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CREDIT SUPPLY AND THE MACROECONOMY: AN EMPIRICAL ANALYSIS

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Table of Contents

Table of Equations

Abbreviations

ACFs	Autocorrelation Functions
BLS	Bank Lending Survey
CLR	Composite Lending Rate
CPI	Consumer Price Index
DSGE	Dynamic Stochastic General Equilibrium
EA	Euro Area
EBP	Excess Bond Premium – proxy for credit supply in the U.S. (Gilchrist and Zakrajsek, 2012).
ECB	European Central Bank
EONIA	Euro Overnight Index Average
EPU	Economic Policy Uncertainty index
FIBOR	Germany 3-month Interbank Rate
GDP	Gross Domestic Product
GZ spread	High content corporate bond credit spread for the U.S. constructed by Gilchrist and Zakrajsek (2012).
HHs	Households
IRFs	Impulse Response Functions
MFI	Monetary Financial Institution
NBER	National Bureau of Economic Research
NFC	Non-Financial Corporations
NFCI	Chicago Fed's National Financial Conditions Index
OLS	Ordinary Least Squares
ROA	Return On Assets
SLOOS	Senior Loan Officer Opinion Survey (for the U.S.)
SVAR	Structural Vectoral Autoregressive
Tbill	3-month Treasury Bill rate
U.S.	United States (of America)
VAR(k)	Vectoral Autoregression with k lags
VMA	Vector Moving Average

Introduction

The improvements in the loan market affects the real economy significantly. Therefore, policy against the weakness in the lending sector is crucial. However, the process is not a uniform incident, since there are two main columns of the lending activity: credit supply and loan demand. It is essential to know the transmission mechanism of the shock from lending sector to the real economy, because supply and demand forces may change the policy decisions. For instance, if the malfunction is in the banking sector because of their balance sheet constraints, then supporting the banks would be the right decision. Though declining demand requires support to the real economy.

In my research paper, I study the effect of an adverse credit supply shock on the macroeconomy. I do my research about three different economic regions: the United States, Euro Area and Germany. I exploit the proxy variables in the identification of the effects of a loan supply shock. This way of identification is mainly done either by short run restrictions or external instrumental methodology, which are also known as Recursive SVAR and Proxy SVAR approaches, respectively. The difference of external instrument approach to Recursive SVAR is that the initial does not include the proxy variable in a VAR model as an endogenous variable, instead utilizes it as an instrument in the estimations. Lown & Morgan (2006), Ciccarelli, Maddaloni, & Peydro (2010), Gilchrist & Zakrajsek (2012), Bassett, Chosak, Driscoll, & Zakrajsek (2014) identify the empirical responses of macro variables to a loan supply shock using recursive SVAR models. Stock & Watson (2008, 2012), Mertens & Ravn (2013, 2014), on the other hand, have developed external instrumental methodology where the structural models are also identified by the help of the proxy variables. This approach is used by Altavilla, Darracq-Paries, & Nicoletti (2015), Gilchrist & Mojon (2018), Mumtaz et al. (2018) in the identification of credit supply shocks. Mumtaz et al. (2018), for good measure, analyzes the performance of proxy SVAR scheme together with other identification schemes, e.g. sign restrictions, short run restrictions, etc., after generating an artificial data using dynamic stochastic general equilibrium (DSGE) models in the Monte Carlo Experiment. Comparing the impulse response functions (IRFs) of the SVARs and the DSGE models, the authors state that the external instrumental and the sign restriction methods perform eminently well in matching the reaction functions of the underlying models (Mumtaz, Pinter, & Theodoridis, 2018).

It is noteworthy to mention that in the external instrument identification, we do not comprise the proxy variables in a VAR model as an endogenous variable. Instead we use it as an instrument to identify the shock of interest. This way of utilization provides some advantages. Firstly, less strict assumptions are in charge compared to other identification schemes. Indeed, the only requirement being necessary is the non-zero correlation between the instrument and the shock of the interest, and zero correlation with the rest of the shocks. Furthermore, measurement error in the proxy variable becomes no more an issue, in other words, does not cause an attenuation bias in the estimations (Carriero, Mumtaz, Theodoridis, & Theophilopoulou, 2015).

In the baseline model, I use a 5-variable model that is very common in the literature (Hristov, Hülsewig, & Wollmershäuser, 2012; Gambetti & Musso, 2012; Bijsterbosch & Falagiarda, 2014; Altavilla, Darracq Paries, & Nicoletti, 2015; etc.). The macro variables are output, inflation, total loans, composite lending rate and short-term interest rate. Besides, I integrate the proxy variable to the model for the identification of a credit supply shock. These variables are Excess Bond Premium (EBP) that is constructed by Gilchrist and Zakrajsek (2012) for the U.S. and European Central Bank's (ECB) Bank Lending Survey (BLS) that provides information on bank lending conditions in Germany and EA. The essential advantage of EBP index in my eyes is its coverage period and actuality. The data is available for each month starting from mid-1970s up to quite recently and is revised backwards each month in accordance with the historical updates (Giovanni, Gilchrist, Lewis, & Zakrajsek, 2016). The EBP index has been widely used in the literature to assess the credit supply shocks in the U.S. economy, e.g. by Metiu et al. (2016), Mumtaz et al. (2018), Caldara & Herbst (2019), et cetera. Bank Lending Survey (BLS), on the other hand, is conducted four times a year by ECB Governing Council and provides information on bank lending conditions, e.g. supply of and demand for credits to households and corporations. It was started the first in 2003, and so has an available data commencing from the first quarter of 2003. I construct the series in the light of De Bondt, Maddaloni, Peydro, & Scopel (2010) and Ciccarelli, Maddaloni, & Peydro (2010), where pure loan supply is calculated as a net percentage of banks reporting that the competition pressure and their balance sheet capacity contributed to the tightening of the credit standards. Considering the previous studies, I take the bankers' assessment on credit availability granted and consider the shock to the lending standard index as a loan supply shock. My choice of BLS as a proxy variable further relies on the paper of Bijsterbosch & Falagiarda (2014), where the authors plot the BLS together with the sign restriction identified structural shocks and report high positive correlation between the series for all nine European Countries in their sample, including Germany. The index, apart from this, used by De Bondt et al. (2010) and Altavilla et al. (2015), the second of which exploits it in the construction of new loan supply indicator for the euro area.

Studies stress the importance of the loan demand in the analysis. The correlation between the supply and the demand of loans due to cyclical changes is quite possible, e.g. a simultaneous fall in demand and supply of credits depending on negative disturbances. The solutions for this in the literature is an addition of further variables to the models, e.g. business failure rate by Lown & Morgan (2006), corporate bond spread by Busch et al. (2010) and De Bondt et al. (2010), debt securities and corporate bond spread by Altavilla et al. (2015), Chicago Fed's NFCI index by Mumtaz et al. (2018). Therefore, I extend my five-variable VAR model to the six variables in the second specification. My variable choice for the U.S. is Chicago Fed's National Financial Condition index (NFCI), which is a weekly index that contains comprehensive information on U.S. financial and economic conditions[1]. The positive values of the index indicate tighter financial conditions in the economy. Next, I construct loan demand index for Germany and the EA. I exploit the data from the Bank Lending Survey (BLS) of ECB in the installation of the index. The similar approach can be seen in Ciccarelli et al. (2010), too.

The impulse response functions from the baseline model show that, in general, the confidence intervals of the responses in the external instrument identifications are narrower compared to the short run counterparts. This is in line with the literature that stresses the power of the Proxy SVAR approach in adjusting the measurement error bias (Carriero et al., 2015). This difference in confidence bands being not glaring evokes the reliance to the chosen proxy variables. Significant identification of the responses to the shock in the Recursive SVAR models strengthens this insight further. Overall, the identification via external instrument outperforms the one with short term restrictions in German and US economies. The GDP growth falls instantaneously after the shock to the tightness of credits in all three economies. This finding tallies with Gambetti & Musso (2012), Jermann & Quadrini (2012) and Bijsterbosch & Falagiarda (2014). Besides, the identification via the proxy SVAR is not significant for the EA estimations. I reckon that the violation of the second requirement, zero correlation of an instrument with the rest of the shocks, is an issue here. Therefore, I continue

[1] For the further information about the index see https://www.chicagofed.org/publications/nfci/index

with sign restrictions approach in the sensitivity analysis and examine the possible alternative response functions to an adverse loan supply shock since that is one of the most commonly used approach for the identification of a credit supply shock in the literature (Peersman, 2011; Gambetti & Musso, 2012; Bijsterbosch & Falagiarda, 2014; Mumtaz, Pinter, & Theodoridis, 2018; etc.). This method considers the economic theory and defines the parameters' sign ex ante, in other words, identification of the structural shocks is done by restricting the directions of the impulse response functions (Kilian & Lütkepohl, 2017). The restrictions that I impose in the baseline and the extended models for the U.S. and EA are presented in Table 1, for Germany in Table 2. My way for identifying the credit supply shocks is based on the signs that is already applied by Busch et al. (2010) for Germany, and by Bijsterbosch & Falagiarda (2014), Mumtaz et al.(2018) for EA and US, respectively. Overall, the identification capability of the external instrument approach for the US and Germany is quite satisfactory since their responses fit better to the response functions from the sign restriction approach. Particularly, the excess bond premium in the U.S. confirms the power of the external instrument approach after an installation of a right proxy variable. Although BLS index can identify responses to the loan supply shocks for Germany via the external instrument approach, it has no use for the Euro area. It seems the correlation of the index with the rest of the structural shocks is outstanding for the EA, since the index has a partial explanatory power in the recursive identification method.

The main contribution of my paper to the literature is the studying the effect of the credit supply shock on labor economics. I study this effect using three different identification methods: recursive, proxy SVARs and sign restriction approach. The estimations are done using five-variable VAR model. The labor variables – employment, unemployment rate and wages, are added each time as the sixth variable to the model. Overall, an adverse loan supply shock seems to decrease the employment and increase the unemployment in all three economic regions. Hourly wages, on the other hand falls as a response to the shock only in the U.S and EA. Furthermore, sign restrictions provide narrower confidence bands than the other two identification methods and thus are more reliable in the analyzes. The response of macro labor variables to a credit supply shock is not very wide in the literature. Nevertheless, Gilchrist & Zakrajsek (2011) states a similar response of employment to an adverse loan supply shock with my finding in the United States. Furthermore, Sales (2016) studies the effect of total credit shocks in German and the U.S. economies in comparison. Although this is not exactly the same credit supply shock that I investigate in my paper, it is noteworthy to mention that in her findings the response of unemployment rate to the credit shock is very similar with my findings.

The analyzes using the impulse response functions describe the average effect of the credit supply shock on each variable. However, it is more interesting to investigate the role of the shock in the recessions, e.g. financial crisis of 2008. Therefore, I compute the historical structural shocks for all three identifications and study the importance of the shock using counterfactuals in the United States, Euro Area and Germany, too. Overall, loan supply shock in all three economies worsened the evolution of the macro variables during the financial crisis of 2008-09. Furthermore, the shocks positively contributed to the series during the boom period before the crisis. After the crisis, on the other hand, I observe heterogeneity in the responses depending on economic regions. Analyzes of labor variables reveal that all three economies experience a fall in the employment during the recession. The highest effect is in the U.S., where 25% less decrement would be in the employment once the effect of the shock was turned off in the economy. From the peak of 2008Q1 to the troughs of 2009Q2 the decline for Germany and EA, on the other hand, would be around 12 to 14 %. The unemployment rate is roughly stable in all three economies, except the recession period in the States where the loan supply shock contributed to the increment in rate remarkably. Analyzes show a constant low wage payment based on the credit supply shock in the U.S. Quite similar responses for all labor variables in the U.S. are presented by Jermann & Quadrini (2012) and Biovin, Giannoni, & Stevanovic (2013) as well.

I continue with the empirical methodology in the next section, where I discuss the recursive and proxy SVAR analysis in detail. Afterwards, I present my data and discuss the variables that I exploit in my estimations broadly. The impulse response functions for macro and labor variables are given after the overview of the data. In historical decomposition section, I present the counterfactuals for my macro and labor variables. At the end I make a conclusion and present the future works that can be done in further studies.

