Policy Rate Shocks Beyond Zero [*]

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Abstract

This paper shows that the aggregate effects of policy rate shocks on economic and banking activity do not exhibit significant differences when policy rates are above or below zero. We use a suit of VAR models in conjunction with macroeconomic, financial and banking data for the Eurozone. Policy rate cuts below zero significantly improve borrowing conditions for non-financial corporations and are also passed onto depositors by banks. The easing in bank lending conditions, however, does not translate into higher systemic financial risk in the banking sector, reflecting positive effects on the financial soundness of banks and non-financial corporations. Moreover, both corporate and household deposit rates respond with the same sign and magnitude to policy rate shocks. Yet, we find substantial heterogeneity in the way banks respond to policy rate cuts below zero: the pass-through of policy rate shocks to lending rates is increasing in the initial level of the deposit rate.

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1 Introduction

Monetary policy rates in most developed economies have been close to zero since the Great Recession. Several central banks, including the European Central Bank, The Sverige Riksbank and the Bank of Japan, actually pushed their policy rates even below zero. While there is no evidence of significant changes in the economy's performance at the zero lower bound (see Debortoli et al. 2020), there is, instead, significant disagreement regarding the effectiveness of policy rate cuts below zero.

A crucial question in the debate is whether loan and deposit rates fall in response to a policy rate cut when the policy rate is already below zero. To maintain profitability, banks close to an effective lower bound on the deposit rate might pass-through less of a policy rate cut onto their loan rates. This behaviour would weaken the transmission of monetary policy to the real economy. Alternatively, even if banks actually do cut their lending margins, they could become less profitable and hence more fragile. On aggregate a general increase in the fragility of the banking sector could be leading to increased financial instability and hence potentially have recessionary effects.

This paper provides comprehensive empirical evidence that helps to resolve this debate. It does so by investigating the monetary transmission mechanism both when the level of the policy rate is positive or when it is negative. The results rely on the use of vector autoregressive (VAR) models in conjunction with euro area macroeconomic, financial and banking data. In describing our results it is convenient to think of the analysis as comparing two situations: one where policy rates are above zero and the other where policy rates are below zero. We will refer to these two situations as *positive* and *negative territory*. Our key results are as follows. First the quantitative effects of policy rate shocks on lending rates, deposit rates and economic conditions are the same in positive and negative territory. Second, in both territories policy rate shocks have positive impacts on the financial soundness of both the corporate sector and the banking sector. Third, we find substantial heterogeneity among banks in the way that their lending rates respond to policy cuts in negative territory. Specifically, we show that the pass-through from policy rate cuts to lending rates is increasing in the initial level of the deposit rate charged by banks.

Our last result suggests an interesting form of state dependency in the effects of monetary policy shocks. When interest rates are low for a long time, more banks charge lower deposit rates to their costumers. Hence, our results suggest that the pass-through of additional interest rate cuts will be lower moving forward. This channel for state dependency complements the one documented by Berger et al. (2021) and Eichenbaum et al. (2022). These authors focus on state dependency of the effects of monetary policy due to mortgage prepayment and household refinancing decisions. In contrast, we emphasize state dependency that arises from asymmetries in the pass-through from policy rate cuts to lending rates.

We focus our analysis on the euro area. This is motivated by three facts. First, in the aftermath of the Great Recession, the European Central Bank (ECB) was the first major central bank to lower one of its key policy rates into negative territory. Second, in the Euro zone, bank lending plays a crucial role in firms' external financing.[1] Third, the richness and coverage of the proprietary euro area bank-level data allow us to track the transmission of monetary policy shocks through the banking sector. The latter is at the center stage of the discussion on the effectiveness of policy rate shocks in negative territory.

Our analysis proceeds in two steps. In the first step, we adopt a stochastic volatility time-varying coefficients VAR model (TVP-VAR) as in Cogley and Sargent (2005) and Primiceri (2005). The model is a generalization of the standard constant parameter VAR model and allows us to evaluate whether there has been a progressive change in the transmission mechanism of the systematic and non-systematic components of monetary policy when moving from positive to negative territory.[2] Hence, this approach is particularly suitable to explore the effects of policy rate shocks in positive, zero and negative territory. In this stage of our analysis we identify policy rate shocks using a standard Choleski ordering of variables.

Our results support the view that the aggregate effects of policy rate shocks in negative territory are not less powerful as compared to positive territory. In particular, the dynamic impulse response functions of GDP and inflation are not significantly different over time. We also find that the pass-through to deposit and loan rates is not impaired when policy rates move into negative territory, with corporate deposit rates always being more responsive than household deposit rates. Our results are consistent with the fact that after an initial decrease in the pass-through of policy rate cuts to deposit rates, banks quickly adapted to the news environment and started charging negative rates to their deposits, and primarily to the corporate sector. Figure 1 shows that the median of the overnight deposits to corporations reaches zero already in early 2016. Hence, it is not very surprising that we do not find significant differences in the transmission of policy rate cuts above and below zero.

Drawing on bank lending survey data, we also document that policy rate cuts lead to a relaxation of banks' lending standards, even when controlling for contemporaneous changes in the reported demand for loans. We interpret this evidence as pointing in the direction of the credit channel (see e.g. Bernanke 1992; Ciccarelli et al. 2015) retaining its importance in the transmission of policy rate shocks also in negative territory.

The relaxation of banks' lending standards in response to policy rate cuts could signal increased risk taking by banks (see e.g. Maddaloni and Peydró 2011; Dell'Ariccia et al. 2017). One of the main

[1] Bank lending accounts for about 50% percent of the total external corporate debt, and 12% of total corporate liabilities in the EA. See Adalid et al. (2020).

[2] Costant Parameters VARs have a long history of applications for the analysis of policy rate shocks (see e.g. Sims 1980; Christiano et al. 1999)

concerns regarding policy rates in negative territory is that banks might engage in excessive risk taking in an attempt to maintain profitability, building up aggregate financial instability. To address this concern, we take a step further and estimate the responses of aggregate measures of financial risk to policy rate shocks in positive and negative territory. In particular, using Moody's data on expected default frequencies, we find that policy rate cuts actually significantly reduce the default probability of both banks and non-financial corporations in either of the two territories. Consistently with this finding, we also show that policy rate cuts generally decrease aggregate systemic risk in the banking sector as measured by the index of overall systemic risk in the euro area entire banking sector of Brownlees and Engle (2017).

In the second step of our analysis, we explore the heterogeneity in the effects of policy rate shocks in negative territory conditional on banks' characteristics. Informed by recent asymmetries in the behaviour of bank deposit rates, we group banks according to the level of their deposit rates in the year preceding the implementation of negative policy rates. We find that banks with lower initial deposit rate levels are, on average, less responsive to policy rate shocks in negative territory. In particular, the pass-through to lending rates is substantially lower on impact than for banks with initial higher deposit rates. Overall, these findings suggests a novel form of state dependency of the effects of policy rate shocks as a function of the distribution of bank deposit rates. The longer policy rates are low, the more the cross-sectional distribution of deposit rates shifts to the right.

Finally we document the robustness of our results along two dimensions. First, we split Euro zone banks in terms of their geographical location. We show that the pass-thought of policy rate cuts to lending rates is more powerful for banks located in countries which experience on average higher initial levels of deposit rates, e.g. owing to the 2010-2012 Sovereign debt crisis. This result shows that the type of state-dependency that we uncover, has important implications for cross-country heterogeneity in pass-through of policy rate shocks. Second, leveraging further our confidential bank level data, we employ a difference-in-difference identification strategy across banks with high and low levels of deposit rates. Micro-data estimates confirm the heterogeneity result.

Contribution to the literature. Our paper belongs to the large VAR literature that stresses the importance of credit variables for the transmission of policy rate shocks to the macroeconomy (see e.g. Christiano et al. 1996; Gertler and Karadi 2015). We contribute to this strand of the literature by assessing the impact of policy rate shocks not only in positive but also in negative territory. Importantly, we depart from the use of corporate credit spreads and focus on variables that capture more closely the transmission of policy rate shocks through the banking sector (e.g. lending and deposit rates, bank loans and lending standards, default probabilities, systemic risk), which is at the center stage of the debate on the effectiveness of policy rate shocks in negative territory. More broadly, we complement previous studies by providing a comprehensive assessment of the implications of policy rate shocks on banking activity and systemic financial distress over time. Our results hint to a role of the credit channel of monetary policy (see e.g. Bernanke 1992; Ciccarelli et al. 2015) also when policy rates are at or below zero.

Our findings also uncover a novel form of state dependency of the effects of the monetary policy transmission. Existing literature focuses on the mortgage prepayment and household refinancing decision (see e.g. Berger et al. 2021; Eichenbaum et al. 2022) and the state of the business cycle (see e.g. Tenreyro and Thwaites 2016). We show that the pass-through of policy rate cuts to lending rates is increasing in the level of the deposit rate that banks charge to their costumers.

Our paper also connects with the recent and growing number of papers on the effects of negative policy rates. Most of these studies present cross-sectional micro-data evidence on the impact of negative interest rates (e.g. Heider et al. 2019; Eggertsson et al. 2019; Bottero et al. 2020; Bubeck et al. 2020; Altavilla et al. forthcoming; Bittner et al. 2022).The strength of the micro-data identification is to assess in a credible way difference-in-difference effects across banks or firms with different sensitivities to monetary policy. However, it is well known that it cannot provide results on the total effect of a monetary policy shock on real activity and other aggregate variables (e.g. Kashyap and Stein 2000). Our analysis, instead, relies on the use of empirical macroeconomic models, i.e. VARs, to assess the impact of policy rate shocks over time.[3] This approach is particularly suitable to estimate the aggregate overall effects of policy rate shocks in negative territory on economic and banking activity, including their financial stability implications.[4] Finally, the time-varying VAR enables us to draw conclusions on the comparison of the transmission of policy rate shocks in positive, zero and negative territory within a consistent framework.

We share the general equilibrium perspective with the handful of papers that explore the transmission of policy rate cuts in the negative territory using DSGE models (e.g. Rognlie 2016; Brunnermeier and Koby 2018; Sims and Wu 2019). In particular, Ulate (2021) focuses on the impact of negative policy rates on bank return on equity, and argues that they are still effective in Europe. We find that policy rate cuts below zero have a significant effect on banking activity more in general (e.g. interest rates, credit, lending standards). In addition, we also show that they are effective in stimulating the

[3]Starting with Sims (1980), vector autoregressive models became a standard tool to understand the causal effects of monetary policy on the macroeconomy.

[4]Interestingly, despite the different approach our results are consistent with previous micro-data findings for the euro area. In line with the micro-data evidence in Altavilla et al. (forthcoming), results from our empirical macroeconomic approach also clearly shows that the pass-through of monetary policy to corporate deposits is not impaired when policy rates move into negative territory. **In addition, the state-dependency which we uncover in terms of the initial level of deposit rates, also connects to the contemporaneous micro-data analysis in Bittner et al. (2022) which document that lower levels of deposit rates lead to weaker pass-through to banks' funding costs and stronger risk taking incentives.**

real economy, without increasing financial stability risk. This suggests that the bank risk-taking associated to lower policy rates (Maddaloni and Peydró 2011; Dell'Ariccia et al. 2017) does not give raise to excessive systemic risk at the aggregate level.

Finally, this paper connects to the recent work that uses VAR models to assess the impact of unconventional monetary policy shocks (e.g. Gambetti and Musso 2020; Andrade and Ferroni 2021). In particular, Debortoli et al. (2020) show that the response of U.S. output, inflation and the long-term rate to macroeconomic shocks is not affected by the binding zero lower bound experienced in the U.S. over the 2009-2015 period. We complement their findings by assessing the implications of policy shocks also in negative territory. i.e. when any change in the transmission mechanism through banks should be most visible. The additional focus on the transmission of policy rate shocks through the banking sector and the state dependency in the pass-through of monetary policy distinguishes our work from other existing papers.

2 Institutional Details

ECB Deposit Rate Facility. In the aftermath of the global financial crisis, the ECB was the first major central bank to cut one of its policy rates into negative territory, in June 2014.

As part of its regular monetary policy framework, the ECB maneuvers three rates: i) the Deposit Facility Rate (DFR), which defines the interest rate for depositing money with the ECB overnight; ii) the interest rate on the main refinancing operations (MRO), which defines the interest on the bulk of liquidity provided to the banking system with a one-week maturity; and iii) the interest rate on the marginal lending facility, which defines the interest banks pay when they borrow from the ECB overnight.[5] Figure 2 panel (a) displays the evolution of the ECB policy rates. The interest rates on the marginal lending and deposit facilities provide a ceiling and a floor, respectively, for the EONIA rate, i.e. the unsecured overnight interbank lending rate in the Euro zone.[6]

Since the European Sovereign Crisis, the ECB implemented a sequence of cuts to the three policy rates.[7] While there is an evident reduction in all three policy rates, so far only the DFR reached negative levels. The DFR was kept at zero for almost two years (July 2012-June 2014). In June 2014, the DFR was cut from 0 to -0.1 percent. Afterwards the ECB proceeded cautiously, lowering the

[5]The ECB provides liquidity to banks operating in the euro area. Banks can borrow from the ECB in the form of repurchase agreements (repo) against adequate eligible collateral for one week through the main refinancing operations at the MPR rate or overnight through the lending facility.

[6]EONIA is a daily reference rate that a panel of 28 leading global banks charge to each other for short-term loans. Differently from the Federal Funds rate target which is set by the U.S. Federal Reserve, the EONIA rate is an equilibrium rate. While until the 2007-2009 crisis the EONIA rate was moving closely with the MRO rate, afterwards it shifted toward the DFR.

[7]The ECB sets its policy rates every six weeks.

deposit facility rate (DFR) by 10 basis points at the time, until it reached -0.5 percent, at the end of our sample, in September 2019.[8]

Commercial Banks' Rates. Figure 2 panel (b) shows that over time euro area banks charged on average lower deposit and lending rates. The average rates remain above the MRO rate, which since March 2016 reached 0 percent. Figure 3 reports the number of banks which charge negative rates on their overnight deposits. Over time it becomes increasingly more common for banks to pass negative rates on to their depositors. This effect is remarkably more pronounced for rates on corporate deposits (panel a). By the end of 2020, around 35% of banks in our sample charge negative rates to non-financial corporations. Charging negative interest rates to retail deposits is on average much less common (panel b). By the end of our sample period around 15% of banks charge negative rates to household retail deposits. This mainly concerns large retail deposits.[9]

The more sluggish pass-thorough of policy rate cuts to households deposit rates is also reflected in the distribution of the overnight deposits rates reported in Figure 1. While the median of the overnight deposits to corporations reaches zero already in early 2016, the one of the deposits to households becomes zero only in 2017. Importantly the interquartile range shrinks considerably in both cases over the NIRP period showing that banks set rates in a much more similar way compared to previous times.

3 Policy Rate Shocks in Positive and Negative Territory

We start our analysis by formally investigating the transmission of policy rate shocks over time using a time-varying coefficients VAR model with stochastic volatility (TV-VAR) as in Cogley and Sargent (2005) and Primiceri (2005). This approach allows us to explore the effects of policy rate shocks going from positive, to zero and finally negative territory. We estimate the model using euro area quarterly data over the sample 1999:Q1 to 2019:Q4.[10]

3.1 Methodology: Time-Varying VAR

Model. Our baseline model can be summarized as follows:

$$Y_t = B_{0,t} + B(L)_t Y_{t-1} + \varepsilon_t \qquad t = 1, ..., T \tag{1}$$

[8] **After being in negative territory for 7 consecutive years, the ECB DRF reached zero only in July 2022.**

[9] For instance, in late 2019 UniCredit announced to apply negative rates to customer deposits of more than 100,000 euros from 2020, while UBS, planned to charge clients with deposits over 500,000 euros.

[10] See Data Appendix for further details on the dataset.

where Y_t is an $n \times 1$ vector of endogenous variables, $B_{0,t}$ is an $n \times 1$ vector of time-varying intercepts, $B(L)$ is a $n \times n$ matrix polynomial in the lag operator L of time-varying autoregressive coefficients, and ε_t is a $n \times 1$ vector of innovations.

Let $B_t = [B_{0,t}, B_{1,t}, ...B_{l,t}]$ and $\theta_t = vec(B_t')$, where $vec(\cdot)$ is the column stacking operator. The law of motion for θ_t is assumed to be:

$$\theta_t = \theta_{t-1} + \omega_t,$$

where ω_t is a Gaussian white noise with zero mean and covariance Ω.

The innovations in equation (1) are assumed to be Gaussian white noises with zero mean and time-varying $n \times n$ covariance matrix Σ_t that can be factorized as:

$$\Sigma_t = F_t D_t D_t' F_t',$$

where F_t is lower triangular, with ones on the main diagonal and D_t a diagonal matrix. Let σ_t be the vector of the diagonal elements of D_t and ϕ_{it} the off-diagonal element of the matrix F_t^{-1}. We assume that the standard deviations, σ_t, evolve as geometric random walks, belonging to the class of models known as stochastic volatility models. The contemporaneous relationships ϕ_{it} in each equation of the VAR are assumed instead to evolve as an independent random walk, leading to the following specifications:

$$\begin{aligned} \log \sigma_t &= \log \sigma_{t-1} + \zeta_t \\ \phi_{it} &= \phi_{it-1} + \varphi_{it} \end{aligned}$$

where ζ_t and φ_{it} are Gaussian white noise with zero mean and covariance matrices Ξ and Ψ_i, respectively. We assume that $\varepsilon_t, \omega_t, \zeta_t$, and φ_{it} are mutually uncorrelated at all leads and lags and that φ_{it} is independent of φ_{jt} for $i \neq j$.

Estimation. The model is estimated using Bayesian methods. Following Primiceri (2005), we make the following assumptions for the priors densities. The coefficients of the covariances of the log volatilities and the hyperparameters are assumed to be independent of each other. The priors for the initial states, θ_0, ϕ_0 and $\log \sigma_0$, are assumed to be normally distributed. The priors for the hyperparameters, Ω, Ξ and Ψ are assumed to be distributed as independent inverse-Wishart.[11]

[11] See Online Appendix B for further details. In line with previous studies we set the three prior means to be 0.005 (see e.g. Primiceri 2005; D'Agostino et al. 2013b; Debortoli et al. 2020). However, we test the robustness of our results using values for the prior means of these parameters in our baseline specifications in the range [0.001 0.1]. We find the results to be largely stable over the different hyperparameters levels. Results are available upon request.

3.2 Results

We explore the effects of policy rate shocks on a number of variables related to economic and banking activity. Following Primiceri (2005), and for comparability with the long tradition of monetary policy VAR analysis (e.g. Christiano et al. 1999), we rely on the standard recursive identification scheme to isolate the effects of policy rate shocks.[12] The underlying economic assumption is that policy rate shocks are orthogonal to the information set of the monetary authority and the policy rate alone reacts on impact to the shocks while all the other variables are slow moving and react with one period lag.[13]

Economic Activity. First, we assess the impact of a policy rate shock on GDP and Inflation. Figure 4 displays the results based on a VAR that includes the log change of real GDP (GDP), the log change of the Harmonised Index of Consumer Prices (Inflation) and the ECB Deposit Facility Rate (ECB Rate) in percentage points, in this order.[14] Panel (a) reports the dynamic responses of the endogenous variables over the entire sample period, while Panel (b) displays the average responses of GDP and inflation over four different periods: 2000Q1-2007Q3 pre-Global Financial Crisis (pre-GFC), 2007Q4-2012Q2 Financial and Sovereign Debt Crisis (Crisis), 2012Q3-2014Q2 Zero Lower Bound (ZLB), 2014Q3-2019Q4 Negative Interest Rate Policies (NIRP). Panel (a) displays the IRFs constructed such that at each point in time, the initial shock has a size of one standard deviation. To facilitate the comparison across different time periods, in Panel (b) we instead standardize the IRFs and report the response of a 1 percentage point shock to the policy rate.

According to the estimated response patterns shown in Figure 4, GDP picks about two quarters after a monetary policy loosening and then slowly reverts to the initial level.[15] After increasing in the quarter after the shock, consumer price inflation declines and undershoot for a number of quarters.

[12]The TVP-VAR approach is preferred over the regime switching VAR one (see e.g. Cover 1992; Balke 2000; Sims and Zha 2006; Sims et al. 2008), as the latter by definition imposes zero, one or more fundamentally hard structural breaks in the transmission of policy rates, while, in the case of policy rate shocks in negative territory, the change might be a-priori very gradual. In addition, allowing for stochastic volatility is necessary to be able to disentangle the time-varying transmission of the policy rate shock from its time-varying magnitude.

