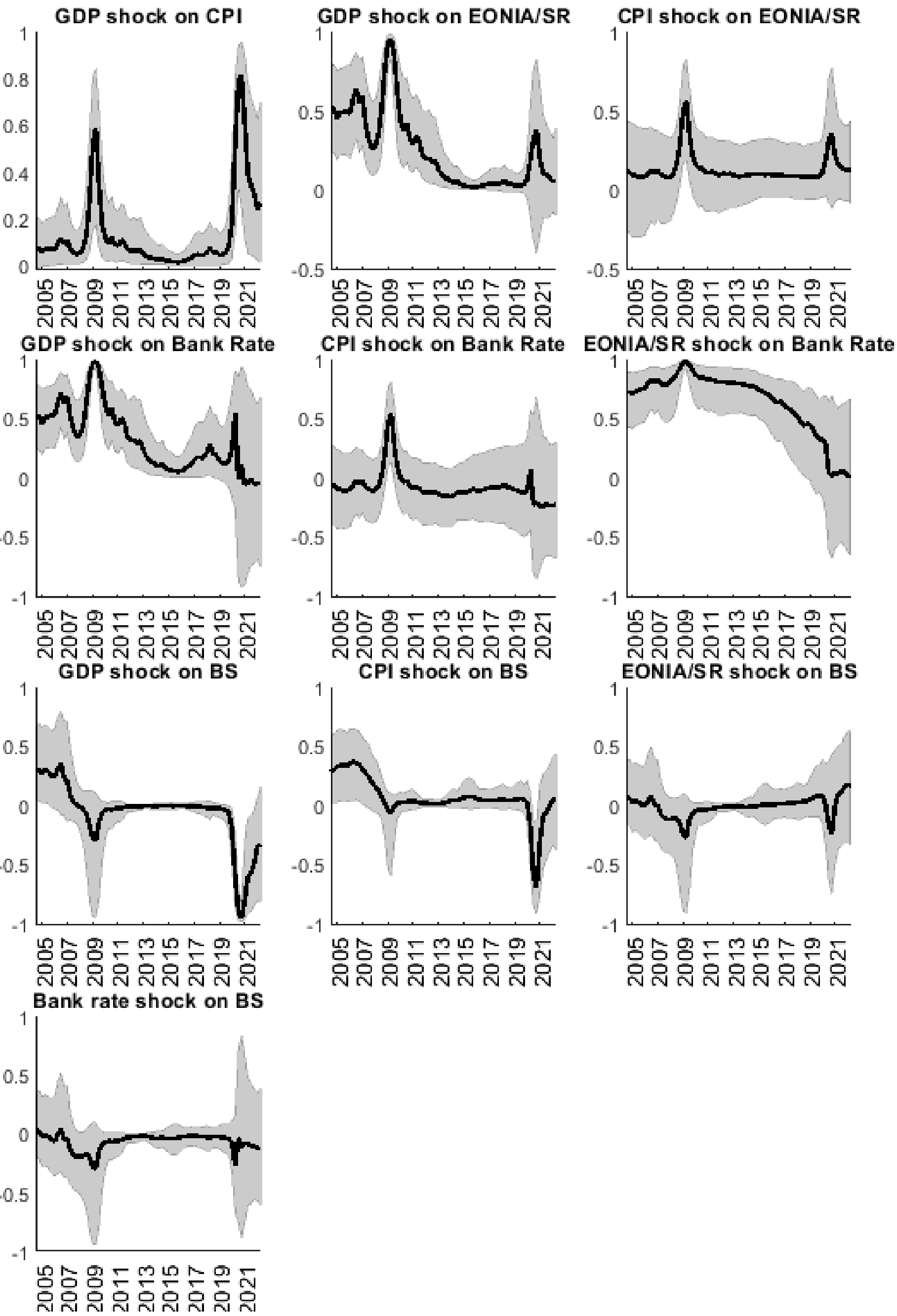
Regarding Σ_t, fluctuations over time are evident for the five endogenous variables. Figure A2.1 illustrates the estimated stochastic volatility for the structural shocks affecting GDP, prices, EONIA/SR, bank rate and the bond spread. It shows the posterior mean along with the 16th and 84th percentiles of the shock's standard deviation. The second matrix, which represents the time-varying simultaneous relations, is shown in Figure A2.2. These also exhibit variability over time for every shock.