Empirical Methodology

The simultaneous movements of economic variables, in other words, the endogeneity, is the main reason that standard OLS estimates of the VAR parameters are vain in the determination of the effect of a variable of interest on macroeconomic aggregates. Therefore, the recovery of the structural shocks that are exogenous to the model is crucial. For simplicity, let Y_t be vector of time series of 2 variables, and let e_t be a matrix of unexpected shocks in a VAR(1) process such as;

$$A_0\, Y_t = A_1\, Y_{t-1} + e_t, \qquad \textit{(Eq. 1)}$$

where, A_0, A_1 are 2x2 and Y_t, e_t are 2x1 matrices by construction[2]. Multiplying each side of the equation by inverse of A_0 yields a reduced form VAR with a coefficient of β_1 and disturbance of u_t, where $\beta_1 = A_0^{-1}\, A_1$ and $u_t = A_0^{-1}\, e_t = H\, e_t$. Thus, VMA(∞) representation of Eq. 1 with lag operator of L can be written as;

$$Y_t = B(L)^{-1}\, H\, e_t, \qquad \textit{(Eq. 2)}$$

where $B(L) = I - \beta_1 L$. In Equation 2, the coefficient $B(L)^{-1}\, H$ is the empirical response of the economic variables to the structural shocks.

The main challenge henceforth is to identify the structural model, namely, H or e_t in the second equation. One of the commonly used approaches for the identification of the credit supply shock in the literature is sign restrictions (Peersman, 2011; Gambetti & Musso, 2012; Bijsterbosch & Falagiarda, 2014; Mumtaz, Pinter, & Theodoridis, 2018; etc.). This approach takes into account the economic theory and defines the direction of the parameters ex ante, in other words, chooses the solutions that satisfies the predetermined signs of H matrix from all possible candidates (Kilian & Lütkepohl, 2017, p. 417). Alternatively, identification of the structural shocks is done by restricting the directions of the impulse response functions. However, in this paper, I am focusing on the identification via the proxy variables. This way of identification is mainly done either by short run restrictions or external instrumental methodology, which are also known as Recursive SVAR and Proxy SVAR approaches, respectively. The difference of external instrument approach to Recursive SVAR is that the initial does not include the proxy variable in a VAR model as an endogenous variable, instead utilizes it as an instrument in the estimations.

Recursive SVAR

[2] For Y_t with n variables please check either Stock & Watson (2012) or Mertens & Ravn (2013).

The identification of a loan supply shock via short run restrictions rests on two main installations. The first is to build a relevant proxy variable that can accurately imitate the variation in the variable of interest. Lown & Morgan (2006), Ciccarelli, Maddaloni, & Peydro (2010), Gilchrist & Zakrajsek (2012), Bassett, Chosak, Driscoll, & Zakrajsek (2014) appoint proxy variables that substitutes the credit supply in their studies and then identify the empirical responses of macro variables to its shock using recursive SVAR models. The proxy variables that I use in my paper are presented in the data section.

The second installation is to set up a model that orders the macro variables according to the economic theory. Since the identification depends on Cholesky decomposition of the variance covariance matrix of the reduced form innovations, the right order of the variables in a VAR model is crucial. Rewriting Equation 2 in a reduced form,

$$Y_t = B(L)^{-1}\, u_t, \qquad \textit{(Eq. 3)}$$

I can show the variance covariance matrix as $\Sigma_u = P\,P'$, where P is a Cholesky decomposed 2x2 lower triangular matrix. In my two-variable simplified model that means the first variable is the most exogenous one and does not simultaneously respond to the changes in the second variable. However, the vice versa is not a case, because the second variable responds contemporaneously to a shock in the first variable (Kilian & Lütkepohl, 2017, p. 216). These restrictions serve as a basis in the identification and for this reason using the economic intuition to decide the most relevant order here is important.

Proxy SVAR

Stock & Watson (2008, 2012), Mertens & Ravn (2013, 2014) have developed external instrumental methodology where the structural models are identified by the help of the proxy variables. This approach is used by Altavilla, Darracq-Paries, & Nicoletti (2015), Gilchrist & Mojon (2018), Mumtaz et al. (2018) in the identification of credit supply shocks. Mumtaz et al. (2018), for good measure, analyzes the performance of proxy SVAR scheme together with other identification schemes, e.g. sign restrictions, short run restrictions, etc., after generating an artificial data using dynamic stochastic general equilibrium (DSGE) models in the Monte Carlo Experiment. Comparing the impulse response functions (IRFs) of the SVARs and the DSGE models, the authors state that the external instrumental and the sign restriction methods perform eminently well in matching the reaction functions of the underlying models (Mumtaz, Pinter, & Theodoridis, 2018).

To understand the intuition behind the proxy SVARs, I continue with Equation 2, where the identification of either H or e_t is sufficient in the estimation of the responses to the shock. Indeed, Mertens & Ravn (2013, 2014) recover the coefficients of interest, whereas Stock & Watson (2008, 2012) the shock itself, in a same frame but with a slight path difference. The core assumption here is the incorporation of an external instrument, say Z_t, that correlates only and solely with the shock of interest. Considering my simplified two-variable model, mathematical notation of the assumption is,

$$E\left(Z_t\, e_t^c\right) = \phi \neq 0, \quad and \qquad (Eq.\ 4)$$

$$E\left(Z_t\, e_t^r\right) = 0, \qquad (Eq.\ 5)$$

where Equation 5 means no correlation between the external instrument and the rest of the shocks. In the model, the external instrument, Z_t, credit supply shock, e_t^c, and the rest of the shocks, e_t^r, all are 1x1 matrices because of the simplified construction[3].

The correlation between the external instrument and the reduced form disturbances, on the other hand, can be written as,

$$E(Z_t\, u_t') = E(Z_t\, e_t'\, H') = \phi\, [H_{11} \quad H_{21}]_{1x2}, \qquad (Eq.\ 6)$$

where transformations are done according to the second, third and fifth equations. The extended form matrix notation of Equation 6 is given in Appendix B. Re-writing the covariance between the external instrument and the reduced form disturbances further in a matrix form, $E(Z_t\, u_t') = \Sigma_{Zu'} = [\Sigma_{Zu_1} \quad \Sigma_{Zu_2}]_{1x2}$, yields the relation between H_{11} and H_{21}, that is;

$$H_{11} = \left(\Sigma_{Zu_2}^{-1}\, \Sigma_{Zu_1}\right) H_{21} \qquad (Eq.\ 7)$$

Because of the simplified construction for the narration purposes, all the factors in Equation 7 are 1x1 matrices. For the model with more than two variables and more than one external instrument please check the original article of Mertens & Ravn (2013).

The extended version of mathematical transformation for Equation 7 is in Appendix B. The term $\Sigma_{Zu_2}^{-1}\, \Sigma_{Zu_1}$ in the equation, can be estimated from the regression of the reduced form

[3] For higher dimension of all variables, please check either Stock & Watson (2012) or Mertens & Ravn (2013).

residuals on the external instrument. Consequently, the coefficients of interest can be precisely estimated using the relation between H_{11} and H_{21} from Equation 7 and the Cholesky decomposition of VAR residuals (Mertens & Ravn, 2013, 2014). The advantage of this identification is in its less stringent conditions. Indeed, the only requirements being necessary are given in Equations 4 and 5 (Mumtaz, Pinter, & Theodoridis, 2018).

Assumptions in Equations 4 and 5 is a starting point for Stock & Watson (2008, 2012) as well. Additional consideration in their track is the variance covariance matrix of the error terms of the underlying model,

$$E\,(e_t\, e_t') = D_{2x2} = diag(\sigma_{e_c}^2, \sigma_{e_r}^2), \qquad \textit{(Eq. 8)}$$

which means nothing but the structural shocks are uncorrelated. Here, the structural shock, e_t^c, is the predicted values from the regression of the external instrument, Z_t, on reduced form VAR disturbance, u_t. In other words, the multiplication of the coefficient, Π, with the regressor;

$$\Pi u_t = E(Z_t\, u_t')\ \ [E(u_t\, u_t')]^{-1}\, u_t = \left(\frac{\phi}{\sigma_{e_c}^2}\right)\, e_t^c. \qquad \textit{(Eq. 9)}$$

yields the vector of interest. Appendix B provides the detailed transformation of the equality in Equation 9. To clarify that the deterministic part from the regression of Z_t on u_t is the credit supply shock itself, let us assume that for some reason we can observe the true structural shock, e_t, in the model. Then, the deterministic part from the regression of Z_t on e_t is going to be;

$$\Pi e_t = E(Z_t\, e_t')\ \ [E(e_t\, e_t')]^{-1}\, e_t = \left(\frac{\phi}{\sigma_{e_c}^2}\right)\, e_t^c, \qquad \textit{(Eq. 10)}$$

which has the exact same result with Equation 9. It is noteworthy that the assumption in Equation 5 dictates the coefficient of e_t^r in Π to be irrelevant, statistically not different from zero. Therefore, the predicted value here is nothing other than the shock of interest, e_t^c. The proof of Equation 10 is further given in Appendix B.

It is noteworthy to mention again that in an external instrument identification, we do not comprise the proxy variables in a VAR model as an endogenous variable. Instead we use it as an instrument to identify the shock of interest. This way of utilization provides some advantages. Firstly, less strict assumptions are in charge compared to other identification schemes. Indeed, the only requirement being necessary is the non-zero correlation between the instrument and the shock of the interest, and zero correlation with the rest of the shocks. Furthermore, measurement error in the proxy variable becomes no more an issue, in other words, does not cause an attenuation bias in the estimations (Carriero, Mumtaz, Theodoridis, & Theophilopoulou, 2015).

Data

The baseline macro variables that I use in the estimations are output, inflation, total loans, composite lending rate and short-term interest rate. Besides, I integrate the proxy variable to the model for the identification of a credit supply shock. All these and further variables are explained broadly in the next subsections. I specify the source of all the used data in Appendix A.

Macro Variables

In the baseline model, I use 5-variable model that is very common in the literature (Hristov, Hülsewig, & Wollmershäuser, 2012; Gambetti & Musso, 2012; Bijsterbosch & Falagiarda, 2014; Altavilla, Darracq Paries, & Nicoletti, 2015; etc.), and study the outcomes of the credit supply shocks in Germany, Euro Area and the U.S. The quarterly data for the U.S. economy includes real GDP, consumer price index for all urban consumers (CPI), total loans, composite lending rate and 3-month Treasury Bill rate. Total loans and composite lending rate are constructed in the light of Gambetti & Musso (2012). Here, total loans are the sum of outstanding amounts of loans (millions of dollars) to households and non-financial corporations. The amounts of loans to households and non-financial corporations are further used as a weight in the calculation of composite lending rate. I present the detailed method of the calculations for the both variables in Appendix A.

The quarterly data for Germany comprises real GDP, growth domestic product implicit price deflator, total loans, composite lending rate and three-month interbank rate (FIBOR). Total loans and composite lending rate are constructed in the light of Gambetti & Musso (2012) and Bijsterbosch & Falagiarda (2014), respectively. Here, total loans are the sum of the outstanding amounts (millions of dollars) of loans to households and non-financial corporations. The composite lending rate is the weighted average of lending rate to households for house purchase and lending rate to non-financial corporations.

The quarterly data for Euro Area is constituted of real GDP, growth domestic product price deflator, total loans, composite lending rate and Euro Overnight Index Average (EONIA). Here, total loans are calculated in the light of Gambetti & Musso (2012) as the sum of the outstanding amounts (millions of dollars) of loans to households and non-financial corporations. The composite lending rate, however, is the weighted average of lending rate to households for house purchase and lending rate to non-financial corporations that is described by Bijsterbosch & Falagiarda (2014). Appendix A incorporates the detailed method of the calculations for total loans and composite lending rates.

It is also noteworthy to mention that total loans that I use for Germany and Euro Area are adjusted against sales and securitization to account for the possible wedge between the actual growth rate of loans and that derived from the monetary financial institutions' (MFI) balance sheet. The wide information about this is available in the box 1 on "The impact of MFI loan securitization on monetary analysis in the Euro Area" and in the box 2 on "The impact of loan sales and securitization activity on recent developments in MFI loans to non-financial corporations and households" in the September 2005 and July 2011 issues of the ECB monthly bulletin, respectively[4,5].

Proxy Variables

The identification of a credit supply shock is done using the appropriate proxy variables in Recursive and Proxy SVARs. These variables are Excess Bond Premium (EBP) that is constructed by Gilchrist and Zakrajsek (2012) for the U.S. and ECB's Bank Lending Survey (BLS) that provides information on bank lending conditions in Germany and EA. Both variables are explained broadly in the next subsections. The sources of the data are given in Appendix A.

Excess Bond Premium

[4] https://www.ecb.europa.eu/pub/pdf/other/mb200509_focus01.en.pdf?b049c3e44a4f87c16af1c1183923b5e4
[5] https://www.ecb.europa.eu/pub/pdf/other/mb201107_focus02.en.pdf?fb4473eef4da6fd053f1a6f28d5a193f

I use Excess Bond Premium, shortly EBP, as a proxy for the credit supply in the United States. Gilchrist and Zakrajsek (2012) extracts EBP by removing the expected default risk of individual firms from the constructed corporate bond credit spread, which is dubbed as GZ spread in their original paper. GZ spread, consequently EBP, is a micro level data that comprises high predictive information for the future economic events. Thus, EBP captures the variation in the pricing of investors' risk appetite over the odds of the compensation for expected defaults, in other words, risk premium beyond the expected delinquency in the corporate bond market, quite well.