[13]We assume that the monetary policy authority observes current economic activity, inflation and credit variables when setting the policy rate. Our ordering of credit variables before the policy rate differs from the common assumption for the identification of monetary policy shocks in the US (see e.g. Christiano et al. 1999). Our assumption is motivated by the fact that the ECB follows a two pillar approach for its decisions on the appropriate level of short-term interest rates. The second pillar, i.e. monetary analysis, consists of a comprehensive analysis of monetary and credit developments. The development of the bank lending survey and of the other variables included in our model are closely monitored within the monetary analysis framework. Hence, placing credit variable before the policy rate is a common assumption for the identification of monetary policy shocks in the euro area (see also Ciccarelli et al. 2015).

[14]In our estimations, we use the ECB Deposit Facility Rate as the monetary policy rate since up to date this is the only interest rate that the ECB lowered to negative levels. The results are however also robust to the use of the overnight money market rate (Eonia). See Online Appendix Figure B1 Panel(b).

[15]Online Appendix Figure B1 shows that the responses of GDP to policy rate shocks are always significantly different from zero over the whole time span. Online Appendix Figure B1 also reports robustness to the use of Consumption and Investment as measures of economic activity instead of GDP.

The dynamic responses of GDP and inflation reported in Panel (a) display a stronger effect during the period of the Financial and Sovereign debt Crisis due to a larger size of the shock. Indeed, once we standardize the responses to the policy shock in Panel (b), no relevant differences can be detected in the response of GDP and Inflation across the different periods. Importantly, there are no signs of a weakening in the effectiveness of policy rate cuts at zero or even in negative territory.[16]

Lending and Deposit Rates. Next, we focus on the transmission of policy rate cuts to key bank interest rates, namely the rate charged on corporate loans and the rates paid on corporate and households overnight deposits by commercial banks in the euro area.[17] There is a general concern that the rates on deposits could become increasingly more detached from the policy rates, due to the fact that setting deposit rates too close to zero or even negative could induce customers to withdraw their deposits, (see e.g. Eggertsson et al. 2019). Hence quantifying the pass-through of policy rate cuts to the deposit rates is crucial to understand if there is any impairment in the monetary transmission mechanism. Finally, the response of the NFC loan rate allows us to measure how much of the decrease in the policy rate is actually transmitted to the private sector by banks.

We proceed by adding to our baseline VAR specification the NFC loan rate and the rate on corporate and household deposits, separately. The results are displayed in Figure 5. Panel(a) shows that both the loan rate and the NFC deposit rate respond similarly and with the expected sign throughout the whole sample period. Panel(b) points to the same conclusion when the household deposit rate is included in the VAR instead of the NFC deposit rate. It is worth noting that the NFC loan rate tends to exhibit a stronger response compared to the deposit rates. This is in line with conventional wisdom that in general retail deposit rates are stickier than loan rates (Drechsler et al. 2017).

In addition, our results highlight that in response to a policy rate shocks household deposits are stickier than corporate deposits. Given that on average the reaction of loan and deposit rates to policy rate shocks is not significantly affected by the level of the policy rate, we can conclude that the interest rate margins, i.e. the spread between lending and deposit rates, are not more adversely affected by policy rate shocks in negative territory. Hence, this suggests that policy rate cuts below zero should not necessarily translate into severe effects on bank profitability and lead to adverse financial stability effects.[18]

To sum up, our findings highlight no significant weakening of the effects and transmission of mone-

[16] Appendix Figure B6 confirms that the response of GDP to a policy rate cut is positive and significant also over a split sample which compares the period of positive policy rates to the period of policy rtes at or below zero).

[17] Due to limitations on the availability of bank interest rates, the sample period starts in 2003Q1. For further details on the data, see the Data Appendix.

[18] Using bank balance sheet data up to end 2016 Altavilla et al. (2018) explore the impact of monetary policy on different components of bank profitability and argue that low and negative rates do not appear to adversely affect bank profitability.

tary policy over time. A policy rate cut retains its expansionary effects on economic activity and there are no signs of impairment in the pass-through to the deposit and lending rates when the policy rate moves to negative territory. Our results on the corporate deposit rates complement the findings by Altavilla et al. (forthcoming) which show that the average pass-through of monetary policy to interest rates on corporate deposits remains unchanged when policy rates move into negative territory.

Credit Market. We now discuss the effects of policy rate shocks on credit conditions. Figure 6 Panel (a) augments the VAR with the log-differences of bank loans to non financial corporations (NFC Loans). Loans reacts with some delay to a policy rate cut and pick only around 6-8 quarters after the shock. Even in this case we do not find statistically significant signs of a weaker transmission of policy rate shocks to bank loans. On the contrary, the response of this variable is somewhat more sizable and persistent over the ZLB and NIRP periods compared to the rest of the sample.[19]

Disentangling the main drivers behind the dynamics of aggregate loans is challenging, since changes in credit demand and supply are mostly unobserved (e.g. Bernanke and Gertler 1995; Bernanke et al. 1996). We tackle this problem by using information from the confidential Bank Lending Survey (BLS) data for the Eurozone. This survey is carried out by all National Central Banks in the euro area at quarterly frequency since 2002.[20] The survey reports detailed information regarding the actual lending standards that banks apply to the whole pool of loan applicants. We include in the baseline VAR two appropriately aggregated responses from the survey. The "Lending Standards" variable measures the net percentage of banks which reported to have tightened their lending standards on loans applications by non financial corporations in the last quarter with respect to the previous one. The "Loan Demand" variable measures instead the net percentage of banks which have experienced higher demand for loans by non financial corporations in the latter quarter with respect to the previous one.[21] In line with previous literature we consider the first variable as an indicator of bank credit supply conditions and the second variable as an indicator of credit demand pressures (see e.g. Lown and Morgan 2006; Maddaloni and Peydró 2011; Bassett et al. 2014; Ciccarelli et al. 2015).

We replace NFC loans in the above specification with the "Lending Standards" and the "Loan Demand" variables. The estimates of the time-varying impulse responses are shown in Figure 6 Panel (b).[22] Following a policy rate cut, the demand for loans, as observed and reported by banks, increases

[19] Online Appendix Figure B4 Panel(a) shows that the responses of NFC Loans to policy rate shocks are always significantly different from zero over the whole time span.

[20] BLS survey information predicts actual movements in lending conditions to firms and output (e.g. Bondt et al. 2010; Del Giovane et al. 2011; Ciccarelli et al. 2015) and can easily be cross-checked with hard bank information available at national central banks.

[21] Data Appendix reports the details of the underlying variables definitions and the construction of the aggregates variable. See also https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/index.en.html for further details on the survey.

[22] The IRFs of the remaining variables are very close to the ones shown for the baseline specification and hence omitted

for the next year and half. At the same time, banks' lending standards decline, reflecting banks' willingness to loosen their application rejection criteria on new loans in order to extend more credit. Interestingly, the level and persistence of the responses are generally similar across the four time periods. The mean impulse responses of both variables do not display particular differences between the Pre-GFC and the NIRP periods. Overall, we can conclude that bank supply factors play a role in the transmission of policy rate cuts over the whole sample even when controlling for positive effects on the demand for loans. Hence, our results suggest an important role for the credit channel of monetary policy (e.g. Bernanke 1992) regardless of the level of the policy rate being positive, zero or negative.

Financial Stability Risks. The loosening of lending standards by banks in response to policy rate cuts is often associated to an accumulation of risk (see e.g. Maddaloni and Peydró 2011; Dell'Ariccia et al. 2017) hence giving rise to concerns regarding possible adverse implications for financial stability.In principle policy rate cuts in negative territory could further exacerbate the willingness of banks to expand credit by lending to riskier borrowers in order to reduce their excess liquidity positions with the central banks.[23] In turn, the increase in risk-taking by banks could be further amplified by pressures to maintain intermediation margins, which in negative territory are squeezed by the constraints acting on the funding side. Such dynamics might lead to the build up of systemic risk in the economy and represent one of the main reasons of concerns of negative policy rates.

In order to assess the extent to which policy rate cuts in negative territory give raise to more severe financial stability concerns, we study the effects of policy rate shocks on the aggregate "SRISK" measure, i.e. the systemic risk index proposed by Brownlees and Engle (2017). This is a market-based measure of financial distress in the banking sector which quantifies the capital shortfall of an individual bank conditional on a severe market decline (i.e. a systemic event). The sum of the individual bank-level systemic risk measures can be thought of as the total amount of capital that the government would have to provide to recapitalize the financial system in the event of a prolonged market decline, at any point in time over our sample.[24] Figure 7 panel (a) displays the results.[25] Policy rate cuts generally decrease systemic risk in the banking sector suggesting that the positive impact on macroeconomic conditions also have a positive effect on banks' balance sheets and their overall riskness. The median IRF for the NIRP period, if anything, points to stronger beneficial effects of policy rate cuts on the economy compared to the pre-NIRP period.

in the figure. See Online Appendix Figure B4 Panel (b) to check the full set of impulse responses.

[23]Negative DFR implies a direct charge for commercial banks on their holdings of excess liquidity with the central bank.

[24]SRISK is a function of banks' size, leverage and risk. This measure is first calculated at the individual bank level by merging market and balance sheet information and then aggregated. See Brownlees and Engle (2017) for further details. Data Appendix reports further information on the underlying data series used for the calculation of the euro area index.

[25]Online Appendix Figure B5 Panel(a) reports the confidence bands.

As a final test we focus on the impact of policy rate cuts on ex-ante measures of default probability. Drawing from Moody's data on expected default frequencies (EDF) for private companies in the euro area we augment the baseline three variables specification with the average EDF for bank's and non financial corporations, respectively.[26] The impulse responses are reported in Figure 7 Panel (b).[27] Policy rate cuts generally decrease the probability of default of both banks and firms. The latter effect reflects the fact that improved macroconomic conditions, together with lower levels of the interest rates, boost the creditworthiness of borrowers. This in turn can affect positively banks' credit riskiness and, hence, profitability. Overall, the impact of a policy rate cut on the probability of default of banks is positive. This result is in line with the effect on systemic risk illustrated in Figure 7 panel (a). Firm and bank default probabilities respond significantly throughout the whole sample period. The median IRF for the NIRP sample period seems slightly stronger and more persistent than in the Pre-GFC.

Overall, our results show no significant weakening of the effects and transmission of policy rate shocks over time. When comparing the NIRP sample period to the ZLB and positive territory period, we find that policy rate cuts below zero retain their expansionary effects on aggregate economic and banking activity without negative repercussions on financial stability.

4 Bank Heterogeneity

We now explore the heterogeneity across banks in the transmission of monetary policy shocks in negative territory. In this way we aim at uncovering patterns which are already significant but still not strong enough to emerge at the aggregate level. The analysis relies on confidential bank level data for the Eurozone. In what follows, we explore the role of the initial (pre-NIRP) level of the interest rate charged by banks on household overnight deposits. We interpret the distance of such a rate from zero as a way to capture how much a bank is constraint in decreasing the deposit rate further down.

Our analysis focuses on the period of negative policy rates. We estimate a Bayesian VAR using monthly data. In previous section, we show the impact of policy rate shocks on the average lending rate to NFC across the whole sample of (about 300) banks. Now we instead explore differences in the dynamic responses of the average lending rate across two subgroups of banks: those with ex-ante high and low deposit rates. More precisely the analysis relies on the following steps:

1. We split the entire sample of Eurozone banks into two groups based on the pre-NIRP level of the bank deposit rate to household.[28]

[26] Moody's estimate ex-ante probability of defaults for a large sample of firms and banks in the euro area. See Data Appendix for details on the construction of the aggregate measures.

[27] The impulse response of GDP, Inflation and the ECB rate are available for inspection in the Online Appendix Figure B5 Panel (b).

[28] The pre-NIRP deposit rate is calculated as the bank-level monthly average rate over the period 2013:01-2013:03.

2. For each of the two sub-groups of banks we compute the average lending rate weighted by the total loans of the individual bank over the total loans of the whole sample of banks.

3. We estimate a VAR which in addition to the ECB rate, unemployment and HICP inflation also includes the two average lending rates computed in step 2.

This approach represents a very simple but efficient attempt to exploit micro-level data in a macro time series model.

4.1 Methodology

We now turn to a different identification of the policy rate shock which is more suitable that the TV-VAR for the bank heterogeneity analysis which focuses on the more restricted sample period of negative policy rates.[29] In what follows we use the high frequency approach pioneered by Romer and Romer (2000) and Kuttner (2001) and thereafter extensively used in the literature (see Gürkaynak 2005; Gürkaynak et al. 2005; Nakamura and Steinsson 2018).[30] In particular, we construct a set of external instruments that help us to disentangle policy rate shocks from other unconventional monetary policy shocks. We employ such instruments to estimate the effects of policy rate shocks using two different empirical methodologies: Bayesian Local Projections and Proxy SVAR. In what follows, before commenting on the results, we outline the procedure adopted for the construction of the external instruments and briefly describe the two methodologies.

4.1.1 Proxy Construction

Following the previous literature, the identification scheme for policy rate shocks relies on external instruments based on high frequency variations of selected asset prices in a window around the time of the ECB monetary policy announcements. The ECB communicates monetary policy decisions in two steps on the day of the policy meetings. First, at 13.45 Central European Time (CET) policy decisions are communicated in a brief press release with information regarding no rationale for the decisions. Second, at 14.30 CET a one hour press conference takes place in which the President first reads the statements explaining the rational behind the decisions and then responds to journalists questions.

The two step communication strategy of the ECB is very convenient to identify different types of monetary policy shocks, as until 2016, the press release would only contain policy rate decisions, omitting any decision on Asset Purchase programs (see e.g. Altavilla et al. 2020). Hence, we focus on asset price changes over the ECB press release. In addition, we only consider instruments with

[29] The analysis cannot be extended to the entire sample period since bank-level interest rate data are only available starting in 2008.

[30] See Ramey (2016) for a thorough survey of this literature.

a maturity less than two years as both forward guidance and asset purchase announcements have been proven to affect mainly longer maturity assets on financial markets (see e.g. Bottero et al. 2020; Gambetti and Musso 2020). We use asset price changes of highly liquid risk free assets, such as Overnight Interest Rate Swaps, in a 35-minute window around the monetary press release and the press conference, separately.[31]

Similarly to Andrade and Ferroni (2021) we summarize the information contained in the time series of the price changes by extracting the two factor components which explain most of the variance. The two main factors extracted are rotated with the following simple restrictions: the first factor is allowed to load on all asset prices and represents the so called *target factor*, i.e. news affecting level of the yield curve; while the second factor is allowed to load on all but the lower than 1-month maturity assets and represents the so called *path factor*, i.e. news affecting the slope of the yield curve at lower frequencies.[32]

4.1.2 Proxy VAR and Bayesian Local Projection

The two factors serve as external instruments to identify a policy rate shock both in the Bayesian Local Projection and the Proxy SVARs frameworks. We perform the analysis on split samples: positive (2000m1-2012m12) and at or below zero (2012m7-2019m12) policy rate levels. Importantly, the frequency of ECB monetary policy decisions occurs with a six-week cycle, which implies more than one policy shock per quarter. Hence, we estimate both models at monthly frequency. Switching to a monthly frequency is convenient also because it allow us to include a reasonable number of observations even after splitting the full sample into two sub-samples.

Bayesian Local Projection. The model structure and estimation procedure closely follows Miranda-Agrippino and Ricco (2021).[33] This methodology allows the model coefficients to be estimated from the composition of the likelihood function and properly specified prior distributions of the

[31] Altavilla et al. (2020) provide a dataset which reports the price differentials on selected assets from 13.25 to 14.10 for the Press Release Window and from 14.15 to 15.50 for the Press Conference Window. The dataset is publicly available at https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx See Data Appendix for further details.

[32] The factor model and rotation details for the construction of the factors is outlined in the Online Appendix B.

[33] The rationale for choosing Bayesian over standard estimation techniques is that it allows to optimally deal with the notorious bias-variance trade-off normally present in the choice between VAR implied and LP impulse response functions in finite samples. See Plagborg-Møller and Wolf (2021) for a thorough discussion of the relationship between VARs and LPs estimated Impulse Response Functions in presence of finite samples. Bayesian VARs typically cope better with estimation variance, but are more prone to bias whenever the one-step ahead model is misspecified. LP is instead more robust to misspecifications than Bayesian VARs but is normally more likely to have highly imprecise estimates. Both weaknesses are obviously particularly pronounced in presence of small samples. By spanning the model space between VARs and LPs and letting the data choose the degree of departure from the prior through the weights in the above equation we are able to optimally deal with the mentioned trade-off at each horizon.

Normal-Inverse Wishart type.[34]

The posterior mean of the Bayesian local projection coefficients can be expressed as follows:

$$B_{BLP}^{(h)} \propto \left(X'X + \left(\Omega_0^{(h)}(\lambda^{(h)})\right)^{-1}\right)^{-1} \left(\left(X'X\right) B_{LP}^{(h)} + \left(\Omega_0^{(h)}(\lambda^{(h)})^{-1}\right)^{-1} B_{VAR}^{h}\right) \tag{2}$$

where h is the horizon of the local projection, $X \equiv (x_{h+2}, ..., x_T)'$ and $x_t \equiv (1, y_{t-h}^{'}, ..., y_{t-(h+1)}^{'})'$ and λ varies with h which implies that an optimal departure from the priors is selected at each horizon h. The posterior mean is given by the weighted average of the mean of standard LP responses B_{LP}^{h} and the prior LP responses B_{VAR}^{h}. The weight is pin-down by the parameter λ which governs the degree of certainty that the econometrician has around the specified prior. In line with Giannone et al. (2015) we impose an uninformative prior on λ.[35]

Proxy VAR. Following Mertens and Ravn (2013) and Stock and Watson (2012) and Stock and Watson (2018), given a matrix of external instruments $z_t^{'}$ the necessary assumptions for the identification of a particular structural shock (i.e. the policy rate shock ε^p) with respect to all the other structural shocks, here indicated as ε^o, are two:

$$\begin{array}{rrcl} (i) & \mathbb{E}\left[z_t \varepsilon_t^{p'}\right] & = & \Phi \\ (ii) & \mathbb{E}\left[z_t \varepsilon_t^{o}\right] & = & 0 \end{array} \tag{3}$$

These are the relevance and exogeneity conditions typical of instrumental variable regressions. Now, considering a VAR model of the form:

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + ... + u_t \tag{4}$$

where u_t is the vector of reduced form residuals, the structural shocks can be recovered as $u_t = A\varepsilon_t$. Given the assumptions (i) and (ii) we are able to recover the coefficients of the A matrix through:

$$\Phi A'_{\cdot,1} = \mathbb{E}\left[z_t u_t^{'}\right] \tag{5}$$

[34] We center the prior around the corresponding iterated coefficients of a similarly specified VAR estimated over a pre-sample. As an alternative and less informative prior we also adopt the single equation version of the random walk prior according to which each variable is simply assumed to follow a random walk process. Given the similarity of the results we present only the estimates obtained using the Iterated VAR prior. Results based of random walk priors are available upon request.

[35] More precisely the λ parameter is estimated at each horizon h as the maximizer of the posterior likelyhood. Details of the approach are provided in the Online Appendix B and in Miranda-Agrippino and Ricco (2021).

where $A_{.,1}$ corresponds to the first column of the matrix pinning down the impact coefficients of the target shock (here assumed to be ordered first) onto the n endogenous variables. Note that if we knew the matrix Φ the system would be exactly identified, while if we don't know the latter matrix, as it is normally the case we are only able to identify $(n-k)k$ parameters. However, by means of a normalization assumption (i.e. the impact coefficients on the diagonal of the matrix A are equal to one), we are able to fully identify the system. The VAR reduced form coefficients are estimated using standard bayesian techniques following the hierarchical approach of Giannone et al. (2015).[36]

4.2 Results: NIRP Period

4.2.1 Loan and Deposit Rates

Figure 8 shows the response of unemployment, inflation and the loan and deposit rates to a policy rate shock identified through external instruments and normalized to a 1 pp decrease of the ECB Rate. The figure depicts the results of both the Bayesian LP (black solid line) and the Proxy Var (blue dashed line). The laste column of panel (a) reports the response of the rate on deposits from corporations, whereas in panel (b) we display the response of the average deposit from households.

The results are in line with those of the TV-VAR reported in the previous section. Both the Bayesian LP and the Proxy-VAR estimates confirm that policy rate shocks in negative territory transmit significantly to both economic and banking activity. In response to a policy rate cut rates on lending and deposits are reduces.[37]

Our findings highlight that there is no significant change in the way macroeconomic and banking aggregates. The results presented in the previous section are robust to the use of different identification methodologies (recursive and external Instrument Identification schemes), different empirical econometric models (TVP-VAR, Constant Parameter Proxy-SVAR and Bayesian Local Projections), different frequencies and splits of the sample period.

4.2.2 Bank Heterogeneity

The main results on the effects of a policy rate shock on the pass-through to lending rates for banks with ex-ante high (HDR) and ex-ante low deposit rates (LDR), are shown in Figure 9. The figure

[36] The full specification and estimation details are presented in the Online Appendix B.