Figure A2.1: Volatility of the structural shocks



Posterior mean (solid line), 16th and 84th percentiles (in grey) of the standard deviation of residuals of GDP, prices, EONIA/SR, the bank rate and bond spread equation.

Figure A2.2: Posterior estimates of the simultaneous relation



Posterior estimates of the simultaneous relations. Posterior mean (solid line), 16th and 84th percentiles (in grey). BS denotes the bond spread.

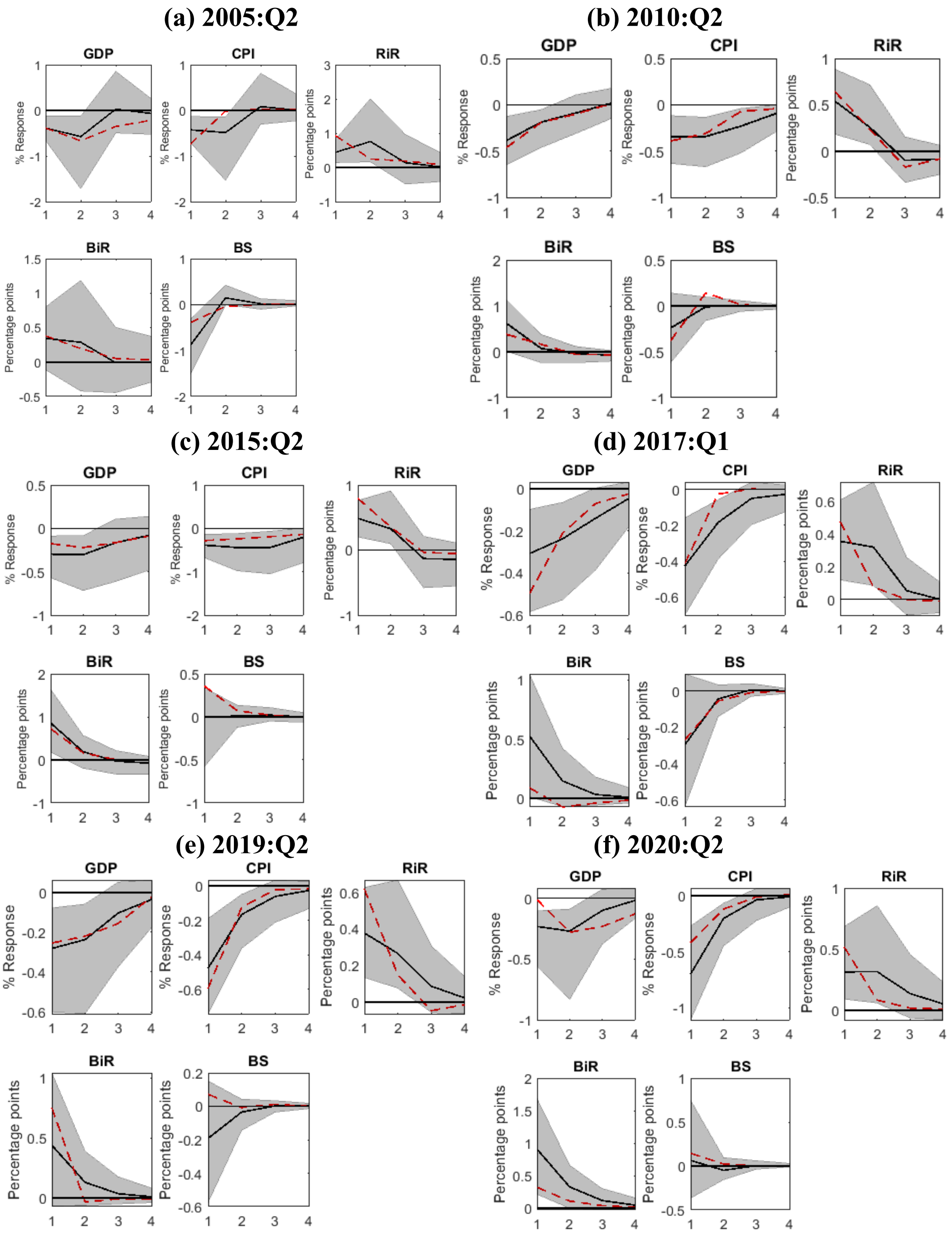
7.3 Forecast Error Variance Decomposition