Following Gilchrist and Zakrajsek (2012), I visualize EBP together with Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS)[6] and with Return on Assets (ROA) for all US banks in Figure 1, for the period of 1990-2018. Panel A shows that the correlation between EBP and the tightness of US banks' credit standards on commercial and industrial loans to large and medium sized firms is remarkably high. Panel B, on the other hand, illustrates that there is a link between the profitability of US banks and EBP, since the increases in ROA correspond to the declines in EBP and vice versa.

The NBER business cycle recessions for US economy are illustrated with shaded bars in Figure 1, where the inclination of EBP is outstanding prior to the both recessions in 2000s. Furthermore, the index is at its minimum for several year commencing from 2003, the period that is known by its lax credit standards (Gilchrist & Zakrajsek, 2012). Hereby, it is salient that the tightening or loosening of credit supply, depending on financial intermediaries' balance sheet conditions or their willingness, is well depicted by the proxy variable – EBP.

Another essential advantage of the index is its coverage period and actuality. The data is available for each month starting from mid-1970s up to quite recently and is revised backwards each month in accordance with the historical updates (Giovanni, Gilchrist, Lewis, & Zakrajsek, 2016). The EBP index has been widely used in the literature to assess the credit supply shocks in the U.S. economy, e.g. by Metiu et al. (2016), Mumtaz et al. (2018), Caldara & Herbst (2019), et cetera. The methodology of Gilchrist & Zakrajsek (2012) is applied to EA by Altavilla et al. (2015) and Gilchrist & Mojon (2018), the first of which generates the similar index to study the effect of an unanticipated EBP shock on EA macroeconomic variables in

[6] For a detailed information about SLOOS Bank Lending Practices please visit the webpage: https://www.federalreserve.gov/data/sloos/about.htm

comparison to bank lending survey indices. Gilchrist & Mojon (2018), on the other hand, studies in general the credit risk in major European countries.

Bank Lending Survey

I exploit Bank Lending Survey (BLS) results as a proxy for the credit supply in Germany and Euro Area. Bank Lending Survey (BLS) is conducted four times a year by ECB Governing Council and provides information on bank lending conditions, e.g. supply of and demand for credits to households and corporations. It was started the first in 2003, and so has an available data commencing from the first quarter of 2003. I construct the series in the light of De Bondt, Maddaloni, Peydro, & Scopel (2010) and Ciccarelli, Maddaloni, & Peydro (2010). All the data is downloadable from the webpage of the Statistical Data Warehouse of ECB[7].

Overall, BLS comprises 18 backward and 4 forward-looking questions that captures the developments in the past and future in credit markets. The answers for credit standards are considered as banks' loan policy due to their internal criteria. Pure loan supply is calculated as a net percentage of banks reporting that the competition pressure and their balance sheet capacity contributed to the tightening of the credit standards. For the euro area that is the weighted net percentage based on the share of each country in the total loan outstanding amounts of the euro area aggregate and of each bank in the total loan outstanding amount of the BLS bank sample. Following Ciccarelli, Maddaloni, & Peydro (2010), this is maintained by taking the average of the responses to A and B in questions 2,9 and 11 that are related to the approval of loans to enterprises, households for house purchase and consumer credits, respectively. These questions are related to the realized changes that cover the previous three-month period.

Figure 2 depicts the BLS index together bank's return on assets for Euro Area and Germany for the period of 2003-2015. The negative correlation between the tightness of banks' credit standards on private loans and the profitability of banks in each economy is incontrovertible. Since it is a yearly data, I have not marked the recession dates on the plot. However, Euro Area Business Cycle Dating Committee identifies two recession, the first from

[7] See Appendix A for further information.

Q1-2008 to Q1-2009 and the second from Q3-2011 to Q4-2012, for the euro area in the period. Considering these recessions, we can observe that the BLS index inclines prior to the both recessions, remarkably during the second half of 2000s. Furthermore, the index keeps declining to its minimum at the first half of 2000s as it was for EBP in the U.S. case in Figure 1. Thus, the changes in credit standards depending on bank's balance sheet conditions are well depicted by the BLS index.

Bearing in mind the previous studies, I take the bankers' assessment on credit availability granted and consider the shock to the lending standard index as a loan supply shock. My choice of BLS as a proxy variable further relies on the paper of Bijsterbosch & Falagiarda (2014), where the authors plot the BLS together with the sign restriction identified structural shocks[8] and report high positive correlation between the series for all nine European Countries in their sample, including Germany. The index, apart from this, used by De Bondt et al. (2010) and Altavilla et al. (2015), the second of which exploits it in the construction of new loan supply indicator for the euro area.

Macro Labor Variables

The macro labor variables that I use in my analysis are employment, unemployment rate and wages. The employment for the U.S. is civilian labor force in thousands of persons, whereas for Germany and the EA it is total amount of worked hours. Wages, on the other hand, is hourly earnings for the private sector in all three economic regions. I use log growth transformation of the employment and wages in the estimations. The sources of all the labor variables are available in Appendix A.

Overview of the Data

The macro variables in the baseline model and the credit supply indices are illustrated in Figure 3 for all three economic areas, covering the periods from 2004 to 2013. Real GDP,

[8] See Figure 8 in the paper of Bijsterbosch & Falagiarda (2014).

total loans and prices are calculated as growth rates from quarter to quarter. Monetary policy rate and composite lending rate, on the other hand, are given in percent. All in all, the series for each variable shows similar trends across countries. Moreover, all three economies experienced severe recession of the recent financial crisis with little variations in turning points. GDP growth shows negative correlation with loan supply indices, particularly it reaches to its minimum when the proxies are at their maximum during the financial crisis.

Inflation is positive in the pre-crisis period for the EA and US and reaches to its minimum during the financial crisis. For Germany, however, the inflation shows very high variation in the pre-crisis period and increases significantly during the financial crisis of 2008-2009. After the crisis, particularly starting from 2010, EA and Germany experience slight upward trend in the inflation, which is not a case for the U.S. economy. This is in accord with the lower policy rates in the U.S. after crisis compared to Germany and EA. The movements in the policy rates seems to explain the variation in the lending rates for all three economic areas as well.

In the pre-crisis period lower tightness level of loan supply indices accompanies the higher loan growth rates in the U.S. and EA. Besides, the decreasing tightness conditions seems to increase the total loans in Germany. Loan growth rates keep decreasing to its minimum to the end of the crisis in the United States and Euro Area. In Germany, however, loan growth rate apparently follows the BLS tightness index starting from the financial crisis of 2008-2009. This is a sign of other confounding factors that may drive the corresponding changes in loans. Furthermore, total loans keep decreasing in the U.S. after the crisis in despite of relative constant lending conditions. This may be explained by decreasing lending rates arising from very low policy rates.

Results – Macro

In this section I mainly discuss the response of the macro variable to an adverse loan supply shock. I focus on the identification via proxy variables using short run restrictions and external instrument approach. I present two different VAR models, here. The first is the baseline model with five main macro variables. I opt for this model, since it is very common in the literature (Hristov, Hülsewig, & Wollmershäuser, 2012; Gambetti & Musso, 2012;

Bijsterbosch & Falagiarda, 2014; Altavilla, Darracq Paries, & Nicoletti, 2015; etc.). Afterwards, I extend the baseline model with an additional variable to six variables. I specify the reason for this extension in the next section widely, right after I present the identification method for the baseline model.

Identification

Identification of the credit supply shock depends on the Recursive and Proxy SVARs. As it is mentioned above, the baseline VAR comprises five endogenous variables with the following order: log difference of real GDP, log difference of prices, log difference of total loans, composite lending rate and the short-term interest rate. The ordering of the variables in the short-run restrictions is important. Therefore, I posit the proxy variable after total loans, which implies that credit the supply shock can have an instantaneous effect on GDP growth, inflation and loan growth. Economical intuition behind this is the exclusion of macroeconomic and bank related factors that may drive the demand for loans (Bassett et al., 2014; Lown & Morgan, 2006; Mumtaz et al., 2018; et cetera).

Apart from it is stringent restrictions, the performance of the Recursive SVAR is sensitive to a measurement error in the series of interest. Therefore, I take the advantage of the external instrumental approach in the identification of the structural model. This approach is robust to the measurement error in addition to its less stringent conditions (Carriero et al., 2015). Indeed, the only requirement being necessary is the non-zero correlation between the instrument and the shock of interest, and zero correlation with the rest of the shocks. Here, we do not incorporate the proxy variables in a VAR model as an endogenous variable. Instead we use it as an instrument to identify the shock of interest. The mathematical background and the intuition behind this approach is widely discussed in the sub-section above named as Proxy SVAR.

Since the data that I use is on a quarterly base, I follow the common approach in the literature and estimate the baseline VAR model with four lags. For good measure, I plot the sample autocorrelation functions (ACFs) in Figure 4 and observe whether the disturbances involve any unexplained structures. The figure contains information regarding the Recursive and Proxy models for the U.S., Germany and EA. The ACFs for all three economic areas are in 5% significance limits, which means the VAR estimations are robust to further investigations.

Studies stress the importance of the loan demand in the analysis. The correlation between the supply and the demand of loans due to cyclical changes is quite possible, e.g. a simultaneous fall in demand and supply of credits depending on negative disturbances. The solutions for this in the literature is an addition of further variables to the models, e.g. business failure rate by Lown & Morgan (2006), corporate bond spread by Busch et al. (2010) and De Bondt et al. (2010), debt securities and corporate bond spread by Altavilla et al. (2015), Chicago Fed's NFCI index by Mumtaz et al. (2018). Therefore, I extend my five-variable VAR model to the six variables in the second specification. My variable choice for the U.S. is Chicago Fed's National Financial Condition index (NFCI), which is a weekly index that contains comprehensive information on U.S. financial and economic conditions[9]. The positive values of the index indicate tighter financial conditions in the economy.

I construct loan demand index, on the other hand, for Germany and the EA. I exploit the data from the Bank Lending Survey (BLS). BLS is conducted four times a year by ECB Governing Council and provides information on bank lending conditions, e.g. supply of and demand for credits to households and corporations. It was started the first in 2003, and so has an available data commencing from the first quarter of 2003. Overall, BLS comprises 18 backward and 4 forward-looking questions that captures the advancements in the past and future in credit markets. The focus of the questions about loan demand is the need of enterprises and households for bank loan financing, irrespective of credit approval decision[10]. These questions are related to the realized changes that cover the previous three-month period. In addition, bankers assess the effect of confounding factors related to the financing needs of counterpart borrowers. The index is calculated as a net percentage of banks reporting an increase in the demand for loans. For the euro area that is the weighted net percentage based on the share of each country in the total loan outstanding amounts of the euro area aggregate and of each bank in the total loan outstanding amount of the BLS bank sample. The similar approach can be seen in Ciccarelli et al. (2010), too. Following their method, I take the arithmetic average of the responses for each factor associated with enterprises and households'

[9] For the further information about the index see https://www.chicagofed.org/publications/nfci/index

[10] See the link for more information: https://www.ecb.europa.eu/stats/pdf/bls_user_guide_201811.en.pdf

house purchase and consumer credits. The factors that I use in the calculation of loan demand are given in Appendix A together with their sources.

Impulse Response Functions

The impulse response functions to an adverse credit supply shock related to the proxy variables are given in Figure 5. Overall, the reaction of the variables to the shock follows the similar pattern in all three economic regions. Skimming over the figure, the confidence intervals of the responses in the external instrument identifications appear to be narrower compared to the short run counterparts. This is in line with the literature that stresses the power of the Proxy SVAR approach in adjusting the measurement error bias (Carriero et al., 2015). This difference in confidence bands being not glaring evokes the reliance to the chosen proxy variables. Significant identification of the responses to the shock in the Recursive SVAR models strengthens this insight further.

General observation is that the identification via external instrument outperforms the one with short term restrictions in German and US economies. The GDP growth falls instantaneously after the shock to the tightness of credits in all three economies. The decrement is significant up to two quarters. This finding tallies with the literature, notably the short-term convergence of the GDP is mentioned by Gambetti & Musso (2012), Jermann & Quadrini (2012) and Bijsterbosch & Falagiarda (2014). The response of the GDP in the US and EA via the recursive identification is compatible with the literature, too (Gilchrist & Zakrajsek, 2012; Altavilla, Darracq Paries, & Nicoletti, 2015; Mumtaz, Pinter, & Theodoridis, 2018).