[37] Appendix Figure B7 shows that, in line with the TV-VAR results loans to corporations increase in response o the shock. In addition, the financial soundness of both non-financial corporations and banks improves. This is captured by the reduction in the default probability of both banks and non-financial corporations as well as by the reduction in the aggregate index of systemic risk in the banking sector. Overall, policy rate cuts are effective in improving economic conditions without contributing to the build up of financial stability risks.

presents the impulse responses of the ECB rate, unemployment, inflation are simply reported to show consistency with the results presented in the previous sections.

Turning to the IRFs of the lending rates, we find significant differences in the monetary policy pass-through to lending rates across banks. We can observe that banks with (ex-ante) lower levels of retail deposit rates are on average less responsive to policy rate cuts in negative territory compared to banks with (ex-ante) higher retail deposit rates. Focusing on the impact responses, we observe that banks with a high deposit rate tend to show high pass-through to their loan rate, with a mean response of around -1.8 pp. Banks with low deposit rates instead show a mean response of around -1 pp. In addition, the response is less persistent for low deposit rate banks.

Our result confirm that banks with lower initial levels of deposit rates are less responsive to policy rate cuts. This corroborates the existence of state dependency in the effects of monetary policy shocks (see e.g. Eichenbaum et al. 2022; Berger et al. 2021). In our case, the state dependency arises from asymmetries in the pass-through of policy rate cuts. This finding is very much in line with previous literature (see e.g. Brunnermeier and Koby 2018) which claims that banks with deposit rates close, at or below zero are increasingly more reluctant to further decrease deposit rates. This is because they fear that depositors would start withdrawing their deposits. This in turn implies that constrained banks, i.e. those with already lower ex-ante deposit rates, are more reluctant to pass-through policy rate cuts to their loan rates in order to avoid a compression of the lending margins and a decline in their profitability.

5 Additional Results

In previous sections we have documented that our results hold for different identifications of the policy rate shock (recursive and high frequency), estimation methodologies (TV-VAR, Proxy-Var, Bayesian Local Projection) and sample frequency (monthly vs quarterly). Results shown in the Online Appendix also highlight that our TV-VAR results are robust to the use of an alternative measure for the policy rate (see Online Appendix Figure B1) as well as to the use of alternative measures of economic activity (see Online Appendix Figure B2). In particular, our heterogeneity results are also in line with cross-country results as well as with estimates based on micro-data identification.

5.1 Bank Heterogeneity: Core vs Periphery

First, we explore the implications of the state-dependency of the effects of monetary policy transmission for the heterogeneity in the pass-through of monetary policy across euro area countries. We split the banks in two groups depending on their geographical location: core and periphery. Core euro area

(CEA) countries denotes Austria, Belgium, France, Germany, Luxembourg and the Netherlands while periphery euro area (PEA) countries denote Italy, Spain, Portugal, Ireland, Cyprus, Malta and Greece.

Figure 9 Panel (b) reports the average response of the NFC loan rates for banks located in core and periphery countries in the Eurozone. Our results document substantial heterogeneity in the pass-through of negative policy rate shocks to lending rates across countries. We find that on average the pass-through of monetary policy shocks to NFC lending rates is higher for banks in periphery countries.This is due to the fact that banks located in countries which were more severely affected by the 2010-2012 European Sovereign Debt Crises experience on average ex-ante higher deposit rates.

This finding corroborates our heterogeneity result. In addition, it highlights the importance of the state-dependency of the pass-through of policy rates the for the cross-country transmission of policy rate shocks within the euro area.

5.2 Bank Heterogeneity: Micro Data Identification

Second, we use micro-data identification techniques to explore if banks with ex-ante higher deposit rates are more affected by policy rate shocks in negative territory than banks with ex-ante lower deposit rates. We adopt the following specification:

$$y_{b(c),t} = \alpha_b + \alpha_{c,t} + \beta X_b \times Post_t + \epsilon_{b(c),t} \tag{6}$$

where $y_{b(c),t}$ represents the average interest rate on loans to NFCs of bank b operating in country c at time t. X_b denotes the exposure of bank b to the ECB's rate cuts in July 2014, i.e. when the DFR entered negative territory for the first time. In the baseline specification we measure the exposure using the average deposit rate on household deposits, as of March 2013. $Post_t$ represents a dummy that takes value of 1 after June 2014.[38] We control for bank fixed effects (α_b) to absorb any time-invariant bank characteristics. Second, we incorporate country-time fixed effects ($\alpha_{c,t}$) to absorb time-varying country-specific variations that could affect changes in country-level credit demand.

The results are presented in Table 1. As it possible to observe in the top row, banks with an ex-ante high household deposit rate tend to experience lower levels of corporate loan rates following the shock. According to the regression results, a 1 pp higher deposit rate translates into lower loan rates to NFC by 0.033 pp. This result confirms the heterogeneity result shown in the previous sections.

Additional results, presented on the middle and bottom row of Table 1, measure the exposure to the policy rate cut using, respectively, the ex-ante deposit rate charged to corporations and the average retail deposit rate. The estimates show that there are no significant differences in the pass-though of policy rate cuts to borrowers when we split banks in terms of their average rate on corporate deposits

[38] Our sample covers the period from June 2014 until June 2015.

or on the overall deposit rate. This finding is explained by the fact that these other rates respond more strongly to policy rate cuts, as already shown 3 and 4. In contrast, the deposit rate charged by banks to households is the one subject to more stringent constraints.

Overall, results based on micro data identification largely confirm the heterogeneity in the bank pass-through of policy rate shocks to lending rates. The heterogeneity depends on the ex-ante level of the deposit rate charged to households. This finding also points to a future weakening of the effects of policy rate cuts due to the fact that with further policy rate cuts an increasing share of banks will be experiencing lower and lower deposit rates.

6 Conclusions

Are monetary policy rate cuts below zero still expansionary? Yes, with one caveat. Using a suit of VAR models and public and confidential data for the Eurozone, we provide robust evidence on the effectiveness of policy shocks in stimulating economic and banking activity also for policy rates below zero. Our results show that: 1) policy rate cuts below zero still significantly improve economic conditions; 2) the pass-though to deposit and loan rates is not impaired and 3) there are also no signs of higher systemic financial distress. Overall, the aggregate effects show that there is still space for further expansionary policy rate cuts. Our caveat is, however, that banks with higher deposit rates at the beginning of the negative territory period exhibit a stronger pass-through of policy rate shocks to their loan rates with respect to banks with (ex-ante) lower deposit rates.

Our results have two important implication. First, we provide a comprehensive assessment of the implications of policy rate shocks on economic and banking activity for positive, zero and negative levels of the policy rate. We show no significant differences in the transmission of monetary policy to credit variables, including lending standards. This hints to a role of the credit channel of monetary policy (see e.g. Bernanke 1992; Ciccarelli et al. 2015) also when policy rates are at or below zero. By showing that policy rate shocks are effective in stimulating the real economy, without giving raise to financial stability concerns, our results suggest that the bank risk-taking channel of monetary policy (see e.g. Maddaloni and Peydró 2011; Dell'Ariccia et al. 2017) does not bring about adverse effects in terms of aggregate systemic risk, without significant differences in positive and negative territory.

Second, although the aggregate effects show that there is still space for further expansionary policy rate cuts, we show substantial heterogeneity across-banks in the pass-though of policy rate cuts to lending rates. Banks with higher initial deposit rates exhibit a stronger pass-through with respect to banks with lower initial deposit rates. This result highlight a novel form of state dependency of the effects of monetary policy complementary in nature to the ones documented by Eichenbaum et al. (2022) and Berger et al. (2021) which has important implications for the transmission of monetary policy across Euro zone countries.

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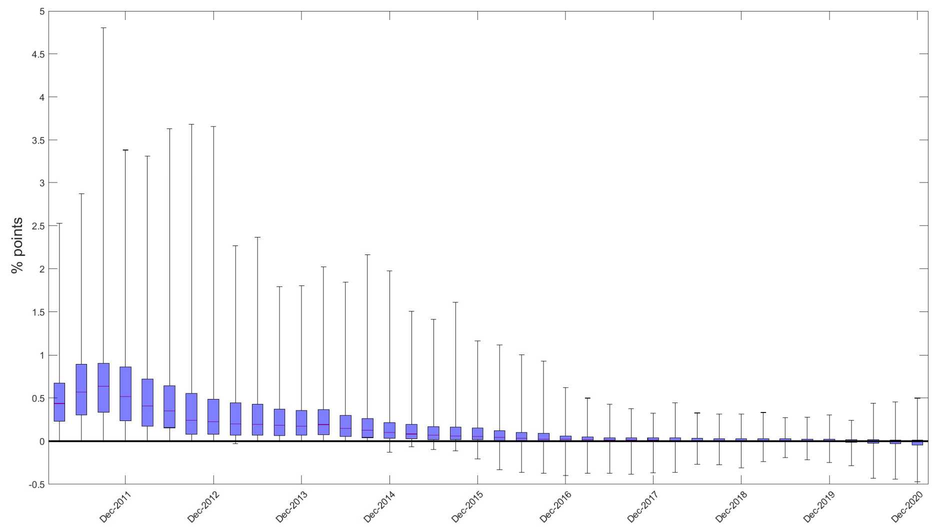
Table 1: *Negative Interest Rates: Effect on NFC Loan Rates*

	$Credit_{b,t}^{NFC}$	Obs	R^2	$Rate_{b,t}^{NFC}$	Obs	R^2
HH Deposit Rate	0.0182**	1236	99.97	-0.0335**	1352	97.60
	(0.0082)			(0.0136)		
NFC Deposit Rate	0.0278**	996	99.97	-0.0102	1073	97.25
	(0.0125)			(0.0387)		
All Retail Deposit Rate	0.0230**	948	99.97	-0.0161	1008	97.15
	(0.0103)			(0.0386)		

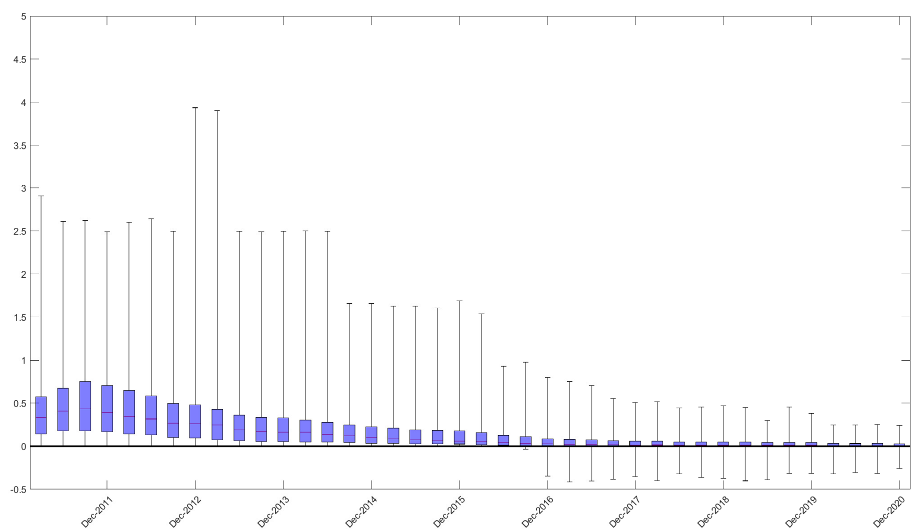
Notes: This table presents coefficients from regressions related to the effect of negative rates as described in equation (6). The regressions include country-time and bank fixed effects. The sample consists of monthly observations. Standard errors in parentheses are clustered at the country-time and bank level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Distribution of Bank Overnight Deposit Rates over time.

(a) **Corporate Deposit Rate**

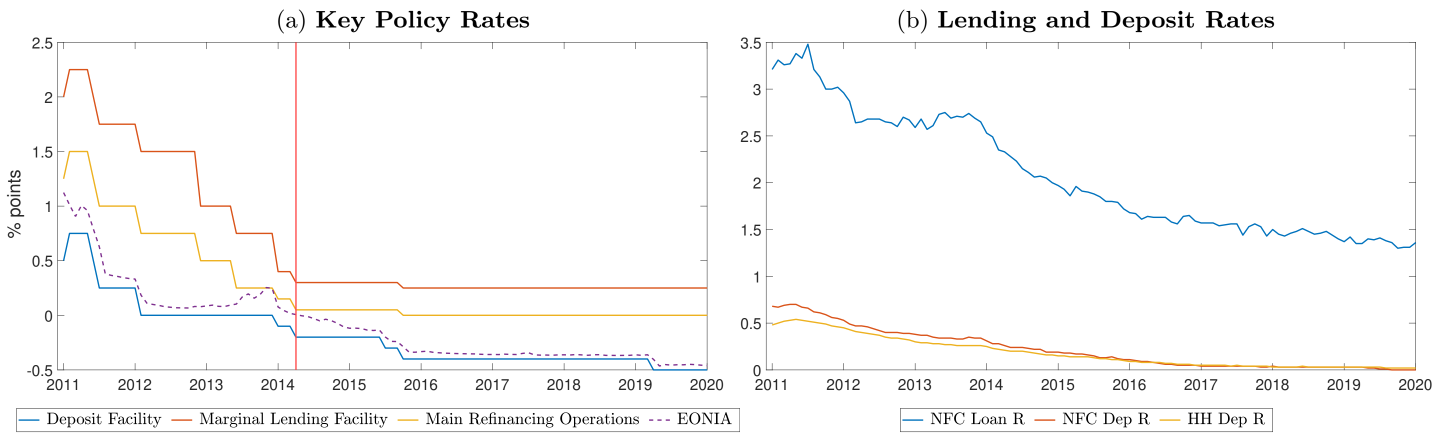


(b) **Household Deposit Rate**



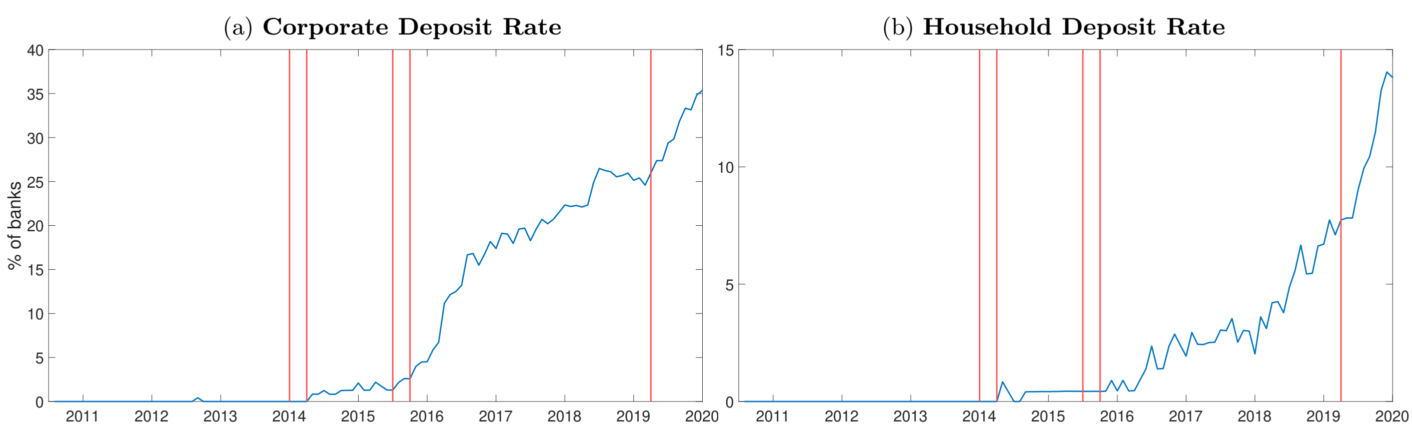
Notes: Evolution of the distribution of NFC and Household overnight deposit rates of euro area banks. Panel (a) refers to the rate on corporate deposits. Panel (b) refers to the rate on household deposits. Total of about 300 banks. The box identifies the 25-75 Interquartile Range the Whiskers identify the 5-95 Interquantile Range.

Figure 2: Interest Rates – Euro Area



Notes: Evolution of the key ECB policy and money market rates. Panel (a) zooms in over the period on zero or negative policy rates; Panel (b) displays the series since the start of the creation of the eurozone. The rates are reported in percentage point on the vertical axis. The red vertical lines indicate the dates of ECB Deposit rate cuts.

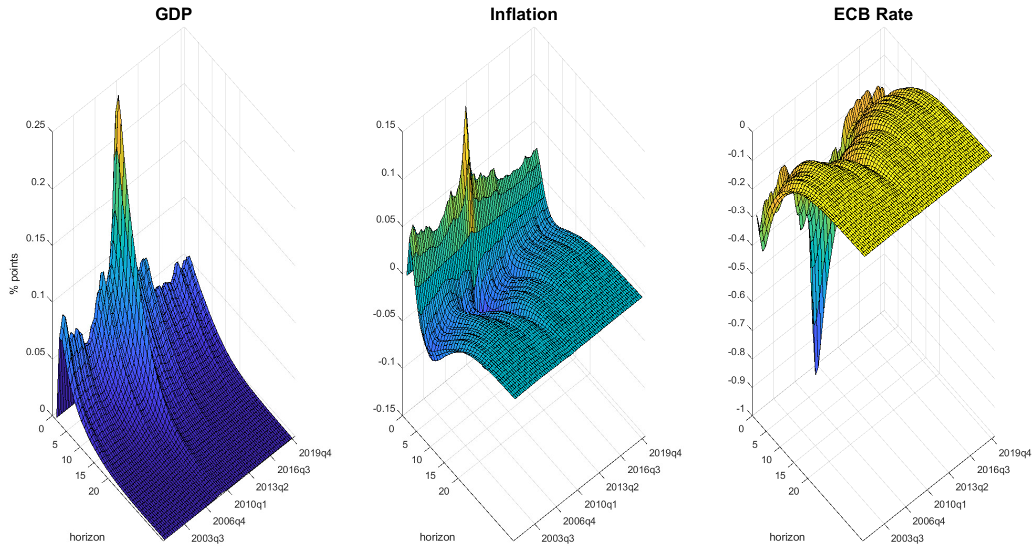
Figure 3: Percentage of Banks with deposit rates below zero



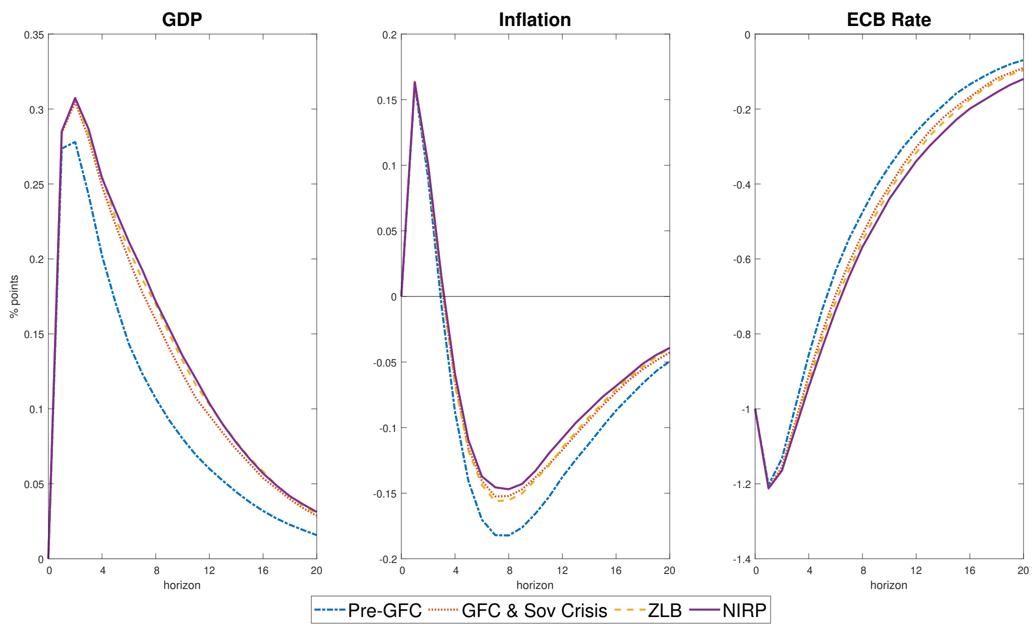
Notes: Evolution of the number of euro area banks with deposit rates below zero by type of deposit. Panel (a) refers to the rate on corporate deposits. Panel (b) refers to the rate on household deposits. The vertical axis report the number of banks (total of about 300 banks). The red vertical lines indicate the dates of ECB Deposit rate cuts.