Figure A3: Forecast Error Variance Decomposition, shock period

7.4 Robustness checks

7.4.1 Close-to-median IRFs

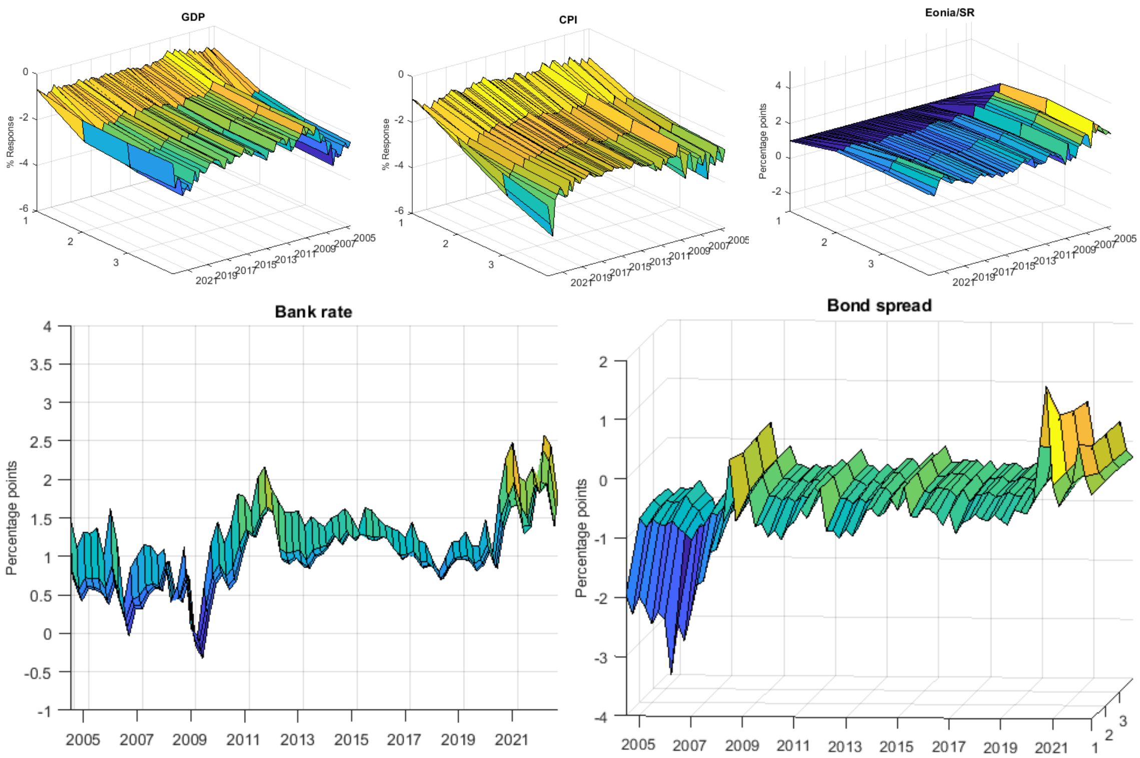
Figure A4.1: Close-to-median IRFs to a monetary policy shock



Solid lines are median impulse responses to a monetary policy shock, grey area the 16th and 84th percentiles of the posterior distribution. Red dashed lines are the close-to-median responses. RiR denotes the reference interest rate and thus depicts the EONIA/SR, BiR refers to the bank rate and BS the bond spread.