Figure 5 reveals that the inflation for Germany and the EA is statistically not different from zero in both identifications, except very short negative response of the EA price change after the Recursive SVAR approach. The similar outcome is stated by Busch et al. (2010), Gambetti & Musso (2012), Hristov et al (2012) for Germany and the Euro Area as well. The reaction of inflation is significant with its decreasing negative value up to two years in the U.S. under external instrument identification, though statistically it is not different than zero under recursive identification. Analogous findings are also found in the other studies regarding the US economy (Lown & Morgan, 2006 ;Gambetti & Musso, 2012; Gilchrist & Zakrajsek, 2012; Mumtaz et al., 2018).

Although an adverse loan supply shock decreases the credit growth in all specifications, the significant response varies depending on the identification and the economic region. The negative credit growth up to 2 years is constant for the U.S. in both identifications. The similar findings for the U.S. economy can be seen in the studies of Lown & Morgan (2006), Gambetti & Musso (2012), Mumtaz et al. (2018), too. Credit growth in Germany, on the other hand, is barely significant in both identifications. Although Bijsterbosch & Falagiarda (2014) states an insignificant response of credit growth starting from the fourth quarter, my finding for the initial three quarters evokes a possible correlation of the proxy variable with other structural shocks, e.g. loan demand shock. Furthermore, the response of credit growth to a loan supply shock in the EA is identified better by short-run restriction compared to the external instrument approach. This can also be a sign for the correlation of the BLS index with the other underlying structural shocks.

Composite lending rate in the U.S. falls after the shock to the tightness of loans in the economy and stays negative in confidence bands more than four years. The external instrument identification reveals that this change happens with a quarter delay. The source of the decrement can be found in the instantaneous negative reaction of the monetary policy rate. Indeed, the reaction of the treasury bill rate to an adverse loan supply shock being significantly negative up to five years seem to be the main driver of the composite lending rate and the short-term recovery of the output growth in the United States. The similar responses of the composite lending rate and the short-term interest rate can also be seen in the studies of Bassett et al. (2014) and Mumtaz et al. (2018). Reaction of the composite lending and the short-term interest rates to the shock in Germany is analogous to the U.S. economy. Decreasing policy rate drives lending rate down and recovers the negative output growth in two quarters, the period when the rates reach to its minimum in Germany. Output growth reaches to its maximum at the seventh quarter when the negative reaction of the monetary policy rate and the lending rate statistically converges to zero. The reaction of all variables dies out commencing from the 10^{th} quarter. The results for Germany tally with the findings of Busch et al. (2010), Bijsterbosch & Falagiarda (2014).

The response functions of lending and policy rates being identified via the external instrument approach in the EA is not statistically significant. On the contrary, the recursive identification reveals that the short-term interest rate drives the composite lending rate down two quarters after the adverse loan supply shock hits the economy. The both rates reach to its minimum at the seventh quarter when the negative output growth turns to the positive phase.

The seventh quarter is also a turning point for the loan growth, where it reaches to its minimum and starts converging towards zero. The effect of the adverse credit supply shock dies out four years later it hits the Euro economy. These impulse response functions via the recursive identification have a similar nature with the visualizations of Altavilla et al. (2015).

Extended VARs

The impulse response functions from the extended VAR model are given in Figure 6. The responses of the U.S. macro variables to an adverse loan supply shock in the extended model have a negligible difference from the responses in the baseline model. The added variable, Chicago Fed's financial conditions index, on the other hand, shows an immediate positive response to the shock up to six quarters in both recursive and external instrument identification. Then the index turns to a negative value, which I interpret as a loosening in the financial markets. That is also a turning point for the decreasing credit growth, since it starts converging to zero starting from the sixth quarter. Statistically, the response of NFCI is significant up to three quarters. The similar outcome for the financial index is illustrated by Mumtaz et al. (2018), too. Moreover, Bassett et al. (2014) reports and increase in the corporate bond spread after an adverse credit supply shock. This further confirms the increased tightness in the financial markets after the loan supply shock.

In Germany, the response of output growth, inflation and credit growth illustrates no difference in the extended model compared to the baseline model. The impulse response function of monetary policy, consequently the lending rate, becomes explicitly significant up to two years in the recursive identification after the loan demand is added as a control variable, though extended and baseline model reveal only a negligible difference for these rates under the external instrument approach. The response of loan demand, on the other hand, is statistically not different than zero. The similar finding can be seen in the paper of Busch et al. (2010), where the authors state no pronounced response of the corporate bond spread to the loan supply shock in Germany. This may be explained by either high savings rate, since no significant debt securities issuance is a case after the shock, or the dominance of banks in the financial markets.

In the Euro area, however, loan demand has decreased significantly up to two years according to the recursive identification method. It seems the quest for an alternative funds in the financial markets is more common for the enterprises and households in the EA compared to Germany. Likewise, Altavilla et al. (2015) states an increase in the EA corporate bond spread in response to a loan supply shock. They also report and increase in the debt securities issuance by non-financial corporations four quarters after the shock. This is a period when the loan demand from the banks is significantly negative in my response functions, on Figure 6. Besides, the identification via the proxy SVAR is still not significant for the EA estimations. I reckon that the violation of the second requirement, zero correlation of an instrument with the rest of the shocks, is an issue here. Therefore, I continue with sign restrictions approach in the sensitivity analysis and examine the possible alternative response functions to an adverse loan supply shock.

Sensitivity Analysis – Baseline

In this section, I do a robustness check of my baseline and extended model before I proceed with the labor variables. The baseline model incorporates five endogenous variables: log difference of real GDP, log difference of prices, log difference of total loans, composite lending rate and the short-term interest rate. I extend my baseline model to six variables in the second specification. My sixth variable for the U.S. is Chicago Fed's National Financial Condition index (NFCI) and loan demand index for Germany and the EA. The detailed information about the additional variables and the underlying reason for the extension of the baseline model is presented in the sub-section called Identification.

In sensitivity analysis, I identify the structural model using sign restrictions since that is one of the most commonly used approach for the identification of a credit supply shock in the literature (Peersman, 2011; Gambetti & Musso, 2012; Bijsterbosch & Falagiarda, 2014; Mumtaz, Pinter, & Theodoridis, 2018; etc.). This method considers the economic theory and defines the parameters' sign ex ante, in other words, identification of the structural shocks is done by restricting the directions of the impulse response functions (Kilian & Lütkepohl, 2017). The restrictions that I impose in the baseline and the extended models for the U.S. and EA are presented in Table 1, for Germany in Table 2. My way for identifying the credit supply shocks is based on the signs that is already applied by Busch et al. (2010) for Germany, and by Bijsterbosch & Falagiarda (2014), Mumtaz et al.(2018) for EA and US, respectively. No any signs specified for the NFCI and loan demand index in the extended models, since I do not want to restrict their responses to the shock.

The underlying intuition in the restrictions on Table 1 & Table 2 depends on four existing structural shocks: aggregate demand, aggregate supply, monetary policy and the credit supply shock in the economy. The responses of the output, inflation, lending and the short-term interest rate are positive to aggregate demand shock. Thus, a credit supply can be differentiated from an aggregate demand by a negative response of the lending rate to the shock. In other words, the response of output, inflation and the short-term interest rate to the credit supply shock is positive, but not the lending rate. The economic interpretation behind this is that the increased loan supply should decrease the lending rates and the increased aggregate demand should increase the lending rates. The difference of a credit supply shock from an aggregate supply shock, on the other hand, is the positive response of inflation to the initial but negative to the latter one. This is also quite intuitional considering the basic supply demand curves in economics. Furthermore, expansionary monetary policy and credit supply shocks have a positive effect on output and inflation. However, these two shocks can be identified according to the response of short-term interest rate that correlates positively with supply of loans, but negatively with an expansionary monetary policy shock, as it is expected. Since I interpret the reactions of the variables to an adverse loan supply shock, I assign negative responses to output, inflation, short-term interest rate and loans, but positive response to lending rate as it is illustrated in Table 1 & Table 2. Being out of my research question, I do not focus on IRFs to the shocks other than loan supply in this study.

The median impulse response functions, along with the 16^{th} and 84^{th} percentiles, to an adverse credit supply shock identified via the sign restrictions are given in Figure 7. Overall, the simulations support the outcomes from the previous analyzes above, with better confidence intervals. The IRFs support the finding that the reactions of the variables to the shock follows the similar pattern in all three economic regions. The identification capability of the external instrument approach for the US and Germany is quite satisfactory since their responses fit better to the response functions from the sign restriction approach. Particularly, the excess bond premium in the U.S confirms the power of the external instrument approach after an installation of a right proxy variable. Although BLS index can identify responses to the loan supply shocks for Germany via the external instrument approach, it has no use for the Euro area. It seems the correlation of the index with the rest of the structural shocks is outstanding for the EA, since the index has a partial explanatory power in the recursive identification method.

Figure 7 also supports the instantaneous fall of the GDP after the shock to the tightness of credits in all three economies. The decrement is significant up to two quarters in Germany and up to five quarter in the US & EA. The inflation, on the other hand, unlike it was in the proxy and recursive SVAR approaches, turns to negative in Germany and the EA. It dies out in two quarters in Germany but persists in convergence up to three years in the EA. The similar responses are stated by Peersman (2011), Bijsterbosch & Falagiarda (2014), and Altavilla et al. (2015) for Germany and the EA. The reaction of inflation for the U.S. support the finding from the external instrument approach but with a longer period, since its negative value is significant up to five years. Analogous finding for the both identifications is mentioned by Mumtaz et al. (2018), too.

Figure 7 supports the finding from the previous identification schemes, that an adverse loan supply shock decreases the credit growth in all three economic regions. Moreover, for the U.S., the negative credit growth is significant up to two years in all three identifications. Credit growth in Germany being not significant up to four quarters, and being significantly negative from quarter four to eight, supports the simulation from the external instrument approach. The similar finding can be seen in the simulations of Busch et al. (2010) as well. This finding, additionally, increases the reliability of the BLS index for Germany. The response of loans for the EA, on the other hand, shows an immediate fall in the credit growth which converges to zero not earlier than four years. This finding for total loans tallies with most of the studies in the literature (Peersman, 2011; Gambetti & Musso, 2012; Bijsterbosch & Falagiarda, 2014; Altavilla et al., 2015).

The response functions of the policy rate and the composite lending rate from the sign restriction identification, together with its narrower confidence bands, confirm all the simulations and the explanations that are given for the U.S. and Germany above in the sub-section called Impulse Response Functions. Furthermore, the reactions of the policy and composite lending rate identified via the sign restrictions in the EA are very similar to the ones from the recursive SVAR method, but with longer convergence horizons. Nevertheless, the simulations confirm that the reaction of the policy rate is crucial in the recovery of output, since it persistently drives the composite lending down and pushes the loans to a convergence phase which is accomplished commencing from the fifth quarter. This is further effective in the recovery of the negative inflation that shows a convergence towards zero between the fifth and twelfth quarters. The response of the lending rate reaches to its minimum at the seventh quarter when the output growth is at its maximum. Short-term interest rate and composite lending rate sustain significantly negative more than five years. The comparable responses can be seen in the articles of Bijsterbosch & Falagiarda (2014), and Altavilla et al (2015).

Results – Labor

In this section I present the response of the macro labor variables to an adverse loan supply shock. I focus on the identification via recursive and proxy SVARs together with sign restriction approach. The estimations are done using five-variable VAR model. The labor variables – employment, unemployment rate and wages, are added each time as the sixth variable to the model. The detailed information about the identification via recursive and external instrument approaches can be found in the section called Empirical Methodology. Here, I find it noteworthy to mention that the addition of the labor variables to the model in the recursive identification is done in the light of Carpenter & Rodgers III (2004), where the labor variables are ordered after the inflation. In the external instrument and sign restriction identifications, however, I add the variables basically to the end of the model, since the order of the variables are not crucial in these specifications.

The sign restrictions that I adopt for the U.S. and EA are in Table 1, whereas for Germany in Table 2. I present detailed information about the choice of signs in the previous section, Sensitivity Analysis – Baseline. No any signs specified for the labor variables on the tables, since I do not want to restrict their responses to the shock. Moreover, I do not present the responses of the macro variables that are estimated in the VAR together with the labor variables, since these variables are extensively analyzed in the section called Results – Macro. Thus, the responses of employment, unemployment, wage to an adverse loan supply shock are illustrated in Figure 8 for all three identification methods. Overall, an adverse loan supply shock seems to decrease the employment and increase the unemployment in all three economic regions. Hourly wages, on the other hand falls as a response to the shock only in the U.S and EA. Furthermore, sign restrictions provide narrower confidence bands than the other two identification methods and thus are more reliable in the analyzes.