Figure 4: Impulse Responses to a Policy Rate Shock: Baseline

(a) **Time-varying**



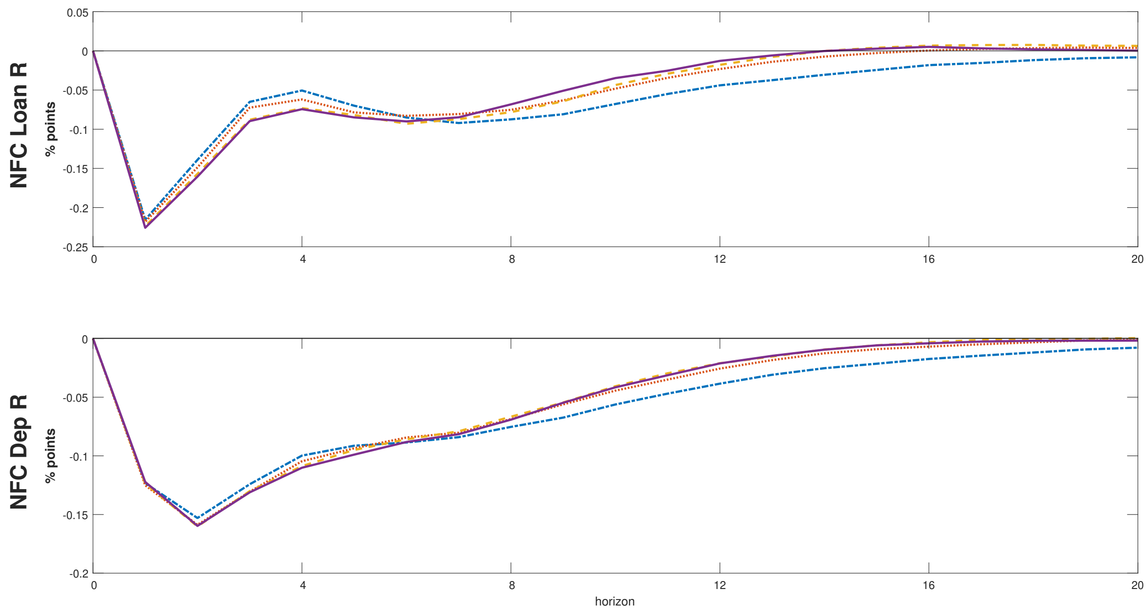
(b) **Selected periods**



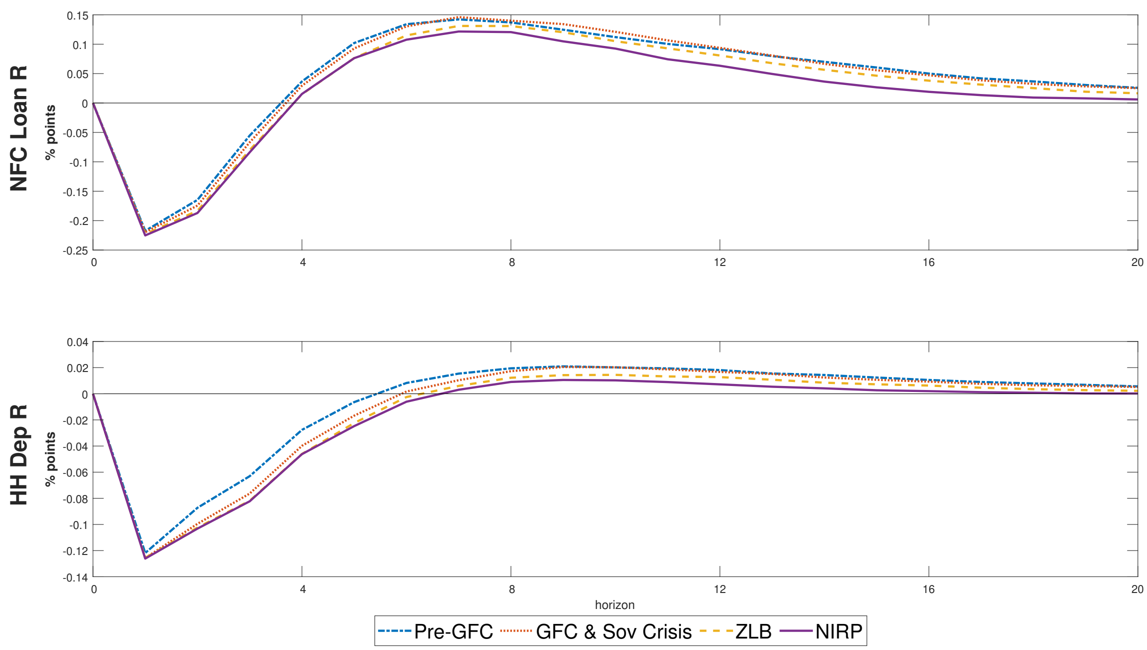
Notes: Impulse response function to an unexpected cut to the ECB deposit facility rate from a 3-variable VAR model and time-varying coefficients and stochastic volatility. Recursive identification (GDP, Inflation and ECB rate). Panel (a) displays the IRFs at different horizons (y-axis) and over time (x-axis). Panel (b) displays the average (standardized) IRFs over selected periods: 2000Q1-2007Q3 (Pre GFC), 2007Q4-2012Q2 (Crisis), 2012Q3-2014Q2 (ZLB), 2014Q3-2019Q4 (NIRP).

Figure 5: Impulse Responses to a Policy Rate Shock: Pass-trough to Banks Interest Rates

(a) **Pass-through to NFC Loan Rate and Corporate Deposit Rate**



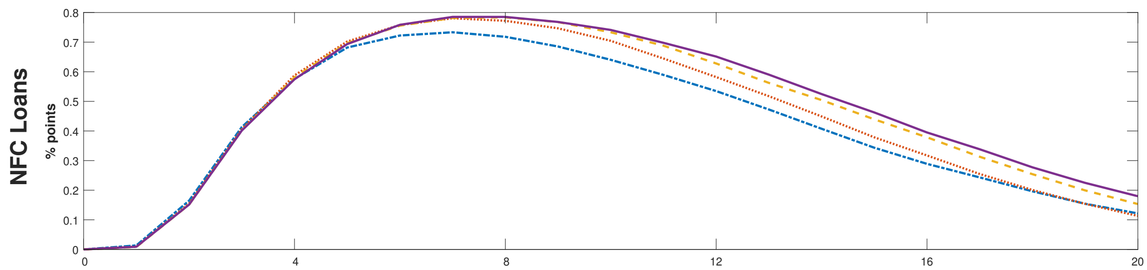
(b) **Pass-through to NFC Loan Rate and Household Deposit Rate**



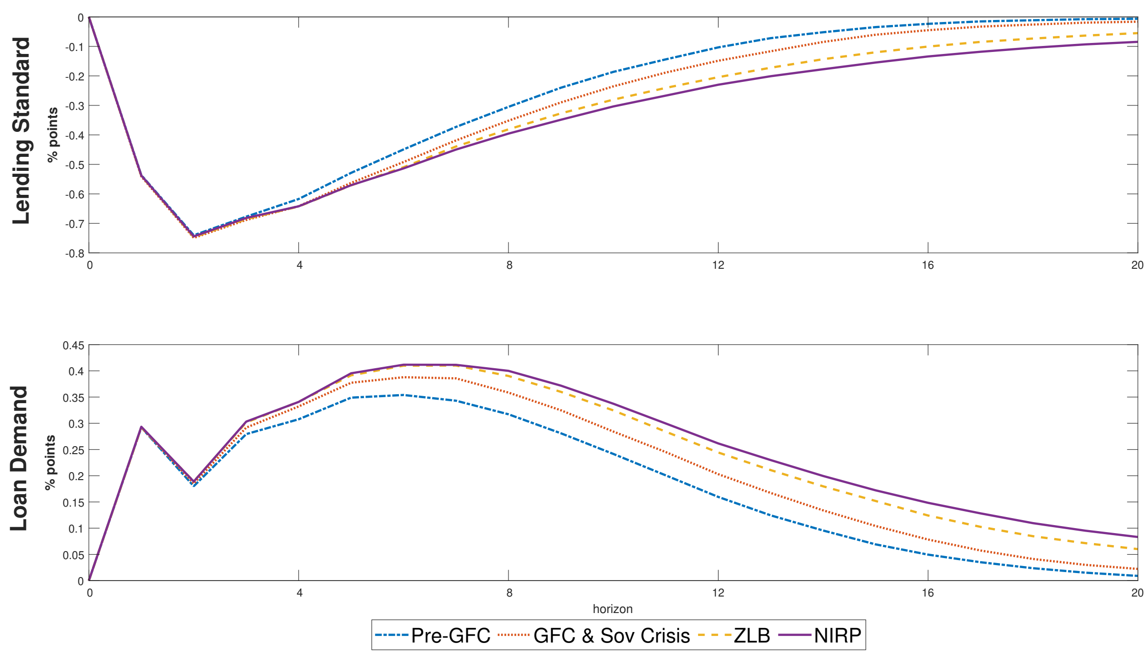
Notes: Impulse response function to an unexpected cut to the ECB deposit facility rate from a 4-variable VAR model and time-varying coefficients and stochastic volatility. Recursive identification (GDP, Inflation, NFC Loan Rate, Deposit Rate and ECB rate). The figure displays the average (standardized) IRFs over selected periods. Due to data availability the sample starts from 2003Q1.

Figure 6: Impulse Responses to a Policy Rate Shock: Bank Lending Survey and Default

(a) **Aggregate Loans to NFC**



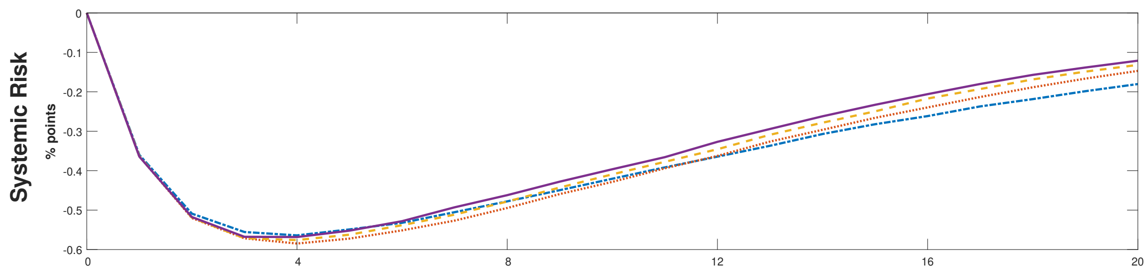
(b) **BLS Demand and supply**



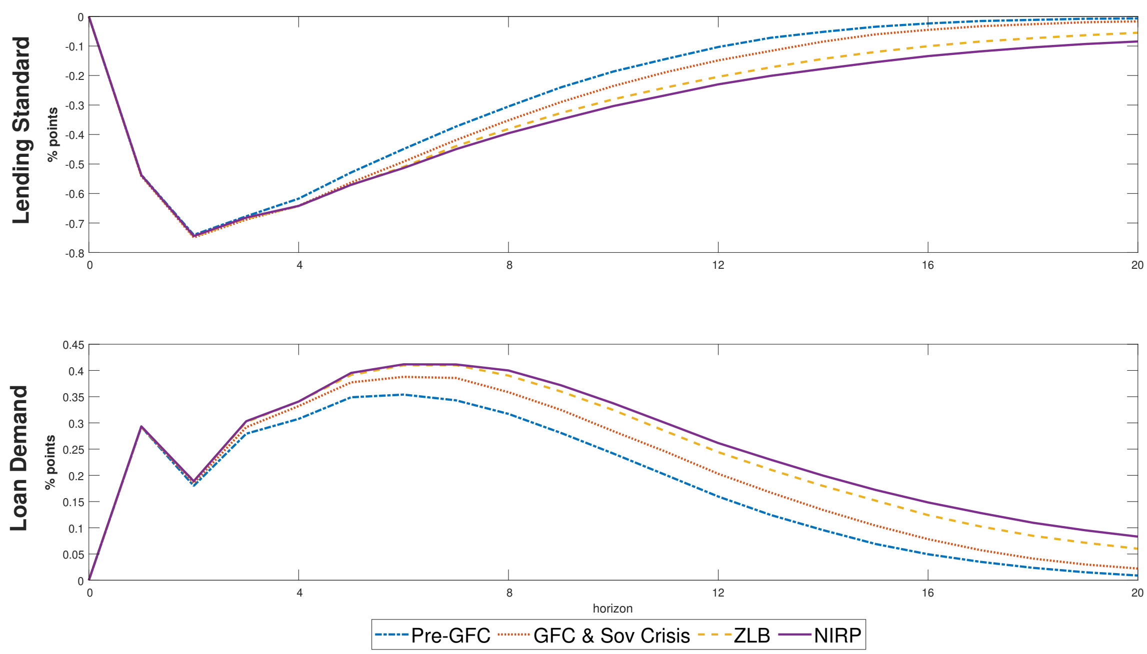
Notes: Impulse response function to an unexpected cut to the ECB deposit facility rate from a 4-variable VAR model and time-varying coefficients and stochastic volatility. The figure displays the average (standardized) IRFs of key variables over selected periods. Panel (a) Recursive Identification: GDP, Inflation, NFC Loans, ECB Rate. Panel (b) Recursive identification: GDP, Inflation, Credit Standards, Loan Demand and ECB rate. Due to data availability the sample starts from 2003Q1.

Figure 7: Impulse Responses to a Policy Rate Shock: Systemic Risk and Default Probabilities

(a) **Systemic Risk**



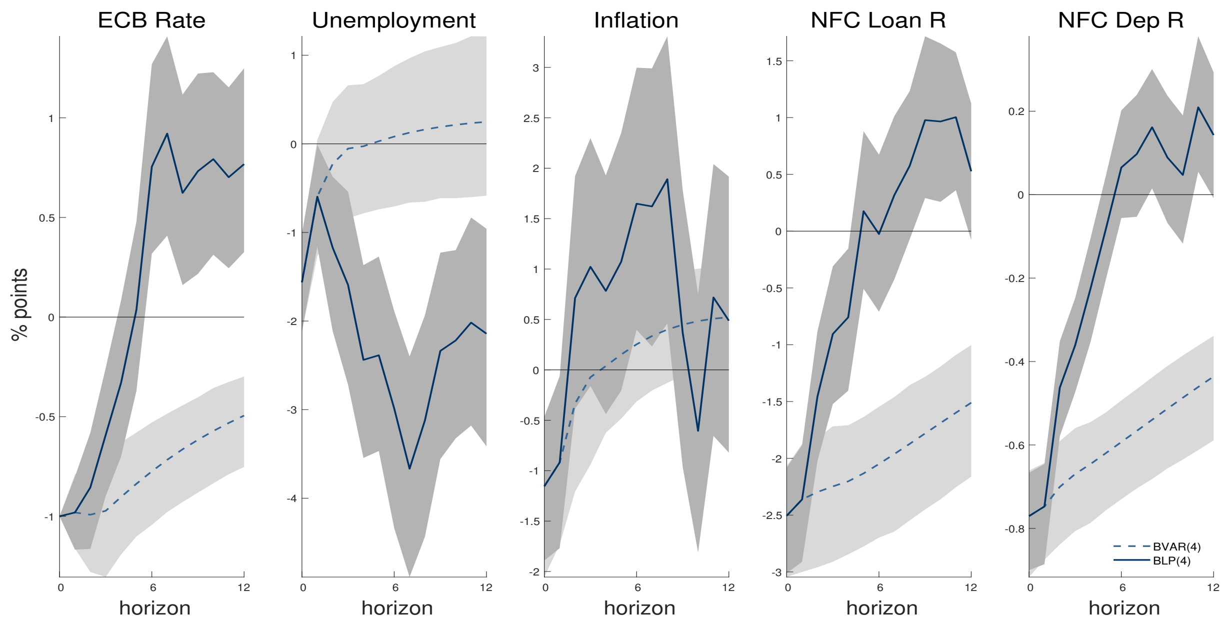
(b) **Expected Default Frequency**



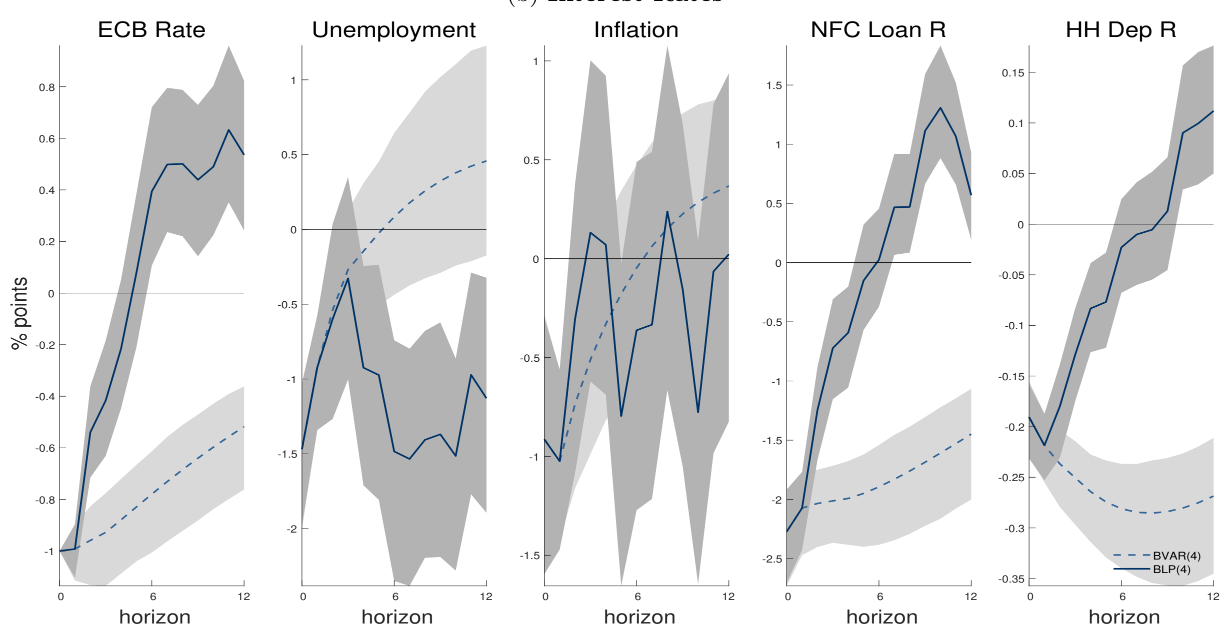
Notes: Impulse response function to an unexpected cut to the ECB deposit facility rate from a 4-variable VAR model and time-varying coefficients and stochastic volatility. The figure displays the average (standardized) IRFs of key variables over selected periods. Panel (a) Recursive identification: GDP, Inflation, Aggregate Systemic Risk and ECB rate; Panel (b) Recursive identification: GDP, Inflation, Bank EDF, NFC EDF and ECB rate.Due to data availability the sample starts from 2003Q1.

Figure 8: Policy Rate Shock: Proxy Identification – NIRP Period

(a) **Interest Rates**

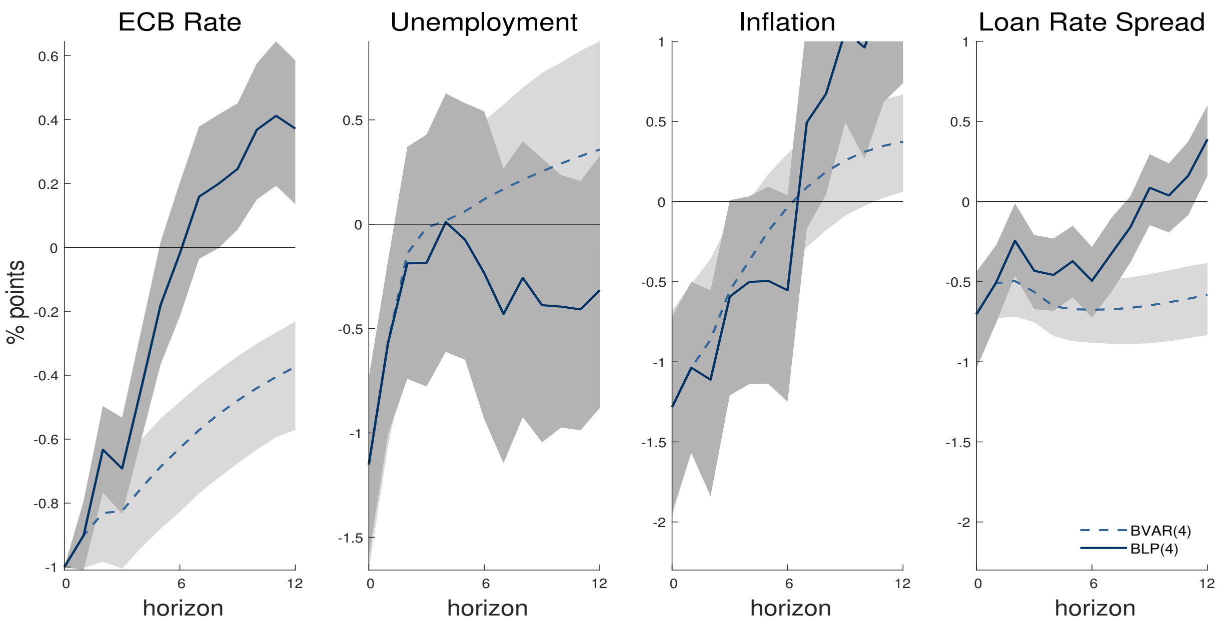


(b) **Interest Rates**



Notes: Proxy VAR model (dashed line) and a Bayesian Local Projection Model (solid line). Panel (a) specification with NFC loan Rate and NFC Deposit Rate; Panel (b) specification with NFC loan Rate and HH Deposit Rate

Figure 9: Loan Rate Spread across Banks: High vs Low Deposit Rate Banks



Notes: Impulse response function to an unexpected cut to the ECB deposit facility rate from a Bayesian Local Projection Model over the NIRP sample (monthly data). The last subplot displays the difference in the response of the interest rate to corporate loans (Loan R spread) across banks with high and low deposit rates. The loan rate spread is constructed as the difference between the average loan rate of banks with (ex-ante) high deposit rates (HDR) and that of low deposit rates (LDR).