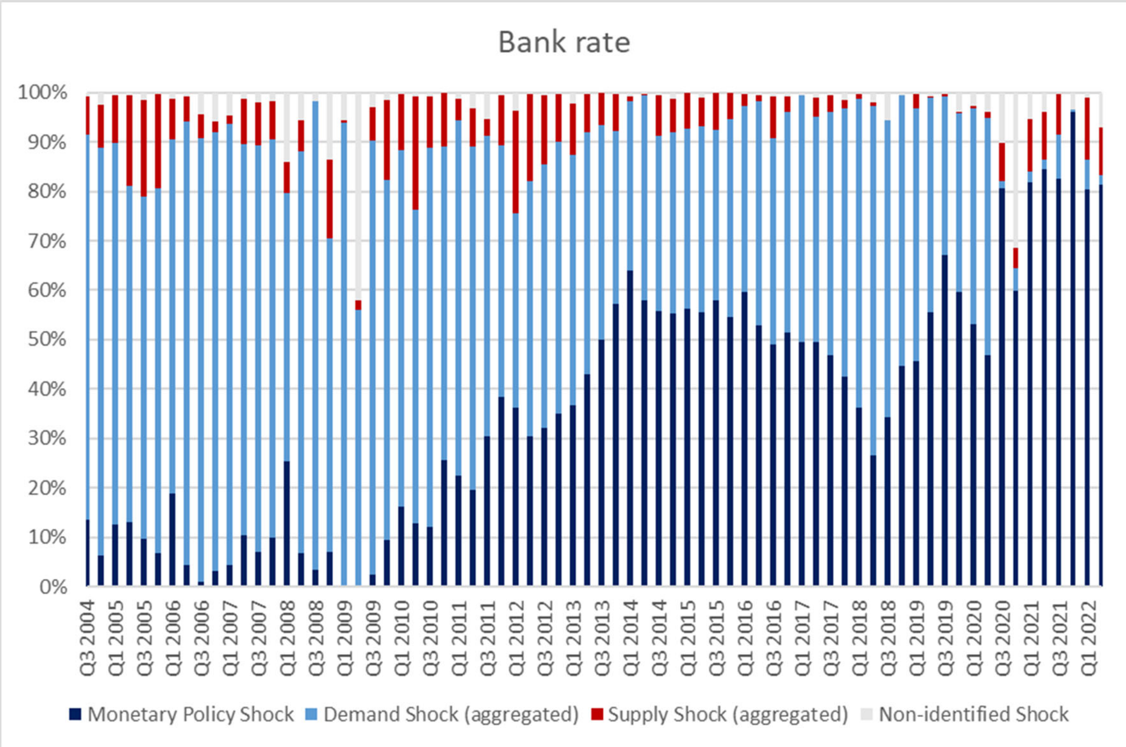
7.4.2 Average shadow rate

Figure A4.2: Median-IRFs following a monetary policy shock



Accumulated median impulse responses to a 1 PP monetary policy shock. Length of the impulse responses is four quarters, whereas quarter one denotes the shock period. The impulse response of the bank rate and the bond spread is in relation to the EONIA/SR impulse response. From 2011:Q2 onwards, the SR is used instead of the EONIA. The SR is an average over the estimates from Krippner (2022), Geiger and Schupp (2018) and Wu and Xia (2022).

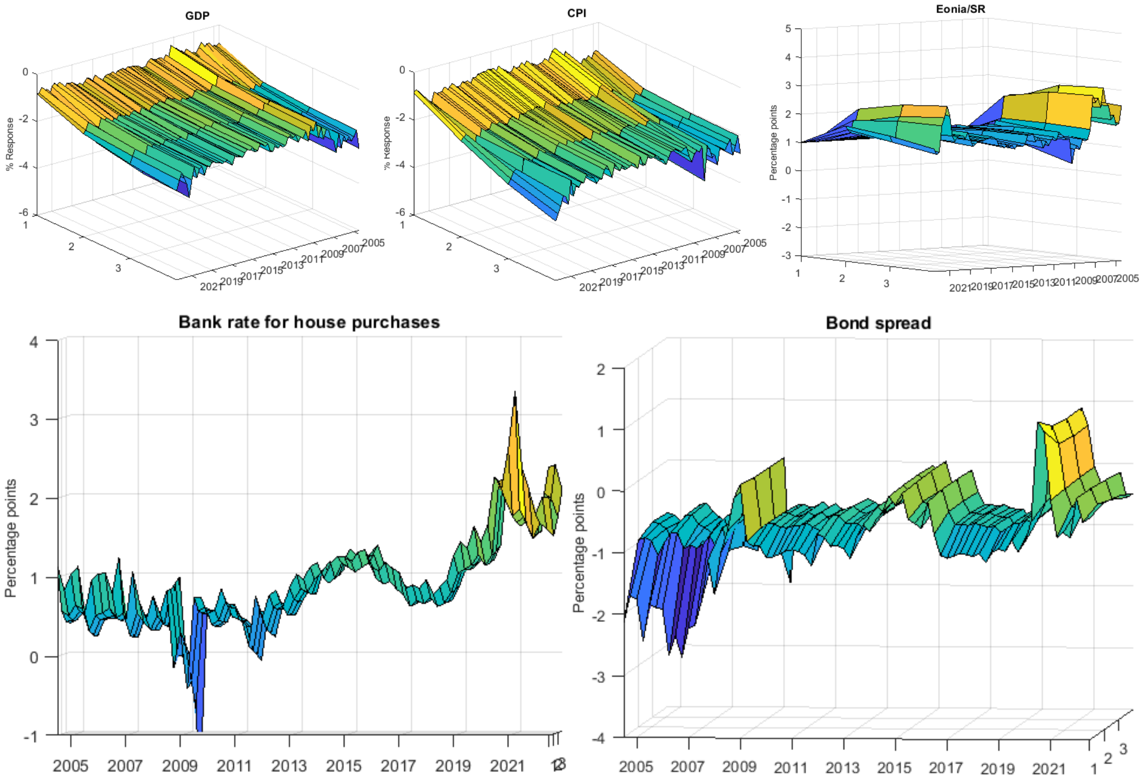
Figure A4.3: Forecast error variance decomposition of the bank rate