Employment in the U.S. shows a negative response when there is a shock to the tightness of credits. This response is partially significant in recursive and proxy SVARs. However, in sign restriction identification, the confidence bands become very tight starting from the second quarter and the negative effect on employment lasts more than two years. Considering the responses from Figure 7, I conclude that the negative effect of the supply shock disappears when output growth reaches to its maximum. Unemployment, on the other hand, increases significantly after the shock hits the U.S. economy. All three specifications are congruent in the positive significant response which lasts more than two years.

Although the median response of the employment and unemployment in Germany is negative and positive, respectively, for a very short period at the beginning, 16^{th} and 84^{th} percentiles of responses reveal no significant change in the employment on average. In the Euro area, however, the decrement in employment is significant up to seventh quarter according to the recursive and sign restriction methods. The change in the unemployment rate follows the similar evolution but with a positive response to the shock. Considering the response of macro variables from Figure 7, both labor variables elude from the detrimental effect of the shock once the output growth reaches to its maximum, as it was in the U.S. economy.

The effect of an adverse loan supply shock on wages is negative in the U.S., particularly starting from the first quarter this effect prevails more than four years. The similar response to the United States can be seen in the Euro area, where the negative effect of the shock hits the wages at the fifth quarter and lasts more than four years. The delay in the initial effect can be explained by wage rigidities in the EA. Wages in Germany, on the other hand, reveals no explicit significant response to the shock, as it was a case for employment and unemployment, above.

The response of macro labor variables to a credit supply shock is not very wide in the literature. Nevertheless, Gilchrist & Zakrajsek (2011) states a similar response of employment to an adverse loan supply shock to my finding in the United States. Furthermore, Sales (2016) studies the effect of total credit shocks in German and the U.S. economies in comparison. Although this is not exactly the same credit supply shock that I investigate in my paper, it is noteworthy to mention that in her findings the response of unemployment rate to the credit shock is significantly negative up to two years in the U.S. and statistically not different than zero in Germany, which is very similar to my findings in Figure 8. Abildgren (2012) also states a similar insignificant response of unemployment to a credit supply shock, though in Denmark.

Historical Decomposition - Counterfactuals

The analyzes above regarding the impulse response functions describe the average effect of the credit supply shock on each variable in the data. However, it is more interesting to analyze the role of the shock in the recessions, e.g. financial crisis of 2008. Therefore, I compute the historical structural shocks for all three identifications and study the importance of the shock using counterfactuals in the United States, Euro Area and Germany. Kilian & Lee (2014) defines the counterfactuals as the difference between the actual variables (e.g. output growth or loan growth in my data) and the historical contribution of the shock to these variables. Hence, counterfactuals show how the macro variables in the model would have evolved if we could shut down the shock of interest in the economy. If the counterfactuals are above the actual series, then for my study, it means that the loan supply shock drives the macro variables down during the period of focus, and vice versa.

Counterfactuals – Macro

In this section I present the counterfactuals identified using recursive, external instrument and sign restriction approaches, initial two of which are estimated in the extended VAR model. Sign restriction model, on the other hand, is identified using the baseline model with five variables. The baseline model incorporates five endogenous variables: log difference of real GDP, log difference of prices, log difference of total loans, composite lending rate and the short-term interest rate. The extended model incorporates, additionally, Chicago Fed's National Financial Condition index (NFCI) for the U.S. and loan demand index for Germany and the EA. The detailed information about the additional variables and the underlying reason for the extension of the baseline model is presented in the sub-section called Identification. The sign restrictions for the U.S. and EA are in Table 1, whereas for Germany in Table 2. I present detailed information about the choice of signs in the Sensitivity Analysis – Baseline section. No any signs specified for the labor variables on the tables, since I do not want to restrict their responses to the shock.

Figure 9 & 10 illustrate the counterfactual series of the macro variables together with actual series. I present the responses from the recursive and proxy SVARs in Figure 9, whereas the sign restrictions in Figure 10. Overall, loan supply shock in all three economies worsened the evolution of the variables during the financial crisis of 2008-09. Skimming over the plots, the shocks seem being positively contributed the series during the boom period before the crisis. After the crisis, on the other hand, I observe heterogeneity in the responses depending on economic regions. Furthermore, the counterfactuals in the U.S. using sign restrictions seem to be the average of the counterfactuals identified by recursive and proxy SVARs.

Actual series of the output growth in the U.S., EA and Germany is above the counterfactual series in the U.S. before the financial crisis, in other words, credit supply shock pushed these economies up in the pre-crisis period. During the downturn, the credit supply shock contributed remarkably to the recession, particularly in the U.S, where the decline in output could be 50 % smaller if the shock were refrained. This amelioration would be 20 % and 15 % in the EA and Germany, respectively. Missing loan supply shock could boost the economy in the recovery period for the United States. The shock turns to contribute to the GDP growth in the U.S. after the recession. The findings for the States are very similar to those of Gambetti & Musso (2012) and Mumtaz et al. (2018).

The effect of the shock in the recovery and the post-crisis period is trivial for the EA. Previous studies also state the heterogeneity for Euro area countries over the aforementioned period (Peersman, 2011; Hristov et al., 2012; Bijsterbosch & Falagiarda, 2014). German output growth is indifferent to the shock during the recovery and post-crisis period under the sign restriction and recursive SVAR identifications. External instrument identification, however, points for a positive contribution in the post-crisis period. The response of output growth for Germany after the crisis is ambiguous in the literature, too. Because Bijsterbosch & Falagiarda (2014) stresses for a positive, whereas Hristov et al. (2012) for a negative contribution.

The effect of the loan supply shock to the inflation is not clear for the U.S. in the pre-crisis period. However, during the downturn and the post crisis period the shock has a deflationary effect on the economy. The same effect can be seen in EA average, though in the pre-crisis period shock contributes positively to the inflation. The similar results are illustrated by Gambetti & Musso (2012) for the U.S and EA, particularly for the recession and post-recession period, too. The inflation in Germany, on the other hand, seems indifferent to a loan supply shock. Counterfactual series of loan growth convey a clear outcome for all three economies in all three identifications that the shock contributes positively to loan growth in the boost period, but negatively over and after the recession. This finding is partially like simulations of Gambetti & Musso (2012) and Bijsterbosch & Falagiarda (2014). Figure 9 & 10 further reveals the negative response of the short-term interest rate during and after the recession in response to the shock. The highest policy response is in the U.S., whereas the lowest in Germany. This finding for the policy rate is consistent with Gambetti & Musso (2012) considering the U.S. and EA.

Counterfactuals – Labor

In this section I present the counterfactual series of macro labor variables identified using sign restriction approach using the baseline model with five variables: log difference of real GDP, log difference of prices, log difference of total loans, composite lending rate and the short-term interest rate. The sign restrictions for the U.S. and EA are in Table 1, whereas for Germany in Table 2. I present detailed information about the choice of signs in the Sensitivity Analysis – Baseline section. No any signs specified for the labor variables on the tables, since I do not want to restrict their responses to the shock. Figure 11 illustrate the counterfactual series of the labor variables together with actual series. Overall, counterfactuals in the States and Europe show significant difference than the actual series, whereas in Germany both series go hand in hand.

The figure reveals that the loan supply shock contributes positively to employment before the financial recession of 2008-9. Furthermore, all three economies, experiences a fall in the employment during the recession. The highest effect is in the U.S., where 25% less decrement would be in the employment once the effect of the shock was turned off in the economy. From the peak of 2008Q1 to the troughs of 2009Q2 the decline for Germany and EA, on the other hand, would be around 12 to 14 %. After the crisis, the difference between actual and counterfactual series is not significant for Germany, whereas actual series persist being under the counterfactuals in the U.S. and EA. The unemployment rate is roughly stable in all three economies, except the recession period in the States where the loan supply shock contributed to the increment in rate remarkably. Figure 11 further reveals a constant low wage payment in based on the credit supply shock in the U.S., whereas a positive contribution is a case in Europe during the boom and recession period. For Germany, however, the differences are negligible. Quite similar responses for all labor variables in the U.S. are presented in Jermann & Quadrini (2012) and Biovin, Giannoni, & Stevanovic (2013) as well.

Conclusion

The improvements in the loan market affects the real economy significantly. Therefore, policy against the weakness in the lending sector is crucial. However, the process is not a uniform incident, since there are two main columns of the lending activity: credit supply and loan demand. It is essential to know the transmission mechanism of the shock from lending sector to the real economy, because supply and demand forces may change the policy decisions. For instance, if the malfunction is in the banking sector because of their balance sheet constraints, then supporting the banks would be the right decision. Though declining demand requires support to the real economy.

In my research paper, I study the effect of an adverse credit supply shock on the macroeconomy. I do my research about three different economic regions: the United States, Euro Area and Germany. This is one of the outstanding points of my paper. I exploit the proxy variables in the identification of the effects of a loan supply shock. This way of identification is mainly done either by short run restrictions or external instrumental methodology, which are also known as Recursive SVAR and Proxy SVAR approaches, respectively. The second outstanding point of my paper is the incorporation of BLS loan supply index in these identification methods. The main contribution of my paper to the literature is the studying the effect of the credit supply shock on labor economics. I study this effect using three different identification methods: recursive, proxy SVARs and sign restriction approach.

Given the weak power of BLS loan supply index in the identification for Euro Area, in future studies, I aim to create and excess bond premium for Europe and investigate the impact of an unanticipated shocks to the EBP and their relative ability to explain macroeconomic developments in EA as it is done by Altavilla et al. (2015), where they state that during the financial crisis of 2008-09, the information from financial markets was crucial in the explanation of macroeconomic developments.

Tables

Table 1 – Sign Restrictions for US & EA

	GDP	Inflation	Loans	Lending Rate	Policy Rate
Loan Supply Shock	–	–	–	+	–

Notes: Restrictions are imposed for one quarter on the responses to an adverse credit supply shock. NFCI / Loan Demand in the extended model and Employment / Unemployment / Wages in the labor models are omitted since I do not want to restrict their responses to the shock.
Source: Bijsterbosch & Falagiarda (2014), Mumtaz et al. (2018)

Table 2 – Sign Restrictions for Germany

		GDP	Inflation	Loans	Lending Rate	Policy Rate
Loan	Q = 0	–		–	+	
Supply	Q = 1	–	–	–	+	
Shock	Q = 2	–	–	–	+	–

Notes: Restrictions are imposed for three quarters on the responses to an adverse credit supply shock. NFCI / Loan Demand in the extended model and Employment / Unemployment / Wages in the labor models are omitted since I do not want to restrict their responses to the shock.
Source: Busch et al. (2010)