Figure 10: Impulse Responses to a Policy Rate Shock: Core vs Periphery Euro-Area

Notes: Impulse response function to an unexpected cut to the ECB deposit facility rate from a Bayesian VAR and a Bayesian Local Projection Model over the NIRP sample (monthly data). The last subplot displays the response of the interest rate to corporate loans (NFC Loan R) by banks located in Core and Periphery Countrie.

Beyond Zero: Are Policy Rate Cuts Still Expansionary?

Data Appendix

A Data

A.1 Macroeconomic Data

- GDP: Gross Domestic Product volume growth. Gross domestic product at market prices - Euro area 19 (fixed composition) - Domestic (home or reference area), Total economy, Euro, Chain linked volume (rebased), Growth rate, over 1 year, Calendar and seasonally adjusted data.
Source: ECB. Main National Statistics (key: MNA.Q.Y.I8.W2.S1.S1.B.B1GQ._Z._Z._Z.EUR.LR.GY)
Link

- Unemployment: Euro area 19 (fixed composition) as of 1 January 2015; European Labour Force Survey; Unemployment rate; Total; Age 15 to 74; Total; Seasonally adjusted, not working day adjusted.
Source: ECB. Labour Force Survey Indicators (key: LFSI.M.I8.S.UNEHRT.TOTAL0.15_74.T)
Link

- Inflation : HICP - All-items excluding energy and food. Euro area (changing composition) - HICP - All-items excluding energy and food, Annual rate of change, Eurostat, Neither seasonally nor working day adjusted.
Source: ECB. Consumer Price Idexes (key: ICP.M.U2.N.XEF000.4.ANR). Link

A.2 Policy Rates

- Deposit Rate Facility: ECB Deposit facility - Level. Euro area (changing composition) - Key interest rate - ECB Deposit facility - date of changes (raw data) - Level - Euro, provided by ECB.
Source: ECB. Financial market data (key: FM.B.U2.EUR.4F.KR.DFR.LEV). Link

A.3 Aggregate Banking Data

A.3.1 Balance Sheet Variables (BSI)

- Loans to Non-Financial Corporations: Loans vis-a-vis euro area NFC reported by MFI excluding ESCB in the euro area (stock). Euro area (changing composition), Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector - Loans, Total maturity, All currencies combined - Euro area (changing composition) counterpart, Non-Financial corporations (S.11) sector, denominated in Euro, data Neither seasonally nor working day adjusted.
Source: ECB, Monetary and Financial Institutions, Balance Sheet Items (series key: MIR.M.U2.B.A2A.A.R.A.2240.EUR.N). Link

- Overnight Deposit from NFCs: Overnight deposits vis-a-vis euro area NFC reported by MFI excluding ESCB in the euro area (stock). Euro area (changing composition), Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector - Overnight deposits, Total maturity, All currencies combined - Euro area (changing composition) counterpart, Non-Financial corporations (S.11) sector, denominated in Euro, data Neither seasonally nor working day adjusted.
  Source: ECB, Monetary and Financial Institutions, Balance Sheet Items (series key: BSI.M.U2.N.A.L21.A.1.U2.2240.Z01.E). Link

- Overnight Deposits from Households: Overnight deposits vis-a-vis euro area households reported by MFI excluding ESCB in the euro area (stock). Euro area (changing composition), Outstanding amounts at the end of the period (stocks), MFIs excluding ESCB reporting sector - Overnight deposits, Total maturity, All currencies combined - Euro area (changing composition) counterpart, Households and non-profit institutions serving households (S.14 and S.15) sector, denominated in Euro, data Neither seasonally nor working day adjusted.
  Source: ECB, Monetary and Financial Institutions, Balance Sheet Items (series key: BSI.M.U2.N.A.L21.A.1.U2.2250.Z01.E). Link

A.3.2 Interest Rates (MIR)

- Interest Rate on Loans to Non Financial Corporations : New corporations - euro area. 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 other than revolving loans and overdrafts, convenience and extended credit card debt, Total initial rate fixation, Total amount, New business coverage, Non-Financial corporations (S.11) sector, denominated in Euro.
  Source: ECB, Monetary and Financial Institutions, Interest Rate Statistics (series key: MIR.M.U2.B.A2A.A.R.A.2240.EUR.N). Link

- Interest Rate on Household Deposits: Overnight deposits from corporations. 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 - Overnight deposits, Total original maturity, New business coverage, Households and non-profit institutions serving households (S.14 and S.15) sector, denominated in Euro.
  Source: ECB, Monetary and Financial Institutions, Interest Rate Statistics (series key: MIR.M.U2.B.L21.A.R.A.2250.EUR.N). Link

- Interest Rate on Corporate Deposits: Overnight deposits from households. 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 - Overnight deposits, Total original maturity, New business coverage, Non-Financial corporations (S.11) sector, denominated in Euro.
  Source: ECB, Monetary and Financial Institutions, Interest Rate Statistics (series key: MIR.M.U2.B.L21.A.R.A.2240.EUR.N). Link

A.3.3 Bank Lending Survey (BLS)

- Lending standards: Share of Banks reporting increased lending standards on loan applications from NFCs in the past three months. Survey Item. Banks participating are asked to report their lending standards during the survey period in the following way: "Over the past three months, how have your bank's credit standards as applied to the approval of loans or credit lines to enterprises changed? Please note that we are asking about the change in credit standards, rather than about their level." (1) tightened considerably, (2) tightened somewhat, (3) remained basically unchanged, (4) eased somewhat, and (5) eased considerably. The net percentage of banks loosening lending standards corresponds to the share of banks whose response is either (4) or (5) minus the share of banks whose response is either (1) or (2).
  Source: ECB. Bank Lending Survey (key: BLS.Q.U2.ALL.O.E.Z.B3.ST.S.BWFNET). Link

- Loan demand: Share of Banks reporting increased Loan demand from NFCs in the past three months. Survey Item. Banks participating are asked to report their lending standards during the survey period in the following way: "Over the past three months (apart from normal seasonal fluctuations), how has the demand for loans or credit lines to enterprises changed at your bank? Please refer to the financing need of enterprises independent of whether this need will result in a loan or not." (1) decreased considerably, (2) decreased somewhat, (3) remained basically unchanged, (4) increased somewhat, and (5) increased considerably. The net percentage of banks reporting increase demand for NFC loans corresponds to the share of banks responding (4) or (5) minus the share of banks whose response is either (1) or (2).
  Source: ECB. Bank Lending Survey (key: BLS.Q.U2.ALL.O.E.Z.B3.ZZ.D.BWFNET). Link

A.4 Default Frequency Data:

- Bank EDFs: Expected default frequency of Euro-Area Banks. Weighted average of individual banks' probability of default. The individual measure is a market-based credit measure developed by Moody's KMV. It provides the probability that a bank will default within a one year, where default means the failure to make scheduled debt payments. The measure is based on the KMV credit model and it relies on three main elements computed for the target bank: Market Valuation, Stock Price volatility and Distance to Default. Individual Data is confidential. The Aggregated series is an average weighted by bank total assets. **Source:** Moody's KMV Dataset. For more information: Link.

- NFC EDFs: Expected default frequency of Euro-Area NFCs. Weighted average of individual NFCs' probability of default. The individual measure is a market-based credit measure developed by Moody's KMV. It provides the probability that a NFC will default within a one year, where default means the failure to make scheduled debt payments. The measure is based on the KMV credit model and it relies on three main elements computed for the target NFC: Market Valuation, Stock Price volatility and Distance to Default. Individual Data is confidential. The Aggregated series is an average weighted by NFC total assets.
  Source: Moody's KMV Dataset. For more information: Link.

A.5 Systemic Risk Data

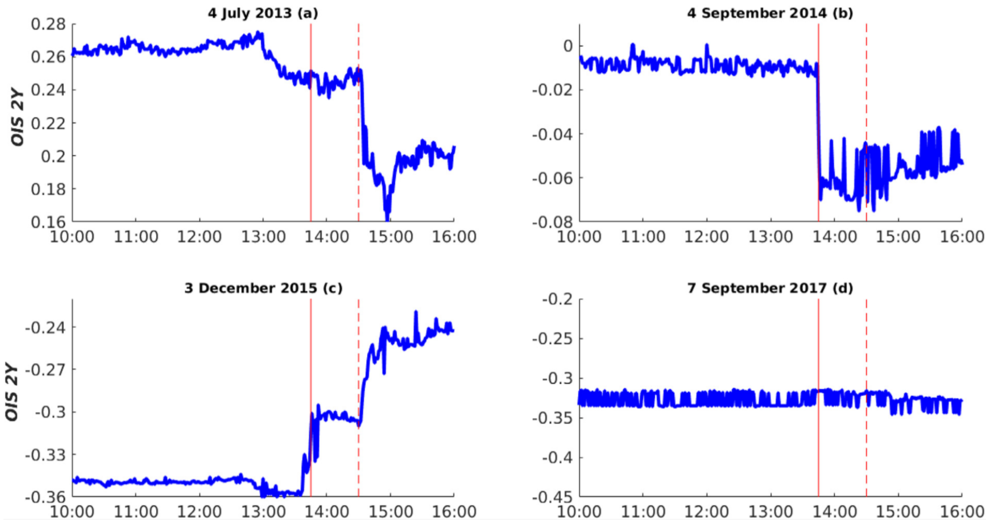
- Aggregate SRISK measure: Bank-level data on Euro-Area banks' returns, market value, book assets, book equity, and market returns are from Thomson Reuters. The aggregate measure is the sum of the individual SRISK measures. The estimation closely follows the procedure described in Brownlees and Engle (2017).

A.6 High Frequency Data

- Euro-Area Monetary Policy Event Study Database: collection of asset price/yield changes constructed for the three event windows characterizing each monetary policy event at the European Central Bank, i.e. the Press Release window, the Press Conference Window and the union of the Press Release and Press Conference Windows. The assets covered are the Overnight Index Swap (OIS) rates with 1, 3, 6 month and 1 to 10, 15, and 20 year maturities, German Bund yields with 3 and 6 month and 1 to 10, 15, 20, and 30 year maturities, French, Italian, and Spanish sovereign yields with 2, 5, and 10 year maturities, the stock market price index and the stock price index comprising only banks, and the exchange rate of the euro. For each of these assets tick by tick data are collected. The asset price/yield changes are hence measured as the difference between the mid quote of a 10 minute window starting 10 minutes after the end of the Event window (either Press, Conference or Total) and the mid quote of a 10 minute window ending 10 minutes before the beginning of the Event Window[39].
  Source: Altavilla et al. (2019), dataset available here. Figure 11 shows a selection of Tick by Tick data for the Overnight Index Swap with Maturity two years around four different monetary policy announcements. As it is possible to see there is a clear jump in either or both windows of the policy announcement which is probably linked to the unexpected component of the announcement being incorporated in the price at the time in which the announcement becomes public.

[39] Note that for the press release window, the event window is simply the time at which the press announcement is released, hence at 13.45 on Thursday every six weeks. Hence the price change reported in the dataset would be the difference between the mid quote over the time interval 13.55-14.05 and the mid quote over the interval 13.25-13.35.

Figure 11: Tick by Tick Data over four different times of ECB Monetary Policy Announcements.



Notes: Overnight Interest Rate Swap 2Y tick by tick data over three different dates. Solid line marks the publication of the Press Release. Dashed line marks the beginning of the Press Conference.

Beyond Zero: Are Policy Rate Cuts Still Expansionary?

Supplementary Material – Online Appendix

TO NOT BE PUBLISHED

A Methodology

A.1 Time-Varying Vector Autoregressive Model

A.1.1 Priors Specification

Following Primiceri (2005), we assume the following priors:

- Time varying coefficients: $P(\theta_0) = N(\hat{\theta}, \hat{V}_\theta)$ and $P(\Omega) = IW(\Omega_0^{-1}, \rho_1)$;
- Diagonal elements: $P(\log \sigma_0) = N(\log \hat{\sigma}, I_n)$ and $P(\Psi_i) = IW(\Psi_{0i}^{-1}, \rho_{3i})$;
- Off-diagonal elements: $P(\phi_{i0}) = N(\hat{\phi}_i, \hat{V}_{\phi_i})$ and $P(\Xi) = IW(\Xi_0^{-1}, \rho_2)$;

where the scale matrices are parametrized as follows $\Omega_0^{-1} = \lambda_1 \rho_1 \hat{V}_\theta$, $\Psi_{0i} = \lambda_{3i} \rho_{3i} \hat{V}_{\phi_i}$ and $\Xi_0 = \lambda_2 \rho_2 I_n$. The hyper-parameters are calibrated using a time invariant recursive VAR estimated using a sub-sample consisting of the first $T_0 = 40$ observations. For the initial states θ_0 and the contemporaneous relations ϕ_{i0}, we set the means, $\hat{\theta}$ and $\hat{\phi}_i$, and the variances, $\hat{V}_\theta$ and $\hat{V}_{\phi_i}$, at the maximum likelihood point estimates and four times its variance. For the initial states of the log volatilities, $\log \sigma_0$, the mean of the distribution is the logarithm of the residuals standard deviation, estimated in a time invariant VAR. The degrees of freedom for the covariance matrix of the drifting coefficient's innovations are set to be equal to T_0, the size of the initial-sample. The degrees of freedom for the priors on the covariance of the stochastic volatilities' innovations, are set to be equal to the minimum necessary to insure that the prior is proper. In particular, ρ_1 and ρ_2 are equal to the number of rows of Ξ_0^{-1} and Ψ_{0i}^{-1} plus one respectively.

The parameters λ_i are crucial since they control the degree of time variation in the unobserved states. The smaller the parameter, the smoother and smaller are the changes in coefficients. The empirical literature has set the prior rather conservatively in terms of the amount of time variations. D'Agostino et al. (2013a) show that, in a three variables VAR (with unemployment rate, inflation and interest rate), small parameters deliver accurate forecasts. In addition, turning to the effects of the parameters on the distribution of fitted values[40] very loose values of λ_i would imply large variance of the coefficients' distribution, hence large variance in the distribution of the fitted values. In this case, the model would tend to overfit the data: confidence bands around the fitted values would include a high percentage of observed data for any given percentile. The opposite would happen if the parameter λ_1 are very tight. Keeping in mind these considerations we still set the parameters closely following the literature, hence using respectively $\lambda_1, \lambda_2, \lambda_3 = [0.005, 0.001, 0.005]$. We do vary this parameters to check at which low level level they deliver almost unchanging estimates for all the coefficients and at which high level they deliver too errand estimates for the coefficients, the selected parameters lie in between this the two threshold with approximately the same distance from each. [41]

[40] Note that here the distribution of the fitted values is available at each point in time, we can hence compute percentiles at each date.

[41] Estimation is performed by discarding the explosive draws.

A.1.2 Estimation: The Bayesian Algorithm

Estimation is done using Bayesian methods. To draw from the joint posterior distribution of model parameters we use a Gibbs sampling algorithm along the lines described in Primiceri (2005). The basic idea of the algorithm is to draw sets of coefficients from known conditional posterior distributions. The algorithm is initialized at some values and, under certain regularity conditions, the draws converge to a draw from the joint posterior, after a burn in period. Let z be $(q \times 1)$ vector, we denote z^T the sequence $[z_1', ..., z_T']'$. Each repetition is composed of the following steps:

1. $p(s^T|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$[42]
2. $p(\sigma^T|y^T, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T)$
3. $p(\phi^T|y^T, \theta^T, \sigma^T, \Omega, \Xi, \Psi, s^T)$
4. $p(\theta^T|y^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi, s^T)$
5. $p(\Omega|y^T, \theta^T, \sigma^T, \phi^T, \Xi, \Psi, s^T)$
6. $p(\Xi|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Psi, s^T)$
7. $p(\Psi|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, s^T)$

Gibbs sampling algorithm

• Step 1: sample from $p(s^T|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$

Conditional on $y_{i,t}^{**}$ and r^T, we independently sample each $s_{i,t}$ from the discrete density defined by $Pr(s_{i,t} = j|y_{i,t}^{**}, r_{i,t}) \propto f_N(y_{i,t}^{**}|2r_{i,t} + m_j - 1.2704, v_j^2)$, where $f_N(y|\mu, \sigma^2)$ denotes a normal density with mean μ and variance σ^2.

• Step 2: sample from $p(\sigma^T|y^T, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T)$

To draw σ^T we use the algorithm of Kim et al. (1998). Consider the system of equations $y_t^* \equiv F_t^{-1}(y_t - X_t'\theta_t) = D_t^{1/2}u_t$, where $u_t \sim N(0, I)$, $X_t = (I_n \otimes x_t')$, and $x_t = [1_n, y_{t-1}...y_{t-p}]$. Conditional on y^T, θ^T, and ϕ^T, y_t^* is observable. Squaring and taking the logarithm, we obtain

$$y_t^{**} = 2r_t + \upsilon_t \quad (7)$$
$$r_t = r_{t-1} + \xi_t \quad (8)$$

where $y_{i,t}^{**} = \log((y_{i,t}^*)^2 + 0.001)$ - the constant (0.001) is added to make estimation more robust - $\upsilon_{i,t} = \log(u_{i,t}^2)$ and $r_t = \log \sigma_{i,t}$. Since, the innovation in (7) is distributed as $\log \chi^2(1)$, we use, following KSC, a mixture of 7 normal densities with component probabilities q_j, means $m_j - 1.2704$, and variances v_j^2 (j=1,...,7) to transform the system in a Gaussian one, where $\{q_j, m_j, v_j^2\}$ are chosen to match the moments of the $\log \chi^2(1)$ distribution. The values are:

[42] See below the definition of s^T.

Table A1: Parameters Specification

j	q_j	m_j	v_j^2
1.0000	0.0073	-10.1300	5.7960
2.0000	0.1056	-3.9728	2.6137
3.0000	0.0000	-8.5669	5.1795
4.0000	0.0440	2.7779	0.1674
5.0000	0.3400	0.6194	0.6401
6.0000	0.2457	1.7952	0.3402
7.0000	0.2575	-1.0882	1.2626

Source: Kim et al. (1998)

Let $s^T = [s_1, ..., s_T]'$ be a matrix of indicators selecting the member of the mixture to be used for each element of v_t at each point in time. Conditional on s^T, $(v_{i,t}|s_{i,t} = j) \sim N(m_j - 1.2704, v_j^2)$. Therefore we can use the algorithm of Carter and R.Kohn (1994) to draw r_t (t=1,...,T) from:
$N(r_{t|t+1}, R_{t|t+1})$, where $r_{t|t+1} = E(r_t|r_{t+1}, y^t, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T,)$ and
$R_{t|t+1} = Var(r_t|r_{t+1}, y^t, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T)$.

- Step 3: sample from $p(\phi^T|y^T, \theta^T, \sigma^T, \Omega, \Xi, \Psi, s^T)$

Consider again the system of equations $F_t^{-1}(y_t - X_t'\theta_t) = F_t^{-1}\hat{y}_t = D_t^{1/2}u_t$. Conditional on θ^T, $\hat{y}_t$ is observable. Since F_t^{-1} is lower triangular with ones in the main diagonal, each equation in the above system can be written as

$$\hat{y}_{1,t} = \sigma_{1,t}u_{1,t} \tag{9}$$
$$\hat{y}_{i,t} = -\hat{y}_{[1,i-1],t}\phi_{i,t} + \sigma_{i,t}u_{i,t} \quad i = 2, ..., n \tag{10}$$

where $\sigma_{i,t}$ and $u_{i,t}$ are the ith elements of σ_t and u_t respectively, $\hat{y}_{[1,i-1],t} = [\hat{y}_{1,t}, ..., \hat{y}_{i-1,t}]$. Under the block diagonality of Ψ, the algorithm of Carter and R.Kohn (1994) can be applied equation by equation, obtaining draws for $\phi_{i,t}$ from a $N(\phi_{i,t|t+1}, \Phi_{i,t|t+1})$, where $\phi_{i,t|t+1} = E(\phi_{i,t}|\phi_{i,t+1}, y^t, \theta^T, \sigma^T, \Omega, \Xi, \Psi)$ and $\Phi_{i,t|t+1} = Var(\phi_{i,t}|\phi_{i,t+1}, y^t, \theta^T, \sigma^T, \Omega, \Xi, \Psi)$.