Variance shares of the monetary policy, demand and supply shock on the bank lending rate to non-financial corporations.

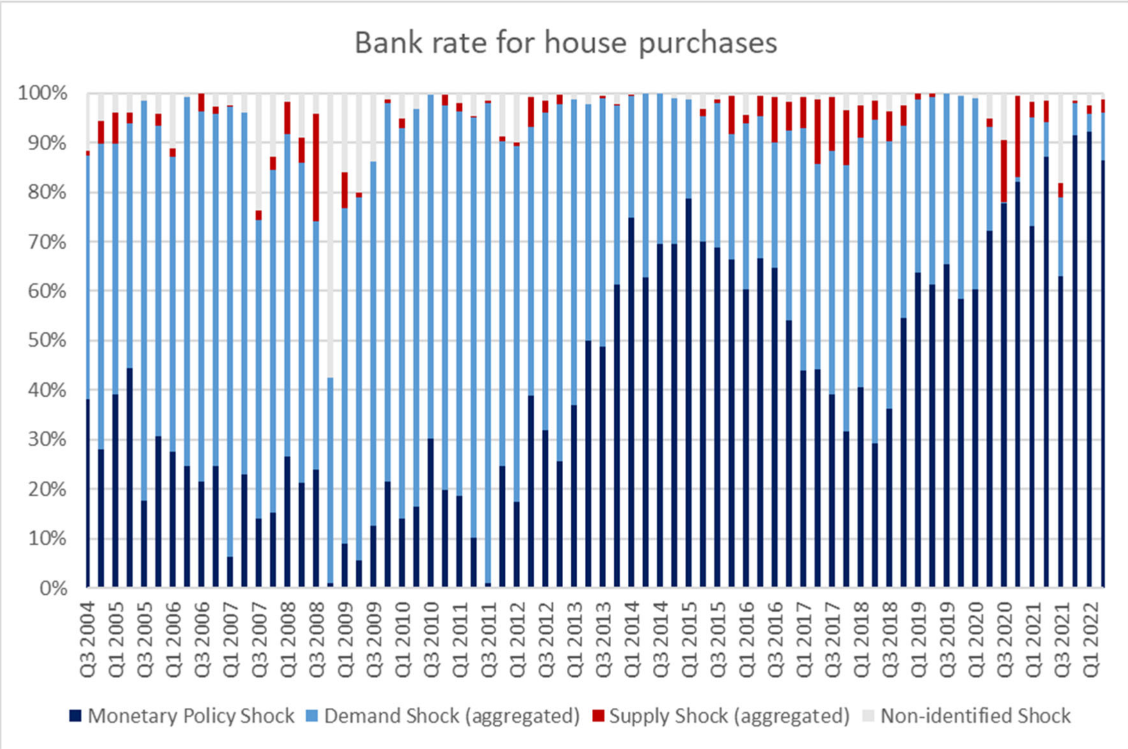
7.4.3 Bank Rate: Lending for house purchase

7.4.4 Figure A4.4: Median-IRFs following a monetary policy shock



Accumulated median impulse responses to a 1 PP monetary policy shock. Length of the impulse responses is four quarters, whereas quarter one denotes the shock period. The impulse response of the bank rate for house purchase and the bond spread is in relation to the EONIA/SR impulse response. From 2011:Q2 onwards, the SR is used instead of the EONIA.

Figure A4.5: Forecast error variance decomposition



Variance shares of the monetary policy, demand and supply shock on the bank lending rate for house purchases.

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