Figures

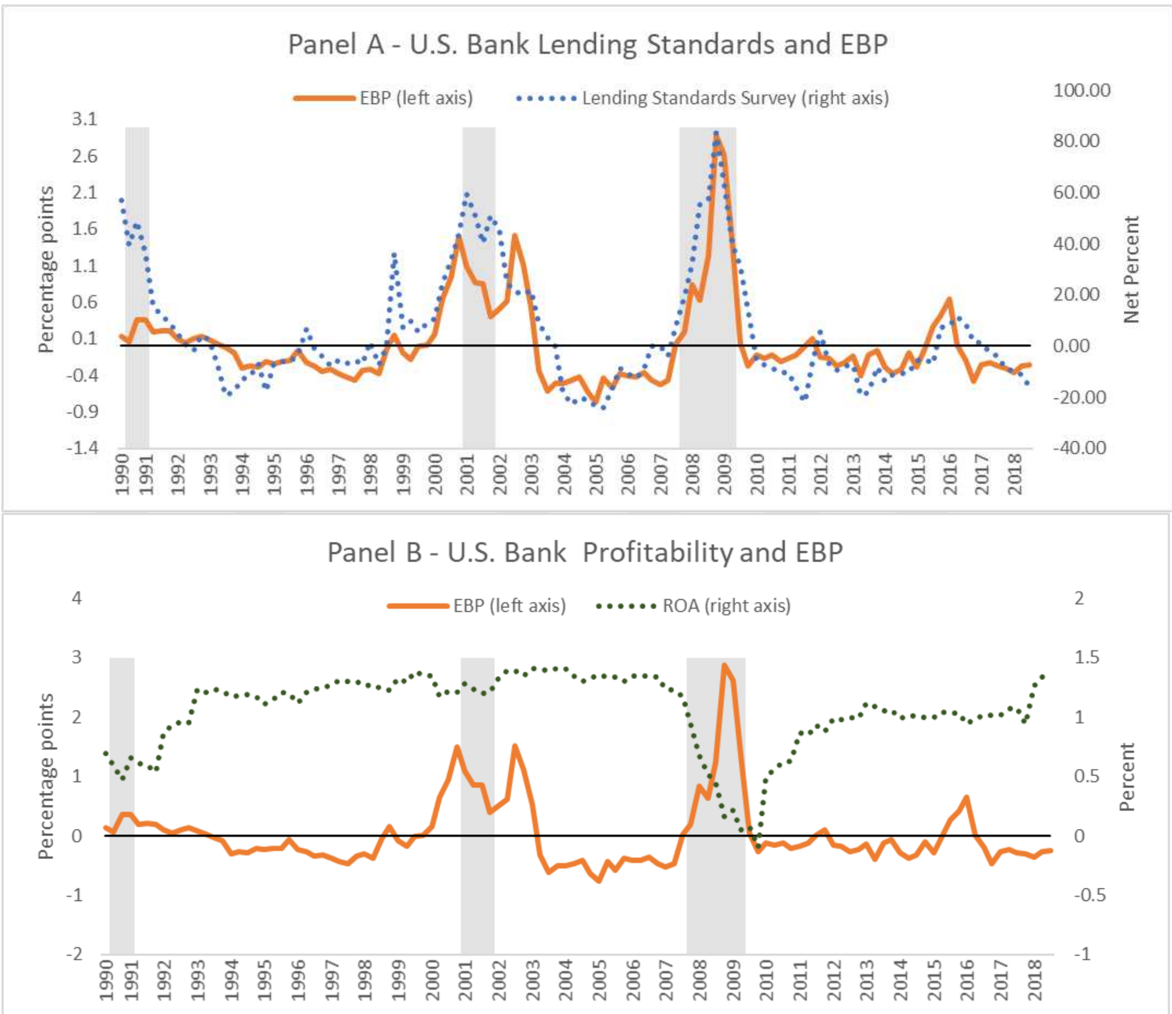


Figure 1: EBP and Financial Market Conditions

Notes: Sample period: Q2.1990-Q3.2018. EBP in both panels is Excess Bond Premium. Lending Standards Survey (dotted line) in Panel A stands for the net percent of Bank Lending Practices Survey's respondents that reported tightening their credit standards on Commercial and Industrial loans. ROA (dotted line) in Panel B stands for Return On Average Assets for all the U.S. Banks. The shaded bars stand for U.S. NBER recessions.
Source: Own visualization. See Appendix A for data sources and definitions.

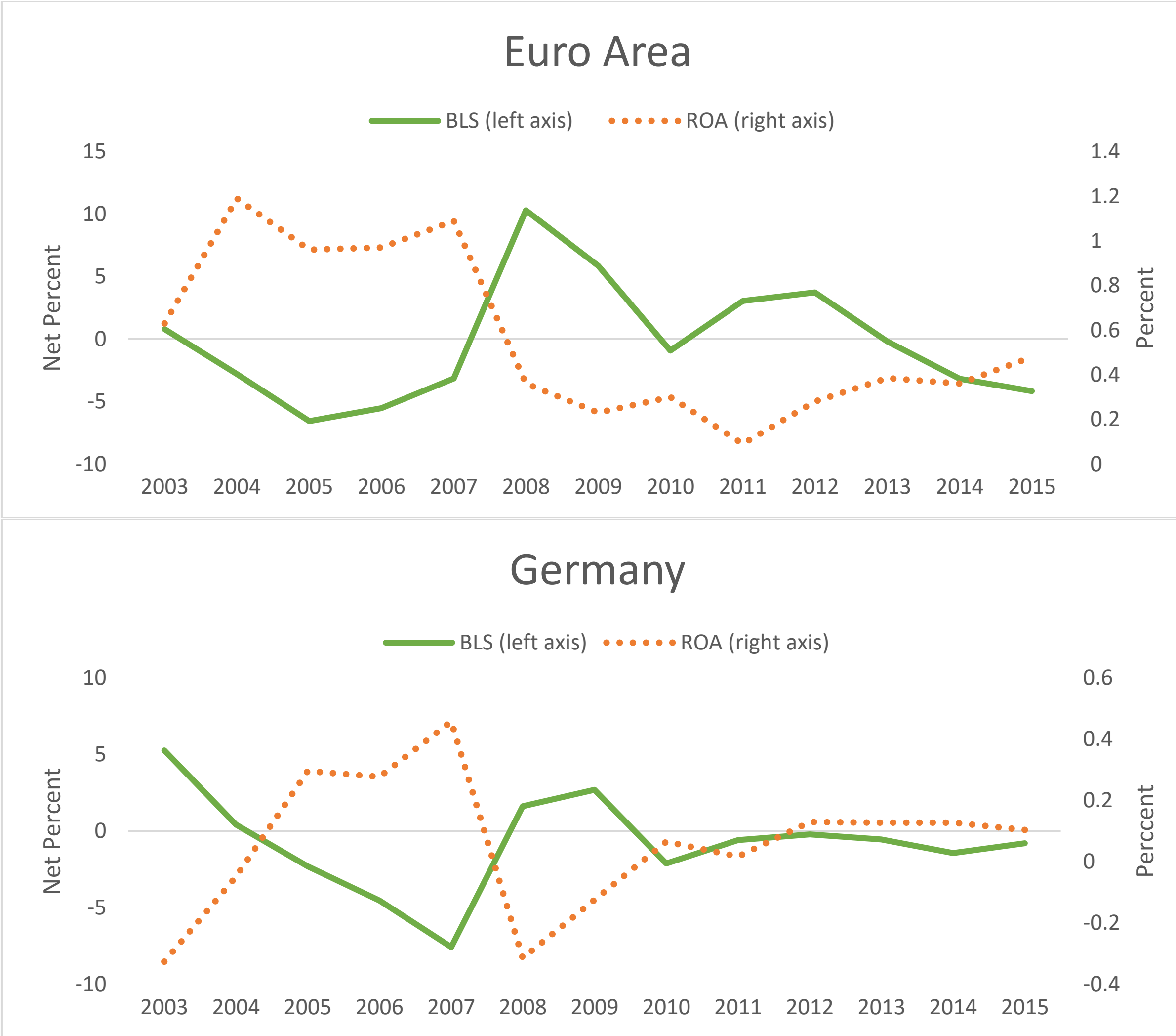


Figure 2: BLS and Bank Profitability

Notes: Sample period: Yearly, 2003-2015. BLS stands for Bank Lending Survey, that reflects the net percentage of banks tightening their credit standards on loans to the private sector. ROA (dotted line) is Bank's Return On Assets for Germany and EA.
Source: Own visualization. See Appendix A for data sources and definitions.

Figure 3: Data – Macro

Germany	Euro Area	United States

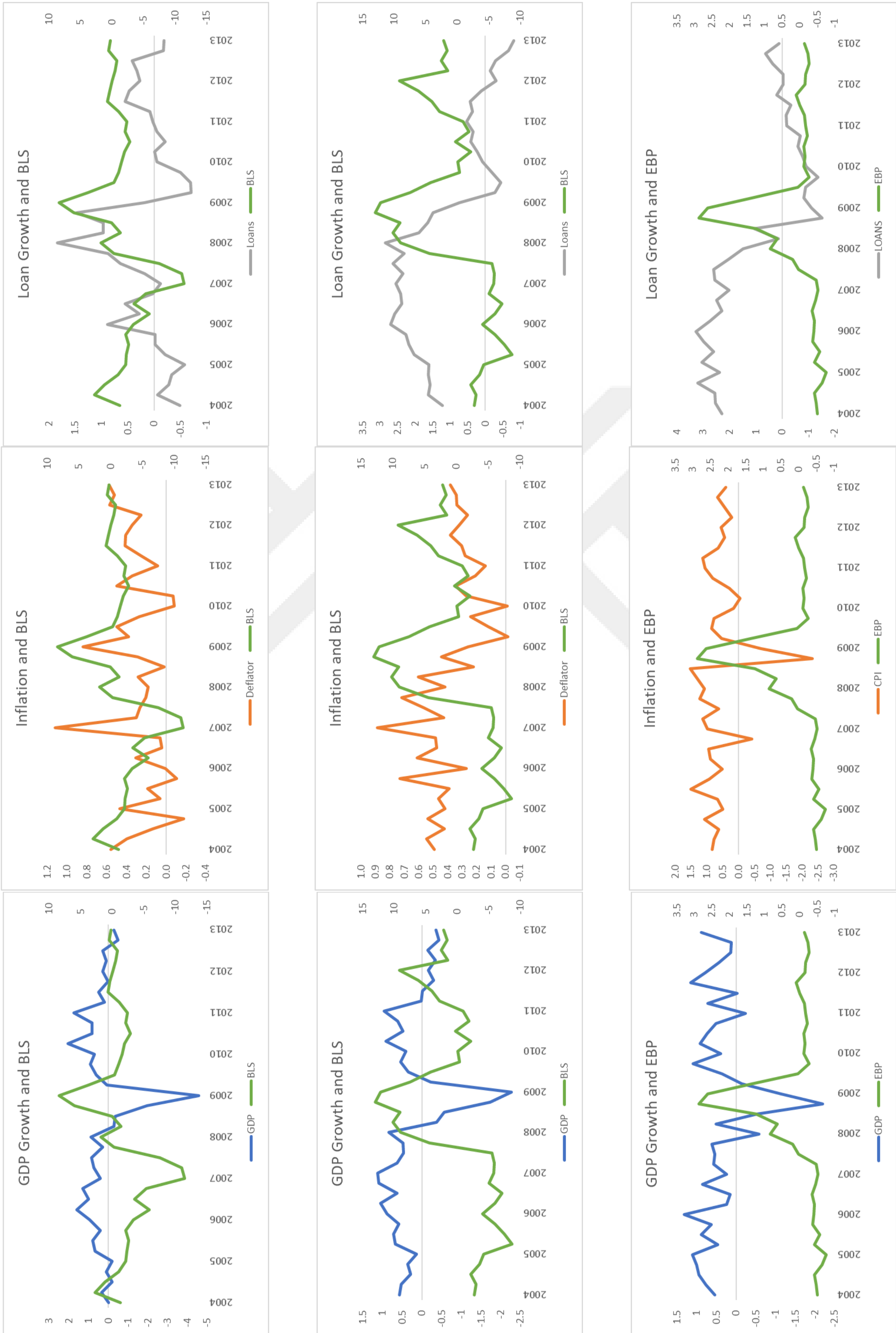
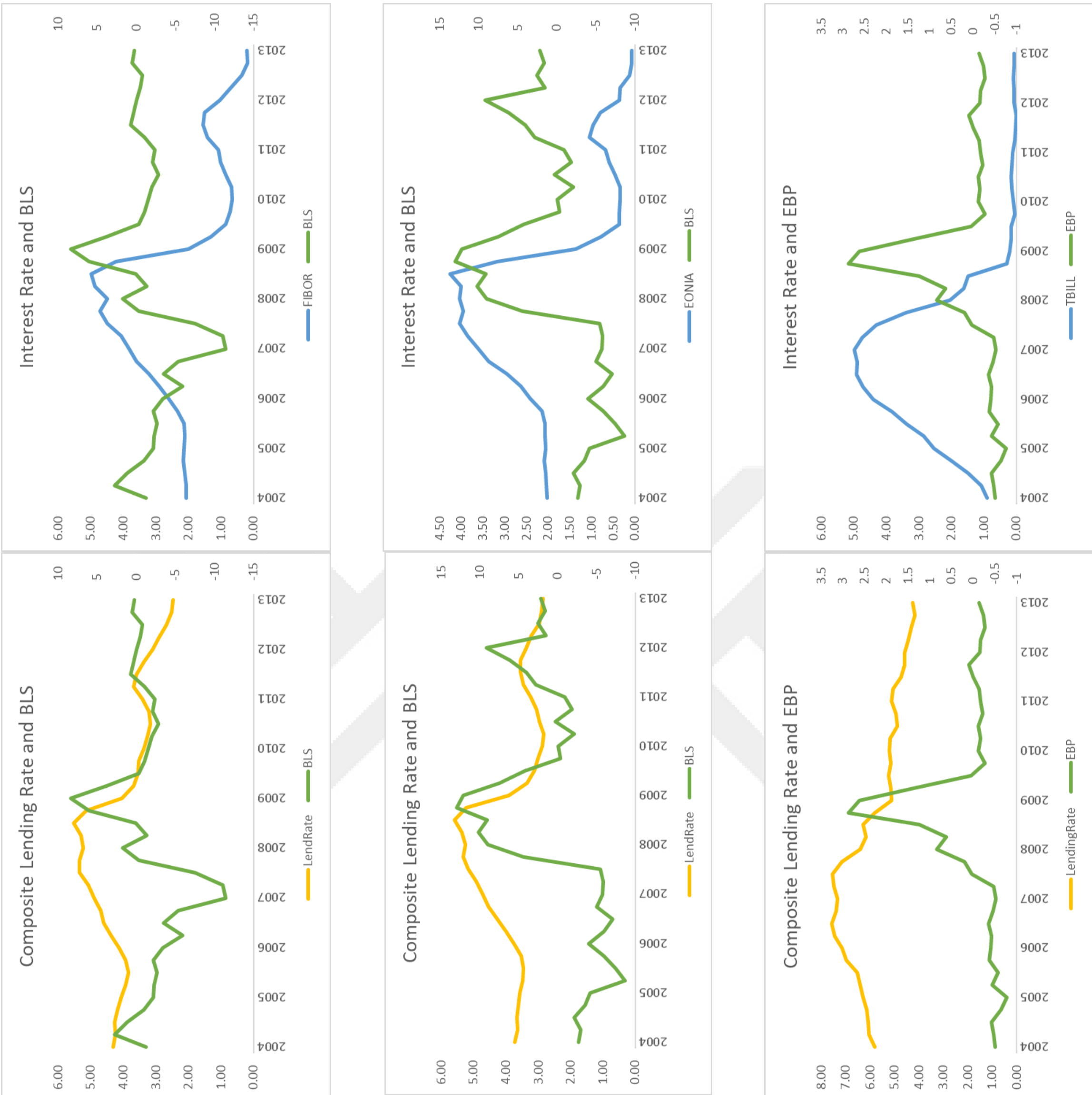