- Step 4: sample from $p(\theta^T|y^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi, s^T)$

Conditional on all other parameters and the observables we have

$$y_t = X_t'\theta_t + \varepsilon_t \tag{11}$$
$$\theta_t = \theta_{t-1} + \omega_t \tag{12}$$

Draws for θ_t can be obtained from a $N(\theta_{t|t+1}, P_{t|t+1})$, where $\theta_{t|t+1} = E(\theta_t|\theta_{t+1}, y^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$ and $P_{t|t+1} = Var(\theta_t|\theta_{t+1}, y^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$ are obtained with the algorithm of Carter and R.Kohn (1994).

- Step 5: sample from $p(\Omega|y^T, \theta^T, \sigma^T, \phi^T, \Xi, \Psi, s^T)$

Conditional on the other coefficients and the data, Ω has an Inverse-Wishart posterior density with scale matrix $\Omega_1^{-1} = (\Omega_0 + \sum_{t=1}^{T} \Delta\theta_t(\Delta\theta_t)')^{-1}$ and degrees of freedom $df_{\Omega_1} = df_{\Omega_0} + T$, where Ω_0^{-1} is the prior scale matrix, df_{Ω_0} are the prior degrees of freedom and T is length of the sample use for estimation. To draw a realization for Ω make df_{Ω_1} independent draws z_i (i=1,...,df_{Ω_1}) from $N(0, \Omega_1^{-1})$ and compute $\Omega = (\sum_{i=1}^{df_{\Omega_1}} z_i z_i')^{-1}$ (see Gelman et. al., 1995).

- Step 6: sample from $p(\Xi_{i,i}|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Psi, s^T)$

Conditional the other coefficients and the data, Ξ has an Inverse-Wishart posterior density with scale matrix $\Xi_1^{-1} = (\Xi_0 + \sum_{t=1}^{T} \Delta \log \sigma_t(\Delta \log \sigma_t)')^{-1}$ and degrees of freedom $df_{\Xi_1} = df_{\Xi_0} + T$ where Ξ_0^{-1} is the prior scale matrix and df_{Ξ_0} the prior degrees of freedom. Draws are obtained as in step 5.

- Step 7: sample from $p(\Psi|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, s^T)$.

Conditional on the other coefficients and the data, Ψ_i has an Inverse-Wishart posterior density with scale matrix $\Psi_{i,1}^{-1} = (\Psi_{i,0} + \sum_{t=1}^{T} \Delta\phi_{i,t}(\Delta\phi_{i,t})')^{-1}$ and degrees of freedom $df_{\Psi_{i,1}} = df_{\Psi_{i,0}} + T$ where $\Psi_{i,0}^{-1}$ is the prior scale matrix and $df_{\Psi_{i,0}}$ the prior degrees of freedom. Draws are obtained as in step 5 for all i.

The estimations are performed with 12000 repetitions discarding the first 10000 and collecting one out of five draws.

A.2 Proxy Identification

A.2.1 Proxy

As outlined in the main text the Common Latent Factors used as proxies in the monthly Bayesian Local Projections and Proxy-SVARs are extracted by means of a standard linear factor model estimated through Maximum Likelihood. The factors are hence rotated for interpretability. In the following section the linear model, its main properties will be outlined together with the assumptions made on data, factors and noise components. Following the Maximum Likelyhood estimation procedure will be briefly discussed. Finally the choice of rotation will be explained.

Let x_t be a $N \times 1$ matrix containing the N time-series of asset price changes selected from the High Frequency Dataset as detailed in Appendix A. Define f_t as the $k \times 1$ matrix of unknown factors, B the corresponding $n \times k$ matrix of factor loadings and ϵ_t the $n \times 1$ white noise vector with $\mathbb{E}\left[\epsilon_t\right] = 0$ and $Cov[\epsilon_t] = \Psi = diag\left(\sigma_i^2\right)$. The linear factor model can be hence described by the following set of equations:

$$x_t = \alpha + Bf_t + \epsilon_t \quad \text{for t } \in \{1, 2, ...T\} \tag{13}$$

Assuming orthonormal factors, i.e. the factor Covariance matrix is a $k \times k$ identity matrix $\Omega_f = I_k$, and that factors are mean zero, i.e. $\alpha^* = \alpha + B\mu_f$ and hence $\mu_f^* = 0$, then the unconditional covariance matrix of x can be derived as:

$$\Sigma_x = BB' + \Psi \tag{14}$$

Now, further assuming gaussianity of all random variables the model can be estimated through Maximum Likelihood. The log-likelyhood function together with the gaussianity assumptions will hence be:

$$x_t \quad i.i.d. \ \mathcal{N}_n\left(\alpha, \Sigma_x\right) \tag{15}$$
$$f_t \quad i.i.d. \ \mathcal{N}_k\left(0_k, I_k\right) \tag{16}$$
$$\epsilon_t \quad i.i.d. \ \mathcal{N}_n\left(0_n, \Psi\right) \tag{17}$$

$$l\left(\alpha, \Sigma_x\right) = logL\left(\alpha, \Sigma_x\right) \tag{18}$$
$$= -\frac{TK}{2}log(2\pi) - \frac{k}{2}log(|\Sigma_x|) - \frac{1}{2}\sum_{t=1}^{T}\left(x_t - \alpha\right)' \Sigma_x^{-1}\left(x_t - \alpha\right) \tag{19}$$

Consequently the MLE estimates $\hat{\alpha}$, $\hat{B}$ and $\hat{\Psi}$ will be the result of the following maximization problem:

$$\begin{aligned} \max_{\alpha, B, \Psi} \quad & l(\alpha, \Sigma_x) && (20) \\ sub \quad & \Sigma_x = BB' + \Psi && (21) \end{aligned}$$

This is numerically solved by applying the well known Expectation-Maximization (EM) Algorithm. Now the factors realizations can be computed through:

$$x_t - \hat{\alpha} = \hat{B} f_t = \hat{\epsilon}_t \tag{22}$$

As outlined in the first paragraph of this subsection, once factors are estimated, they are further rotated to interpretable factors. Indeed recall that factors and factors loadings are identified up to orthogonal rotations. To see this, consider an orthogonal $k \times k$ matrix O such that $O'O = I_k$. And consider the alternative set of factor loadings $\tilde{B} = BO'$ where B is the original matrix of factor loadings. Consider further the alternative set of factors $\tilde{f} = Of$ where f is the original set of factors. It is easy to show that the set of alternative loadings and factors is observationally equivalent given the model at hand to the original set of loadings and factors. Indeed:

$$\begin{aligned} \Sigma_{\tilde{f}} &= \tilde{f}' \tilde{f} = f' O' O f = \Sigma_f \\ \tilde{B} \tilde{B}' &= B O' O B' = BB' \end{aligned}$$

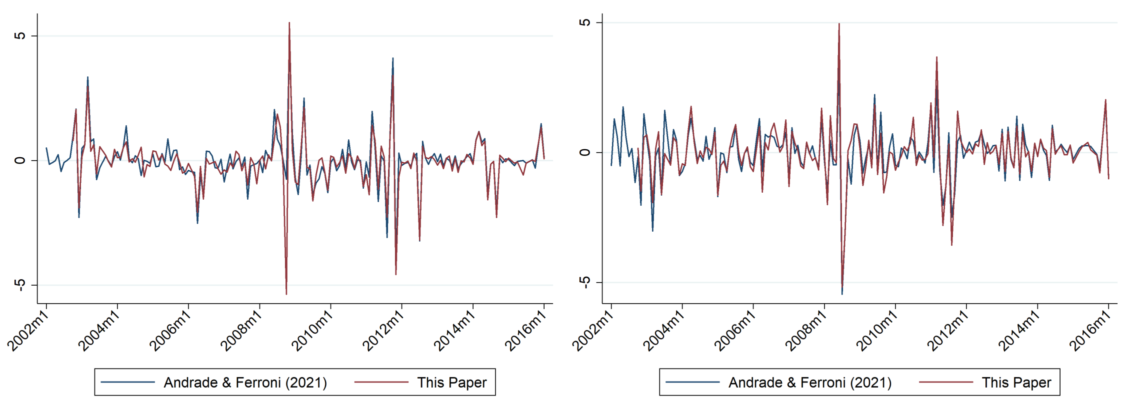
For our specific case at hand we hence direct the rotation at reaching as closely as possible the following target. Imagine the variables in x_t are the assets ordered from the lowest maturity (1 Month) to the highest. We direct the rotation towards the following target:

$$BO(\theta) = \begin{pmatrix} * & 0 \\ * & * \\ ... & ... \\ * & * \end{pmatrix} \tag{23}$$

As explained also in the main text the above rotation would aim at rotating factors such that the first is allowed to load on all maturities with no constraints (and explains the most variance) while the second one would only be allowed to load on the maturities other than 1M. This rotation would allow to interpret the first factor as the induced common level shift, or Target Factor, due to the monetary policy news. The second factor would instead represent the slope shift in the shorter horizon part of the yield curve due to the Monetary policy news. Hence the naming Target and Slope Factors. The obtained proxies closely resemble those of Andrade and Ferroni (2021), which use a very similar rotation approach (although a different estimation technique) and are shown in Fig A 1 below for the common sample period.

Figure A 1: Estimated Proxies Compared with Andrade and Ferroni (2021)

(a) **Target Factor** (b) **Path Factor**



Notes: There are differences in the estimation and rotation procedures used in this paper and in Andrade and Ferroni (2021), for details on the procedure adopted for the extraction of the comparing series check the paper and its online appendix for further details.

A.2.2 VAR: Estimation and Identification

In this subsection the features of the VAR model underlying the evidence presented in the main text will be discussed in detail. After outlining the main structure of the VAR, this subsection will focus on the Bayesian Estimation technique used to recover the estimates of the reduced form parameters and later the identification technique used to recover the structural shocks and estimate the impulse response functions.

The Monthly VAR used in Section 4 takes the following standard reduced form:

$$Y_t = B_0 + B(L)Y_{t-1} + u_t \tag{24}$$

where Y_t is an $n \times 1$ vector of endogenous variables, $B(0)$ is the vector of Intercepts and $B(L)$ is a $n \times n$ matrix polynomial in the lag operator L, finally u_t is the vector of reduced form shocks. The structural form of the VAR can be recovered as:

$$C^{-1}Y_t = A_0 + A(L)Y_{t-1} + \varepsilon_t \tag{25}$$

Such that $u_t = C\varepsilon_t$ and $B = CA_i$ The estimation of the Reduced Form coefficients 24 is obtained through Bayesian Techniques. The Prior chosen belongs to the family of Normal-Inverse Wishart priors which can be formalized compactly in terms of a conditional prior on the matrix of coefficients $\beta = vec\left([B_0, B(1), ...B(p)]'\right)$ and an unconditional prior on Σ:

$$\beta \mid \Sigma \sim \mathcal{N}\left(b, \Sigma \bigotimes \Omega\xi\right) \tag{26}$$

$$\Sigma \sim \mathrm{IW}\left(\Psi, d\right) \tag{27}$$

where b is the vector of prior means for each of the elements of β and $\Omega\xi$ pins down the conditional variance of the conditional prior. Notice that throught the exposition we will always be assuming that the first p observations, where p is the lag order of the VAR model, are given and that we can condition on them. The parameter ξ is key in this specification as it is a parameter which scales up or down the variance covariance matrix of the prior distribution hence pinning down the so called tightness of the prior distribution. The closer will be the estimated posterior distribution of the parameters to the assumed prior distribution. The specific prior form assumed in this case is the so-called famous Minnesota Prior which is centered on the assumption that each endogenous variable follows a random walk process, possibly with drift. This prior was first introduced in Litterman (1979) and (1980) and is characterized by the following form:

$$\mathbb{E}\left[(B_s)_{ij} \mid \Sigma\right] = \begin{cases} 1 \text{ if } i = j \text{ and } s = 1 \\ 0 \text{ otherwise} \end{cases} \tag{28}$$

$$cov\left((B_s)_{i,j}, (B_r)_{hm} \mid \Sigma\right) = \begin{cases} \lambda^2 \frac{1}{s^2} \frac{\Sigma_{ih}}{\psi_j/(d-n-1} \text{ if } m = j \text{ and } r = s \\ 0 \text{ otherwise} \end{cases} \tag{29}$$

Note the key hyperparameter, i.e. ξ in the general specification of the prior family, is here called λ. This is a unique scalar parameter which governs the magnitude of the variance of each parameter prior distribution and hence generally speaking governs the degree of importance of the prior distribution on the final posterior estimate. Following the work of Sims and Zha (1998) we further introduce the two refinements to the standard Minnesota priors namely: the "Sum of Coefficients prior" and the "Dummy Initial Observation prior". Loosely speaking both priors are aimed at reducing the importance of the deterministic component implied by the VAR being estimated conditioning on the first p observations. Both priors are implemented using Theil mixed estimation by adding a set of n artificial observations as follows. The Sum of Coefficients prior has the following form:

$$\underset{n\times n}{y^+} = \operatorname{diag}\left(\frac{\bar{y}_0}{\mu}\right) \tag{30}$$

$$\underset{n\times(1+np)}{x^+} = \left[\underset{n\times 1}{0}, y^+, ..., y^+\right] \tag{31}$$

Here the hyperparameter μ controls the variance of this specific prior belif. The larger is the value chosen for this hyperparameter and the more uninformative will be this prior.

The Dummy Initial Observation Prior has instead the following form:

$$
\begin{aligned}
\underset{1\times n}{y^{++}} &= \begin{pmatrix} \bar{y}_0^{'} \\ \mu \end{pmatrix} && (32)\\
\underset{1\times(1+np)}{x^{+}} &= \left[\frac{1}{\delta}, y^{+}+, ..., y^{+}+\right] && (33)
\end{aligned}
$$

Here the δ hyperparameter will have the same function as μ for the above prior specification.

Summing up the set of hyperparameters assumed by this Prior specification is given by the vector $\left[\lambda, \mu, \delta, \frac{\psi}{d-n-1}\right]$. Following the hyerarchical approach of Giannone et al. (2015), these hyperparameters are treated as estimation targets as well and hence a prior distribution for each of them is introduced. For the first three hyperparameters, gamma densities are assumed as priors with mode equal to respectively 0.2,1 and 1[43] and standard deviations equal to 0.4,1 and 1 respectively. For each of the elements of the $\frac{\psi}{d-n-1}$ hyperparameter instead an inverse-Gamma density with scale and shape equal to $(0.02)^2$ is assumed, in line with the choice of data transformation. The conjugate nature of the priors allows for closed form solutions of the Marginal Likelihood as a function of the hyperparameter vector. The full posterior density is instead estimated by a simple Monte Carlo Markov Chain algorithm. In particular first a Metropolis step is used to draw the low-dimensional vector of hyperparameters. Then conditional on the value of the hyperparameters the matrices B and Σ are drawn from their posterior. The details are contained in the Online Appendix B of Giannone et al. (2015).

We now turn to the identification through external instruments implemented in this paper in order to derive the Impulse Response Functions with respect to the Policy Rate shock. Although the methodology can be applied to retrieve any number of structural shocks, for the purpose of this paper we will only present the case in which only one structural shock needs to be retrieved and this structural shock is ordered first in the unobserved vector of structural shocks ε_t. The target structural shock, a policy rate shock, will be denoted ε_t^p, while the remaining unidentified shocks will be denoted ε_t^o. The key for the identification strategy relies on the availability of an observable set of external instruments z_t which is loosely speaking correlated with the shock we want to identify but uncorrelated with all the other shocks. More formally the set of external instruments has to satisfy two conditions:

$$
\begin{aligned}
(\textbf{Relevance}) \qquad \mathbb{E}\left[z_t \varepsilon_t^{p'}\right] &= \Phi && (34)\\
(\textbf{Exogeneity}) \qquad \mathbb{E}\left[z_t \varepsilon_t^{o'}\right] &= 0
\end{aligned}
$$

where Φ is a matrix of unknown coefficients pinning down the correlation between the External Instrument Matrix and the target structural shock. Assuming the above conditions hold we have a new set of restrictions, namely:

[43] The values recommended by Sims and Zha (1998)

$$\Phi C'_{.,1} = \mathbb{E}\left[z_t u_t^{'}\right] \tag{35}$$

where $C'_{.,1}$ is the first column of the C matrix of the VAR written in structural form. If the matrix Φ was known, the system would be composed of $n \times 1$ equations in $n \times 1$ unknown and hence all the coefficients could be recovered. However Φ is unknown hence only $n-1$ coefficients can be identified. This can be seen by decomposing the Variance Covariance Matrix of the Reduce Form residuals and the External Instruments in the following way:

$$\begin{pmatrix} \mathbb{E}\left[u_t^p z_t^{'}\right] \\ \mathbb{E}\left[u_t^o z_t^{'}\right] \end{pmatrix} = B_0 \begin{pmatrix} \mathbb{E}\left[\varepsilon_t^p z_t^{'}\right] \\ \mathbb{E}\left[\varepsilon_t^o z_t^{'}\right] \end{pmatrix} = (b_1|b_2)\begin{pmatrix} \alpha' \\ 0 \end{pmatrix} = \begin{pmatrix} b_{11}\alpha' \\ b_{12}\alpha' \end{pmatrix} \tag{36}$$

and hence:

$$\mathbb{E}\left[u_t^p z_t^{'}\right]^{-1} \mathbb{E}\left[u_t^o z_t^{'}\right] = b_{11}^{-1} b_{12} \tag{37}$$

It is easy to see from the above equation that the coefficients of the impact matrix are hence identified up to a scale and sign factor. In line with standard practice we hence introduce a normalization setting the coefficient $b_{11} = 1$. Since the above equation is equivalent to regressing u_t^o onto u_t^p using z_t as external instrument the procedure can be practically implemented through the following steps:

- **Step 1:** Estimate the reduced form VAR and reduced form residuals u_t
- **Step 2:** Estimate $\mathbb{E}\left[u_t^p z_t^{'}\right]^{-1} \mathbb{E}\left[u_t^o z_t^{'}\right]$ by regressing z_t onto u_t
- **Step 3:** Calculate $b_{11}^{-1} b_{12}$ as the ratio of the coefficients of the regression in Step 2
- **Step 4:** Apply the normalization to b_{11} and solve for b_{12}.

Notice that the whole procedure can be extended to the case in which there is more than one instrument available for the same shock. In that case identification is achieved by further assuming a Choleski decomposition of the matrix of coefficients:

$$\S_1 S - 1' = \left(I - \beta_{12}\beta_{22}^{-1}\beta_{21}\beta_{11}^{-1}\right)\beta_{11}\beta 11^{'}\left(I - \beta_{12}\beta_{22}^{-1}\beta_{21}\beta_{11}^{-1}\right)' \tag{38}$$

In that case the system would be overidentified and could hence be tested for overidentification. Following Mertens and Ravn (2013) we also construct measures of Instrument Reliability, which allows to assess the degree of "representativeness" of a certain latent shock by the external instruments in presence of measurement errors in the instrument. Intuitively, low levels of the Reliability statistic can indicate that the external instruments do not contain much information useful for identification as measurement errors make up most of the instrument variability. The reliability statistic can be estimated as:

$$\Lambda = \left(\Gamma^2 \sum_{t=1}^{T} D_t(\varepsilon_t^p)^2 + \sum_{t=1}^{T} D_t\left(z_t - \Gamma\varepsilon_t^p\right)^2\right)^{-1}\left(\Gamma^2 \sum_{t=1}^{T} D_t(\varepsilon_t^p)^2\right) \tag{39}$$

where $\Gamma = \left(\sum_{t=1}^{T} D_t z_t u_t^1 / \sum_{t=1}^{T} D_t\right) / \beta 11$ and D_t is a $k \times k$ diagonal matrix containing random (0,1)-indicators tracking zero observations in the measurement error equations assumed for the External Instruments:

$$z_t = D_t \left(\Gamma \varepsilon_t^p + \nu_t\right) \tag{40}$$

Check Mertens and Ravn (2013) appendix for further details and derivations of the above formula[44].

A.2.3 Bayesian Local Projection

In this section we describe the details of the Bayesian Local Projection as in Miranda-Agrippino and Ricco (2021). Loosely speaking the methodology aims at combining the standard local projection first pioneered by Jorda (2005) with bayesian estimation techniques in order to attenuate some of the shortcomings of the standard estimation approach through appropriately specified priors. As it will become clear later such priors will be centered around the coefficients of a Bayesian VAR estimated over a pre-sample. To understand the underlying intuition for the advantages of this approach it is useful recalling the trade-off existing between Iterated and Direct methods to compute impulse response functions. VARs belong to the first method as the estimated coefficients are used iteratively up to a certain horizon in order to recover the relevant IRFs. Local projections belong instead to the second as for each horizon a new set of estimated coefficients is used. Generally speaking the trade-off pending on the choice between the two methodologies relates to the fact that the first type of method tends to deliver more efficient parameters estimates, but at the cost of considerable bias in case of misspecification while the second type of method is much more robust to misspecification, but normally entails high estimation uncertainty especially in presence of small sample. The purpose of Bayesian Local Projections is exactly to avoid taking a stand between the two methodologies, but rather provide a flexible framework spanning the entire model space between Standard Local Projections and BVARs looking for the optimal point between the two. This is achieved by using the Local Projection Regression framework as Likelyhood function and the VAR framework instead to inform the Priors necessary to form the Posterior. As it will become clear below the degree of departure from the Standard Local Projection Estimates will be hence depend on the tightness of the Prior which will be itself also estimated using hierarchical hyperpriors in a very similar fashion to Giannone et al. (2015). To set up notation the Local Projection regression and VAR models for the h-step ahead prediction are reported below:

$$\begin{array}{llll} (LP) & y_{t+h} = & B^{(h)} y_t + \varepsilon_{t+h}^{(h)}, & \varepsilon_{t+h}^{(h)} \sim \mathcal{N}\left(0, \Sigma_\varepsilon(h)\right) \\ (VAR) & y_t = & B y_{t-1} + \varepsilon_t & \varepsilon_t \sim \mathcal{N}\left(0, \Sigma_\varepsilon\right) \end{array}$$

The specified priors will be of the standard conjugate Normal-inverse Wishart family in order to obtained closed form solution:

[44] See Miranda-Agrippino and Ricco (2019) for a thorough discussion of Identification through external instruments in absence of full invertibility.

$$\begin{aligned}
\Sigma_{\varepsilon}^{(h)} \quad &| \quad \lambda^{(h)} \sim \mathcal{IW}\left(\Psi_0^{(h)}, d_0^{(h)}\right) \\
\beta^{(h)} \quad &| \quad \Sigma_{\varepsilon}^{(h)},\, \lambda^{(h)} \sim \mathcal{N}\left(\beta_0^{(h)}, \Sigma_{\varepsilon}^{(h)} \otimes \Omega_0^{(h)}\left(\lambda^{(h)}\right)\right)
\end{aligned}$$

where $\beta^{(h)} \equiv vec(B^{(h)})$ is the vector of all Local Projection Parameters at horizon h, $\lambda^{(h)}$ is the hyperparameter pinning down the variance of the prior on the parameters β^h and thus the above mentioned tightness of the prior, $\beta_0^{(h)} = vec(B_{T_0}^h)$ is the vectorized matrix of VAR coefficients estimated over the presample T_0 and elevated to the h power (hence matching the parameters $\beta^{(h)}$ and finally Σ_{ε}^h is the Variance Covariance matrix corresponding to $\varepsilon_t^{(h)}$ in the local projection framework. As in standard Bayesian estimation the parameter d_0^h is set equal to the number of variables minus 2, the hyperparameters $\Psi_0^{(h)}$ and $\Omega_0^{(h)}$ are set using sample information as in Kadiyala and Karlsson (1997). The posterior distribution for the BLP coefficients can be finally obtained by combining the priors described above with the likelyhood of data conditional on the parameters of the LP regressions. The posterior mean of the BLP responses will hence take the following form:

$$B_{BLP}^{(h)} \propto \left(X'X + \left(\Omega_0^{(h)}(\lambda^{(h)})\right)^{-1}\right)^{-1} \left(\left(X'X\right) B_{LP}^{(h)} + \left(\Omega_0^{(h)}(\lambda^{(h)})^{-1}\right)^{-1} B_{VAR}^h\right) \tag{41}$$

As it is easy to see in the above equation at each horizon h, the relative weighting between VAR and LP impulse responses is pinned down by the set of parameters $\Omega_0^{(h)}\left(\lambda^{(h)}\right)$ which is explicitly a function of $\lambda^{(h)}$, i.e. the tightness of the coefficients prior. The closer is $\lambda^{(h)}$ to 0 the closer will be the BLP IRFs to the VAR IRFs. Viceversa the bigger will be the hyperparameter, the higher will be the prior variance and the closer will be the BLP IRFs to LP IRFs. It is worth recalling that, in a very similar fashion to Giannone et al. (2015), the hyperparameter $\lambda^{(h)}$ is not set manually but estimated from data by means of an hyperprior at each horizon h. As a result the degree of departure from standard local projection is automatically chosen by data to the level which maximizes the likelyhood.

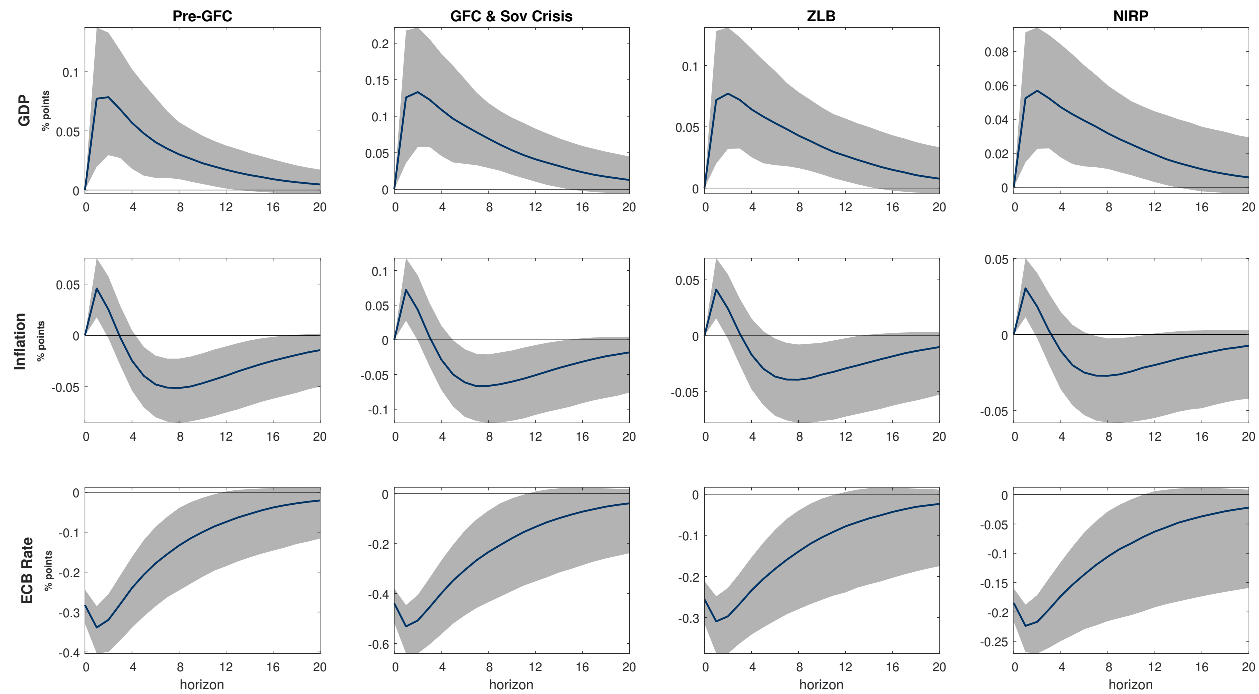
Following the authors who introduced this methodology, in order to overcome the fact that the autocorrelation of the projection residuals in the likelyhood of data is not accounted for, in the implementation the $\Sigma_{\varepsilon}^{(h)}$ matrix is replaced by a HAC-corrected version denoted $\Sigma_{\varepsilon,\mathrm{HAC}}^{(h)}$ obtained similarly to the frequentist literature on the topic. Replacing the HAC-corrected Covariance matrix above in the definitions of the Priors the Posterior variance of the BLP can be hence computed as:

$$\mathbb{V}ar\left(B_{BLP}^{(h)}\right) = \Sigma_{\varepsilon,\mathrm{HAC}}^{(h)} \otimes \left(X'X + \left(\Omega_0^{(h)}\left(\lambda^{(h)}\right)\right)^{-1}\right)^{-1} \tag{42}$$

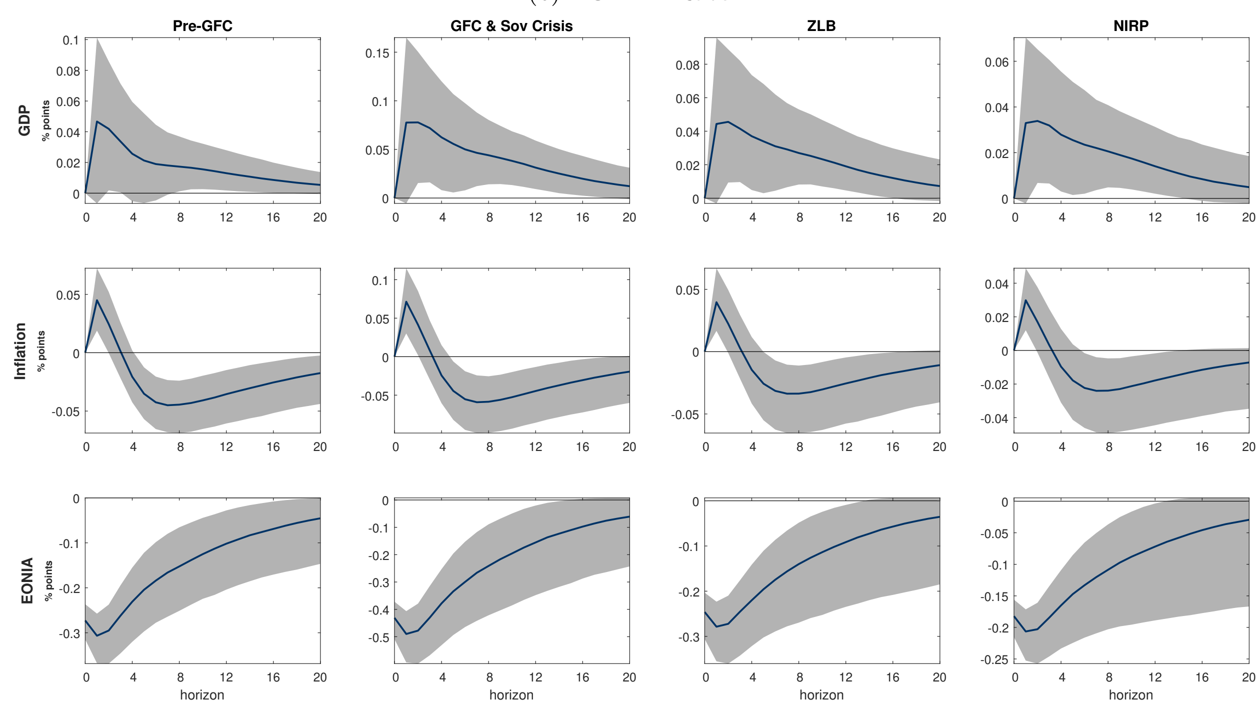
B Additional Results

Figure B1: Policy Rate Shock: IRFs from TV-VAR

(a) **ECB Deposit Rate**



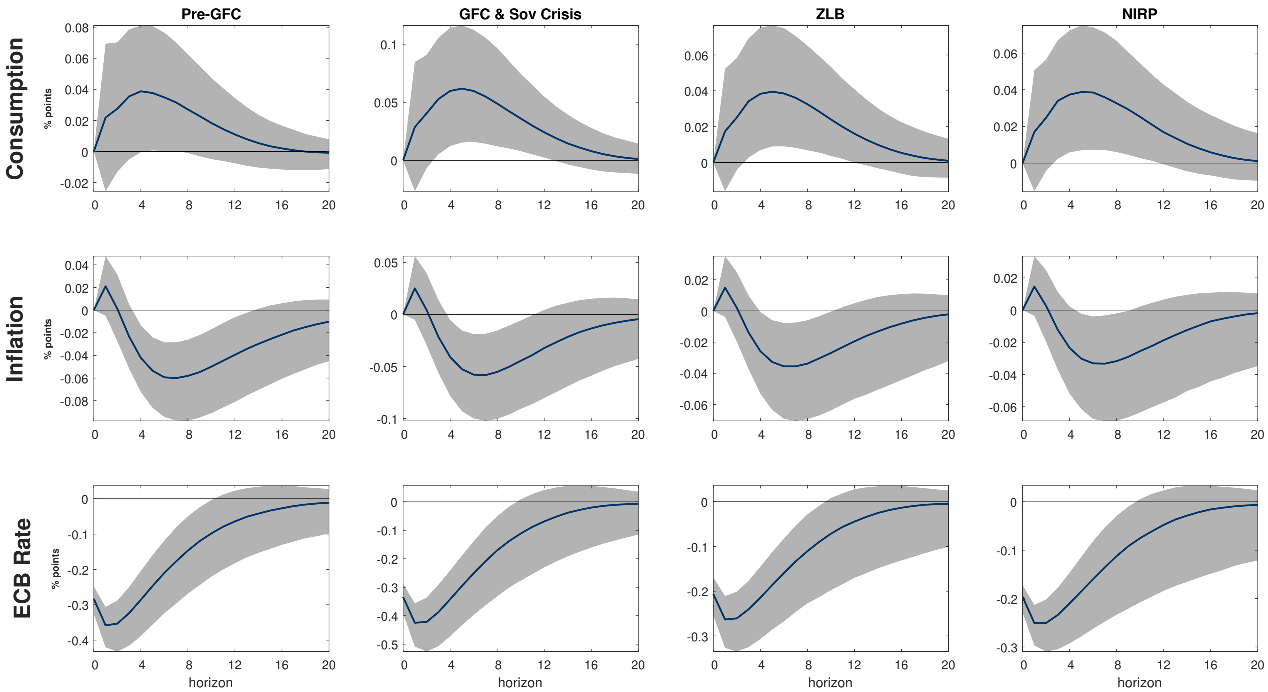
(b) **EONIA Rate**



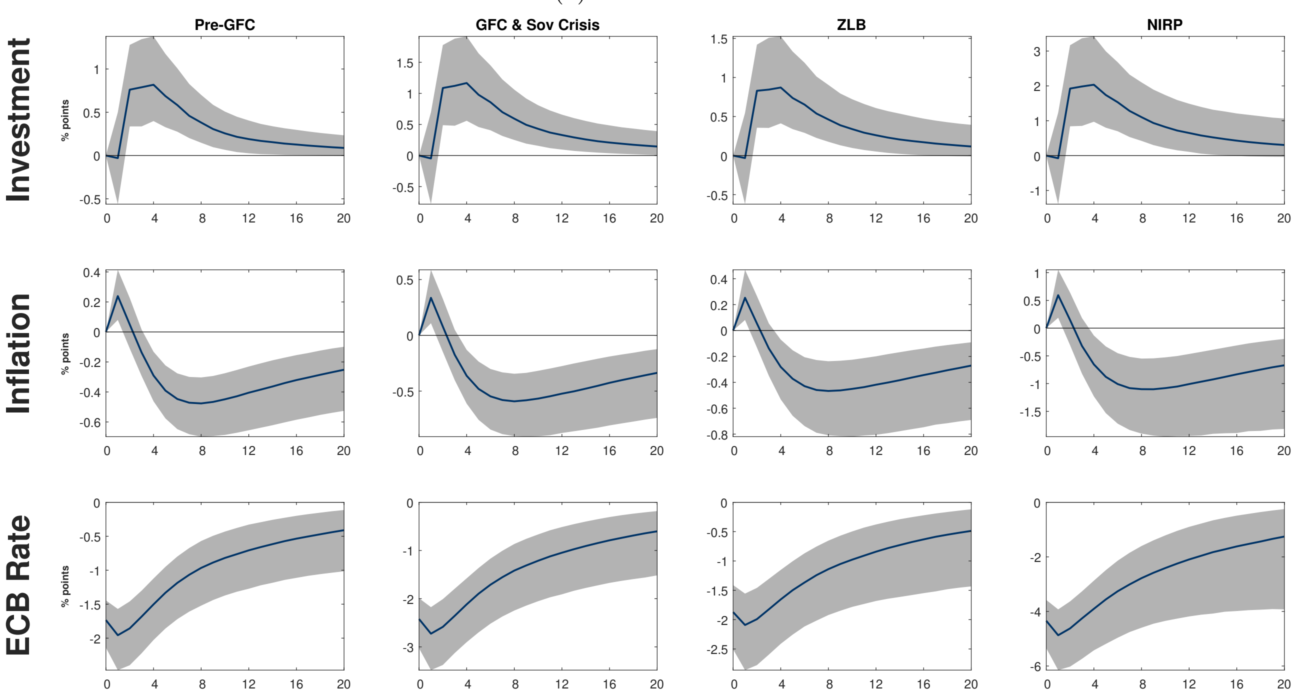
Notes: Confidence bands: 16th and 84th percentile. Selected periods: 2000Q1-2007Q3 (Pre-GFC), 2007Q4-2012Q2 (Crisis), 2012Q3-2014Q2 (ZLB), 2014Q3-2019Q4 (NIRP). 15

Figure B2: Policy Rate Shock: IRFs from TV-VAR

(a) **Consumption**



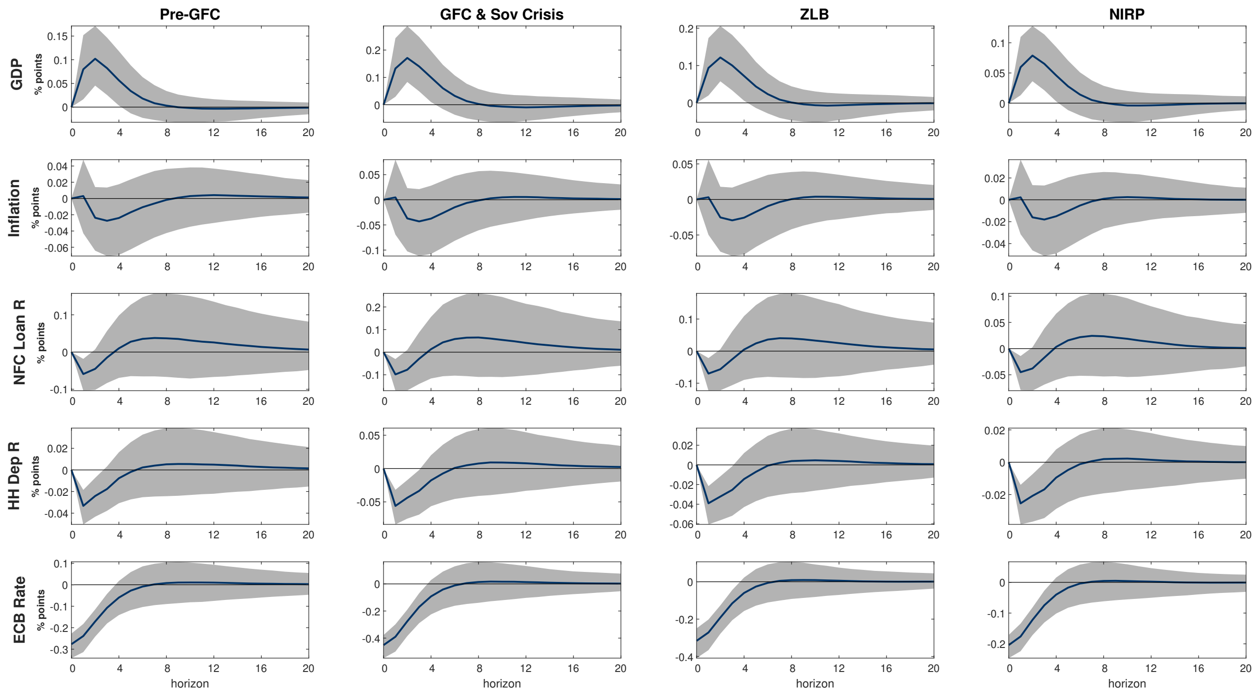
(b) **Investment**



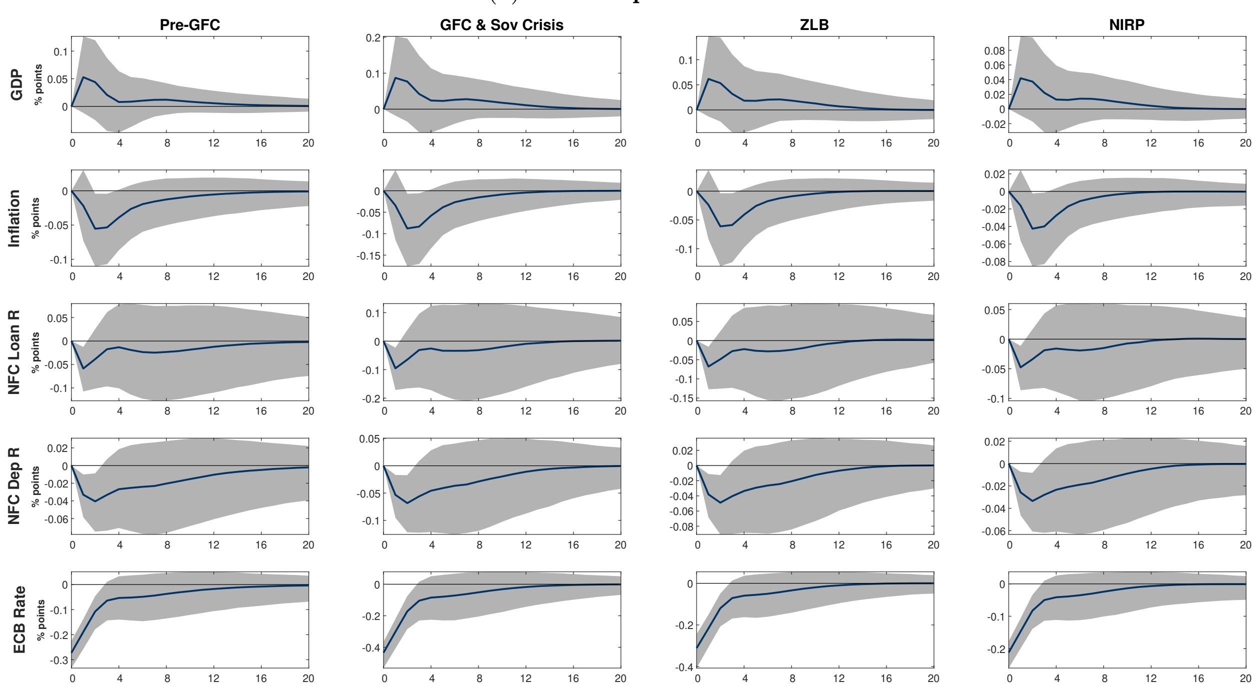
Notes: Confidence bands: 16th and 84th percentile. Selected periods: 2000Q1-2007Q3 (Pre-GFC), 2007Q4-2012Q2 (Crisis), 2012Q3-2014Q2 (ZLB), 2014Q3-2019Q4 (NIRP).