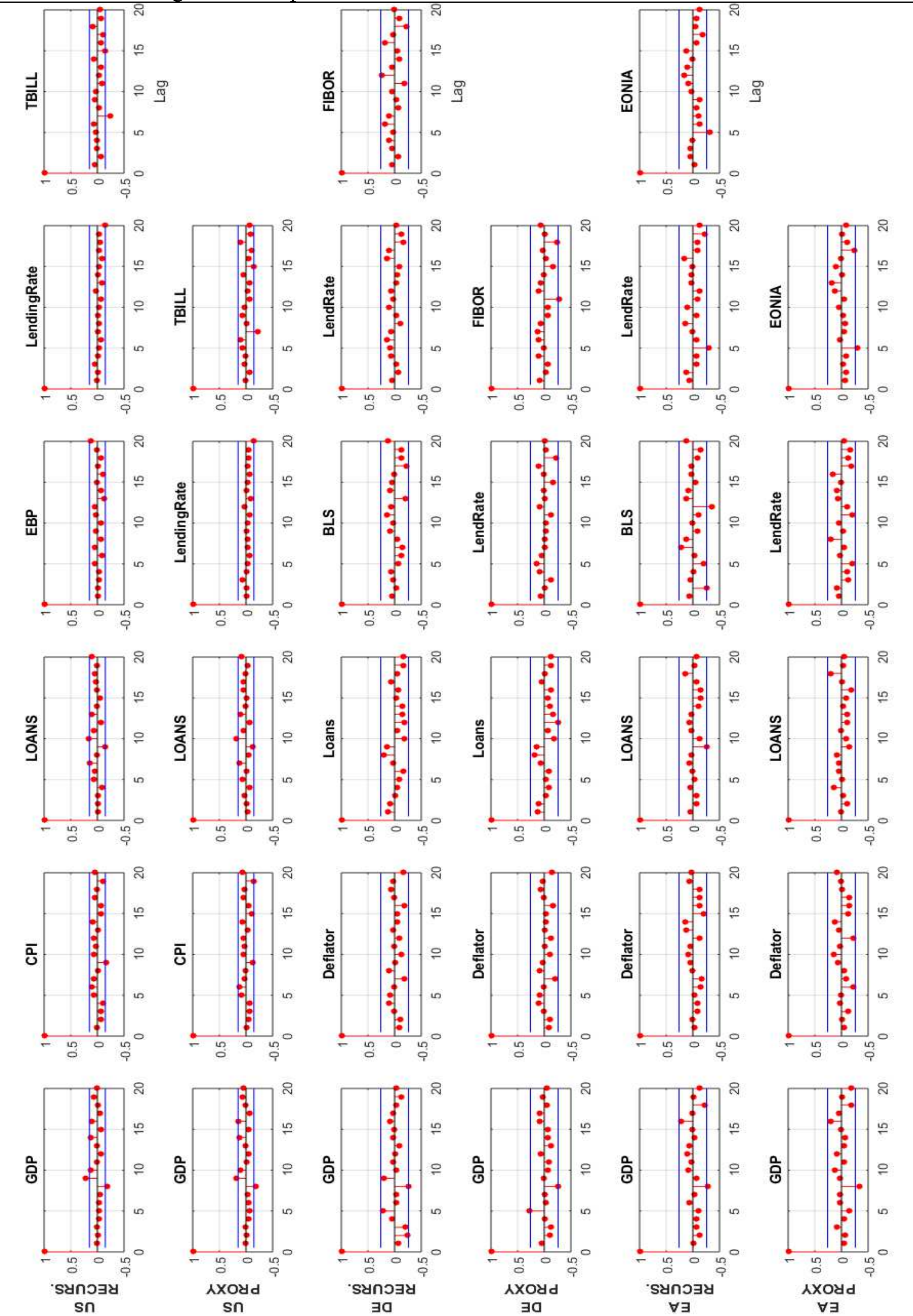
Figure 3: Data – Macro (continued)

Germany	Euro Area	United States



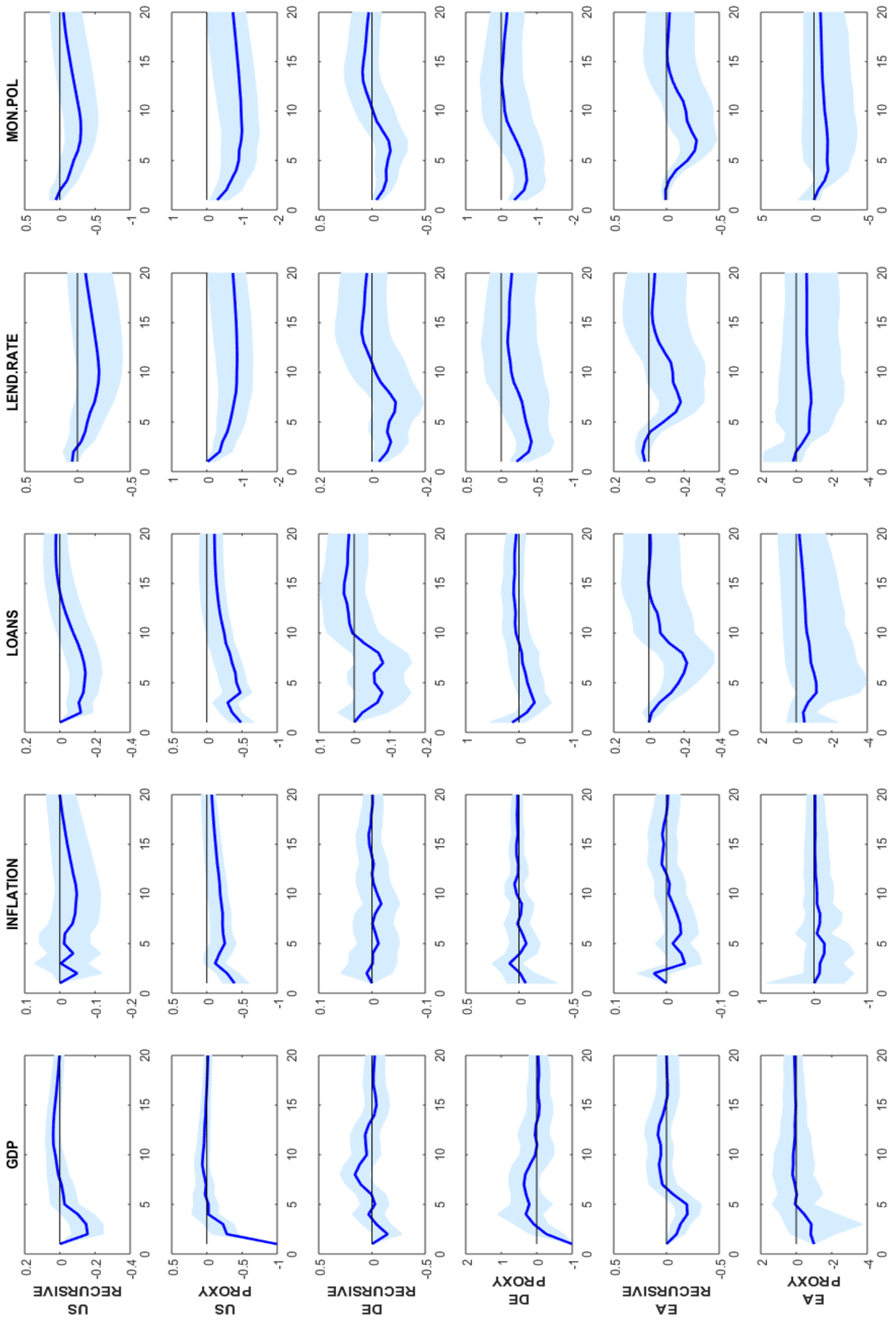
Notes: Sample period: Q1.2004-Q1.2013. BLS (Bank Lending Survey) and EBP (Excess Bond Premium) changes are shown on the right axis. GDP, Prices and Loans are given in log differentials multiplied by 100.
Source: Own visualization. See Appendix A for data sources and definitions.

Figure 4: Sample Autocorrelation Functions – Baseline Model



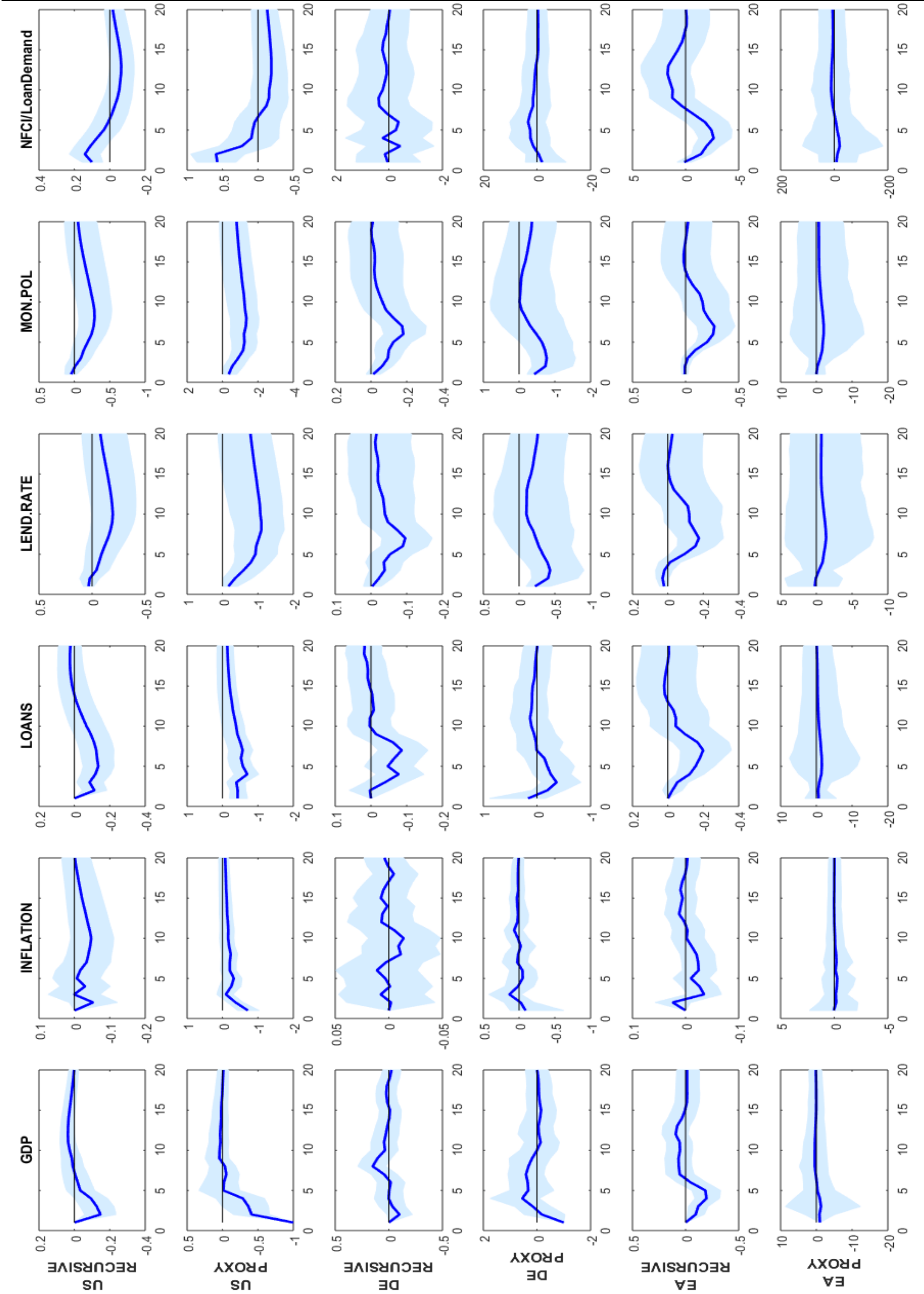
Notes: VAR estimations for Recursive models has 6 variables and for Proxy models has 5 variables. Plots are for the U.S., Germany and Euro Area. 95% Confidence Interval.
Source: Own visualization.