Figure B3: Policy Rate Shock: IRFs from TV-VAR

(a) **HH Deposit Rate**



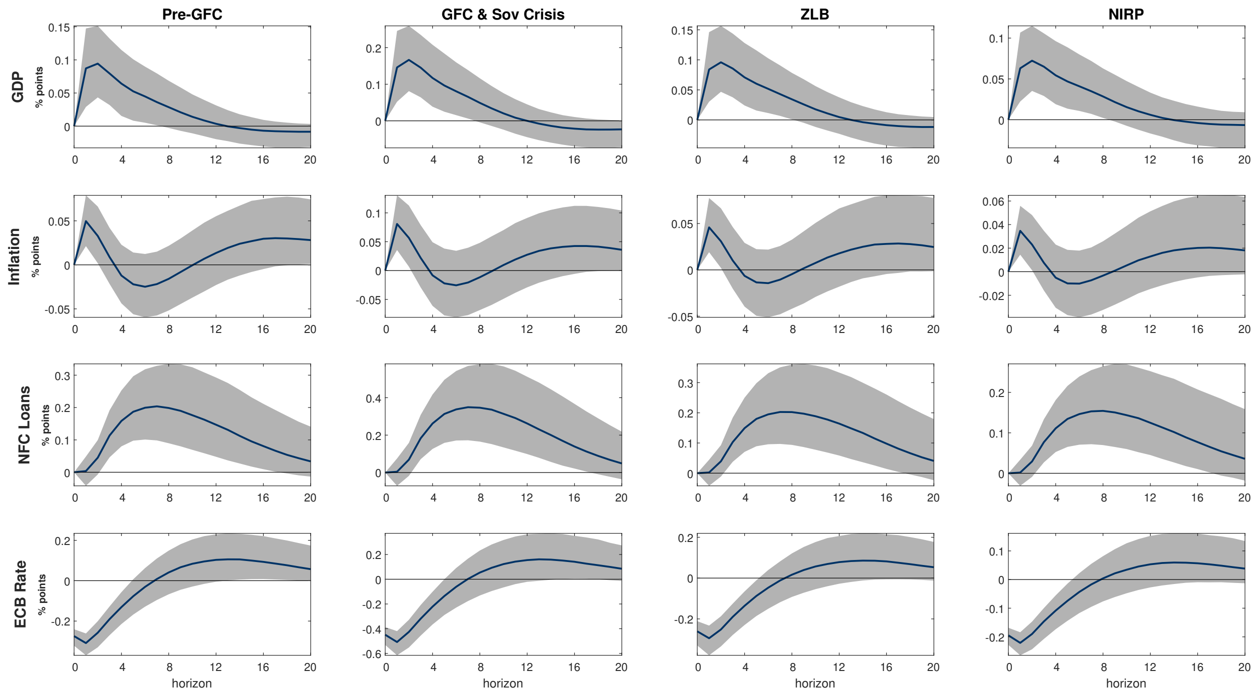
(b) **NFC Deposit Rate**



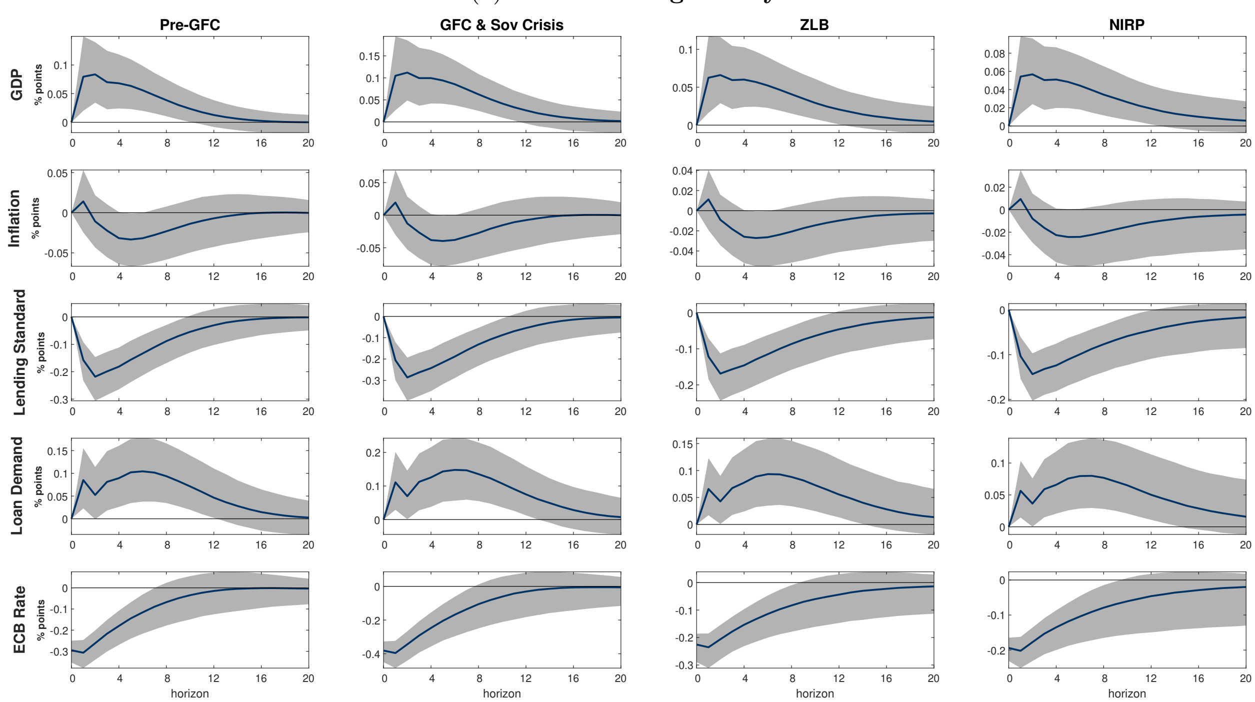
Notes: Confidence bands: 16th and 84th percentile. Selected periods: 2000Q1-2007Q3 (Pre-GFC), 2007Q4-2012Q2 (Crisis), 2012Q3-2014Q2 (ZLB), 2014Q3-2019Q4 (NIRP). 17

Figure B4: Policy Rate Shock: IRFs from TV-VAR

(a) **NFC Loans**



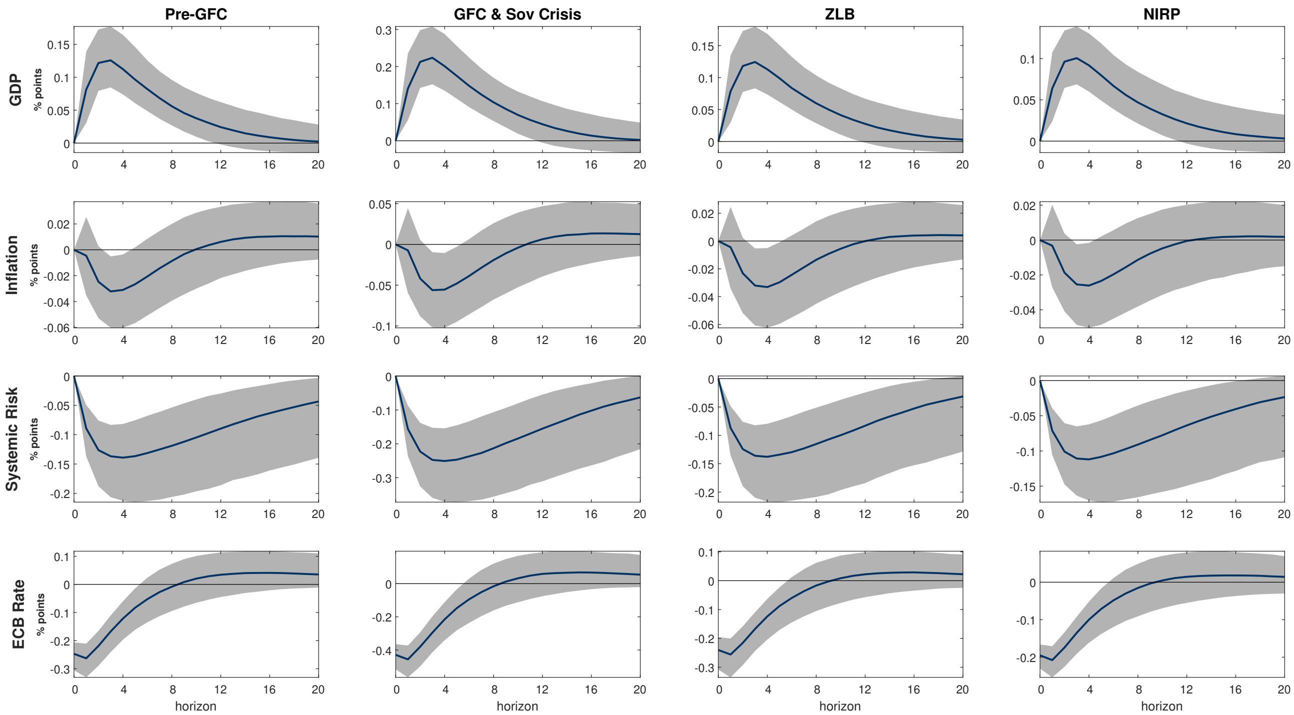
(b) **Bank Lending Survey**



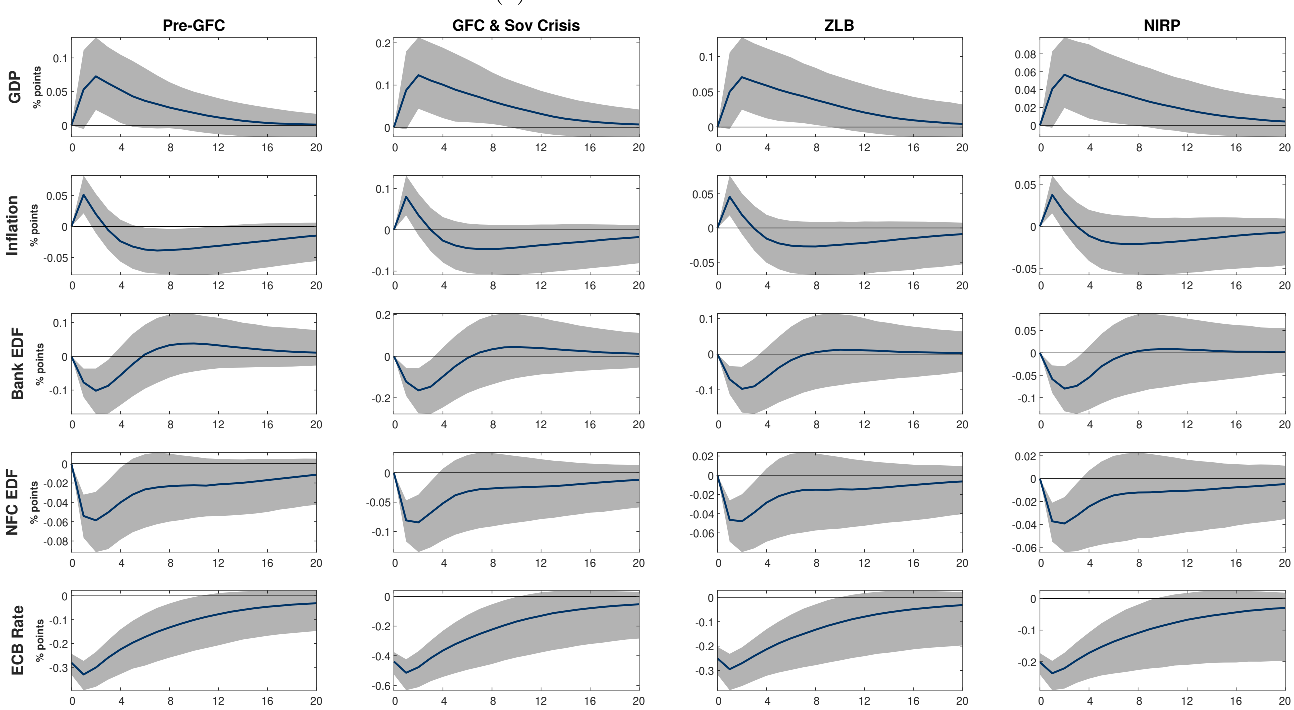
Notes: Confidence bands: 16th and 84th percentile. Selected periods: 2000Q1-2007Q3 (Pre-GFC), 2007Q4-2012Q2 (Crisis), 2012Q3-2014Q2 (ZLB), 2014Q3-2019Q4 (NIRP).

Figure B5: Policy Rate Shock: IRFs from TV-VAR

(a) **Systemic Risk**



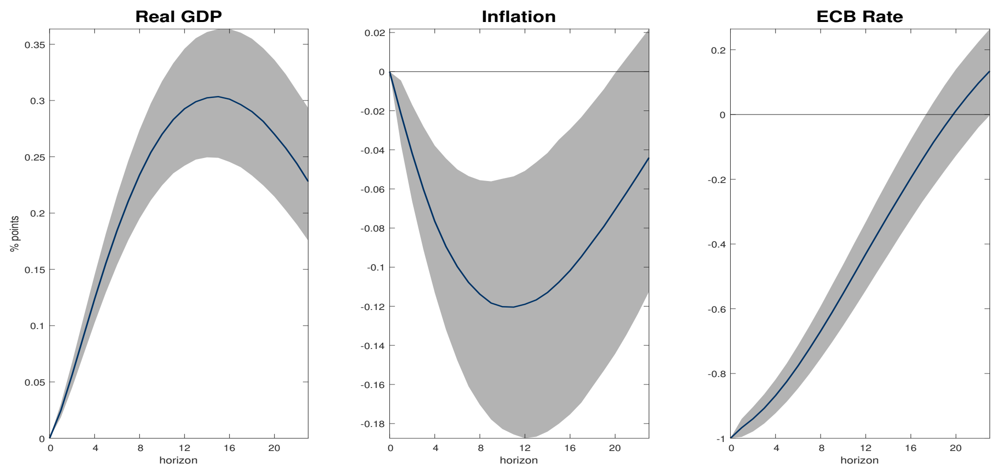
(b) **Default Probabilities**



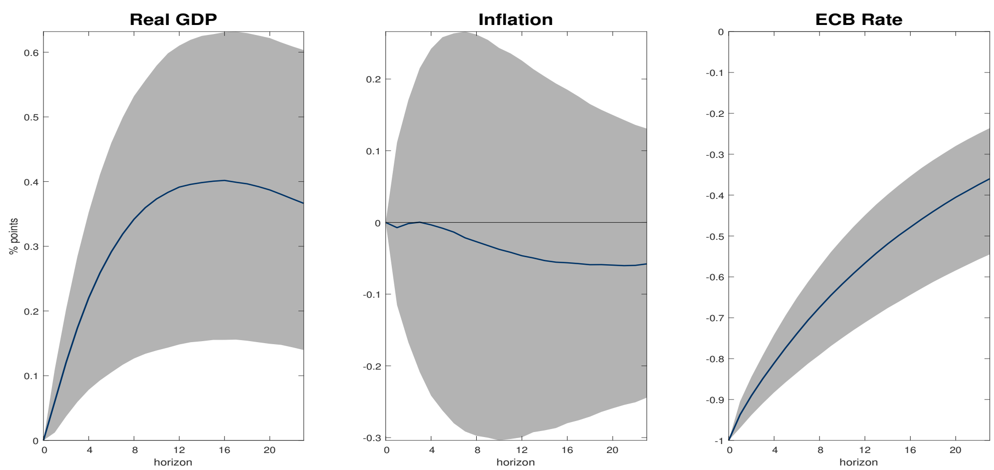
Notes: Confidence bands: 16th and 84th percentile. Selected periods: 2000Q1-2007Q3 (Pre-GFC), 2007Q4-2012Q2 (Crisis), 2012Q3-2014Q2 (ZLB), 2014Q3-2019Q4 (NIRP).

Figure B6: Cholesky Identification: Split Sample

(a) **Pre NIRP Period**



(b) **NIRP Period**



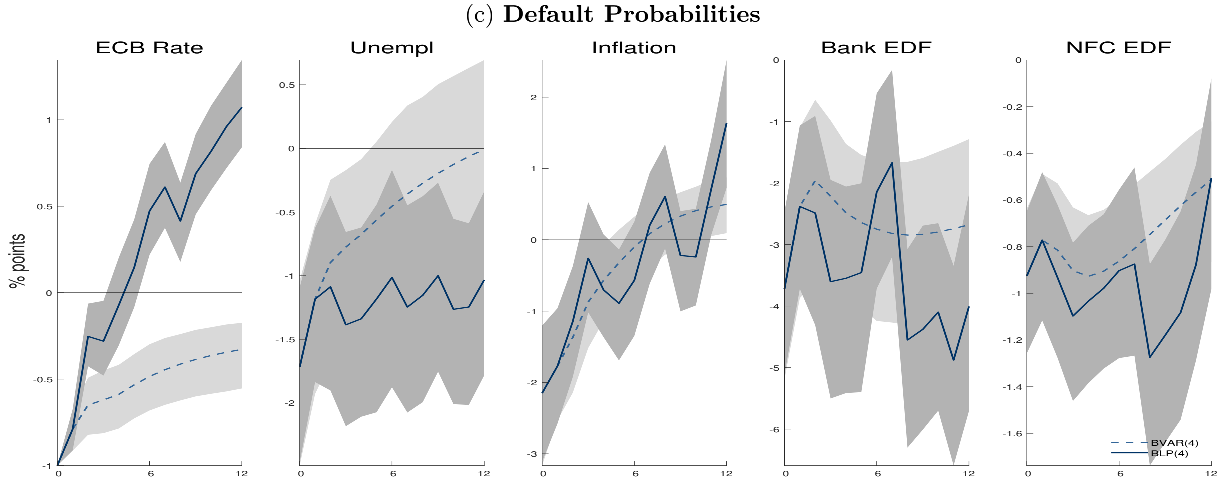
Notes: Impulse response function to an unexpected cut to the ECB deposit facility rate from a Proxy VAR model (dashed line) and a Bayesian Local Projection Model (solid line). Panel (a) displays the effects over the 2000M1-2011M12 period (Pre NIRP); Panel (a) displays the effects over the 2012:M01-2020:M2 period (NIRP);

Figure B7: Policy Rate Shock: Proxy Identification – NIRP Period

(a) **NFC Loans**

(b) **Systemic Risk**

(c) **Default Probabilities**



Notes: Proxy VAR model (dashed line) and a Bayesian Local Projection Model (solid line). Panel (a) specification with NFC loans; Panel (b) specification with banks' systemic risk; Panel (c) specification augmented with Bank and NFC Expected Default Frequency.