Figure 5: Impulse Response Functions – Baseline Model



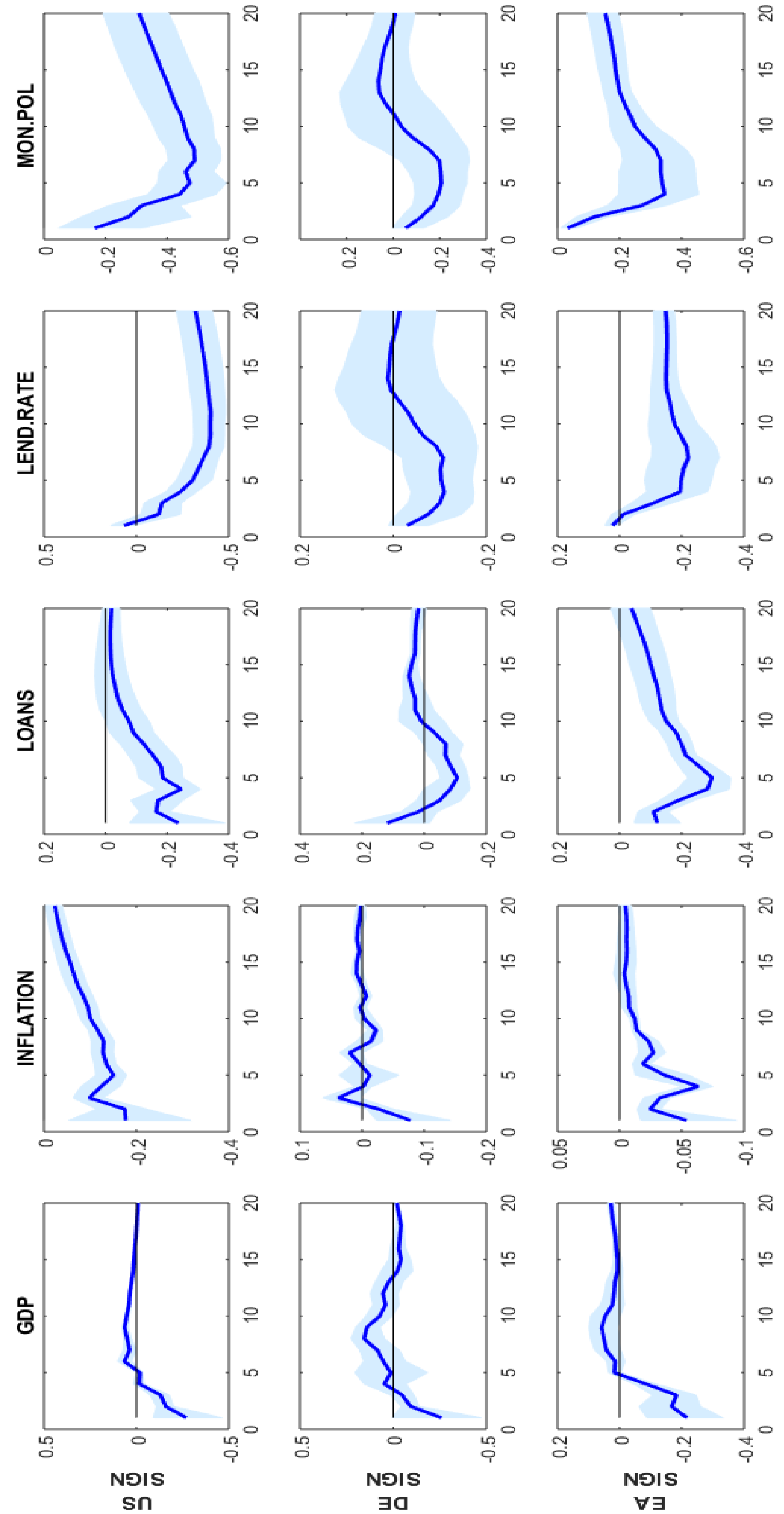
Notes: Median IRFs with 95% Confidence Interval (shaded area). VAR estimation for Recursive SVAR has 6 variables, since the proxy variable is ordered after total loans. Plots are for the U.S., Germany and Euro Area.
Source: Own visualization.

Figure 6: Impulse Response Functions – Extended Model



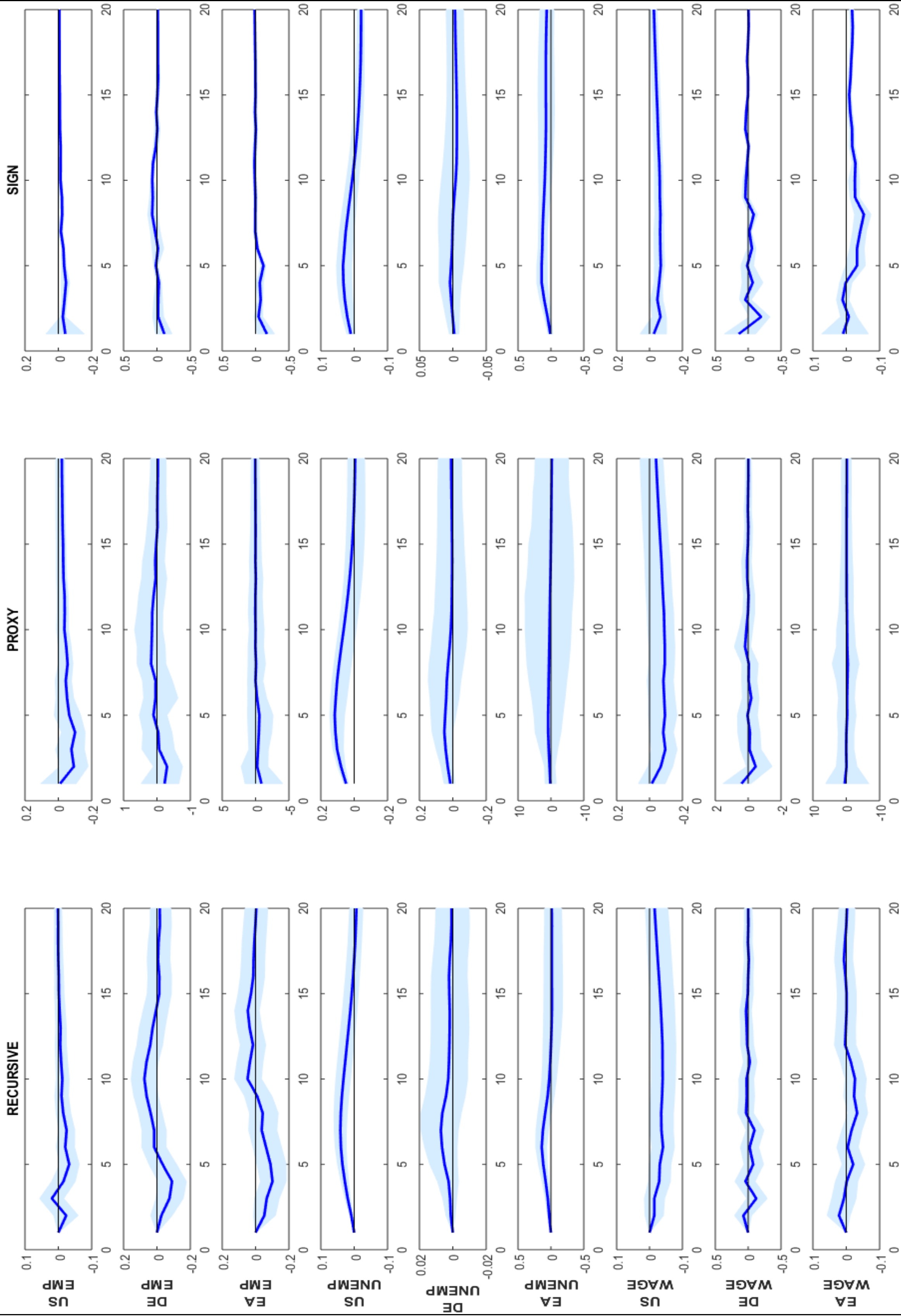
Notes: Median IRFs with 95% Confidence Interval (shaded area). Recursive VAR models have 7 variables, since the proxy variable is ordered after total loans. Plots are for the U.S., Germany and Euro Area. NFCI is used in the U.S. estimations, whereas loan demand index in Germany and EA.
Source: Own visualization.

Figure 7: Sensitivity Anaylsis – Baseline Model



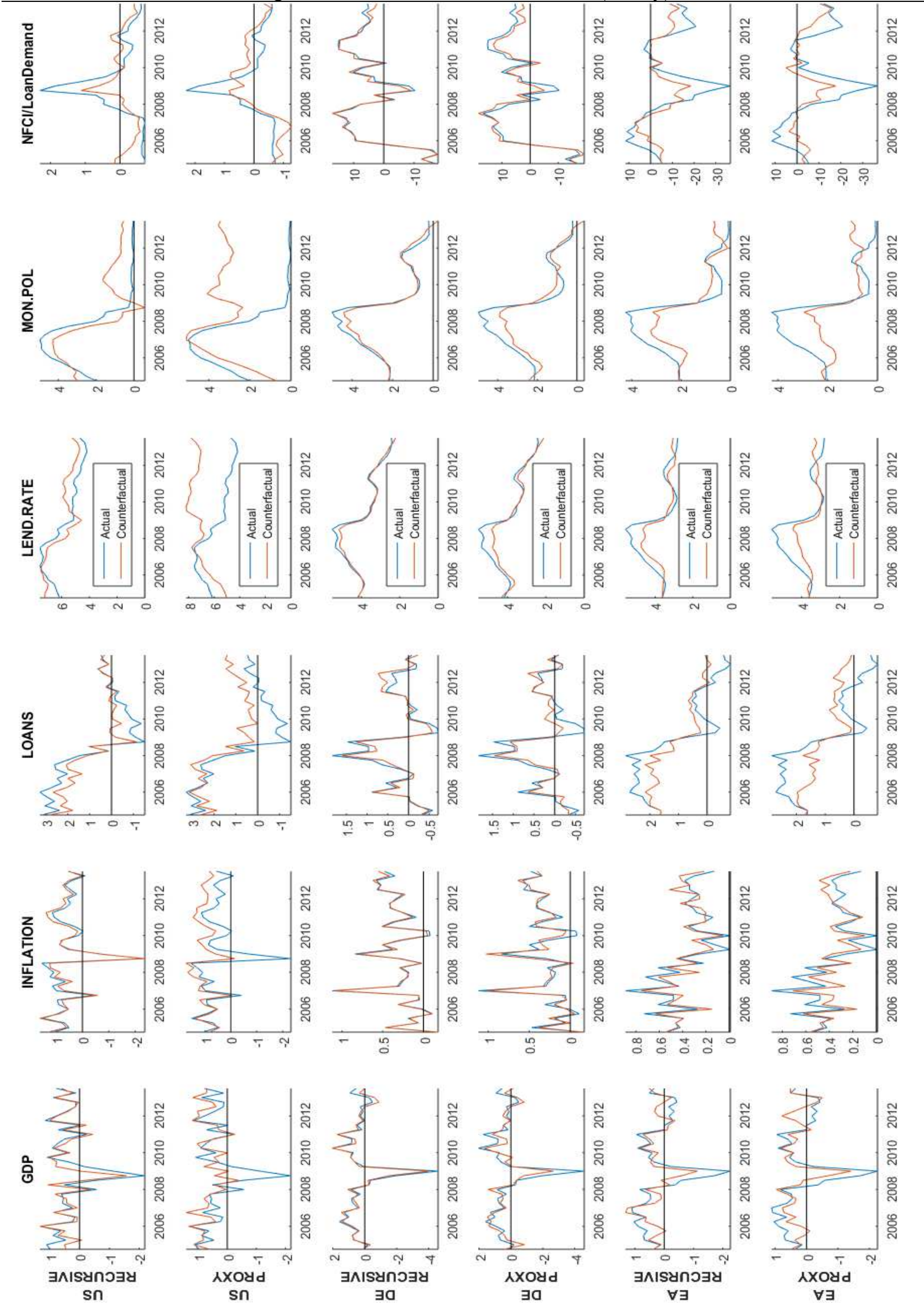
Notes: Median IRFs to an adverse credit supply shock with the space between the 16th and 84th percentiles (shaded area). Plots are for the United States, Germany and Euro Area.
Source: Own visualization.

Figure 8: Impulse Response Functions – Macro Labor



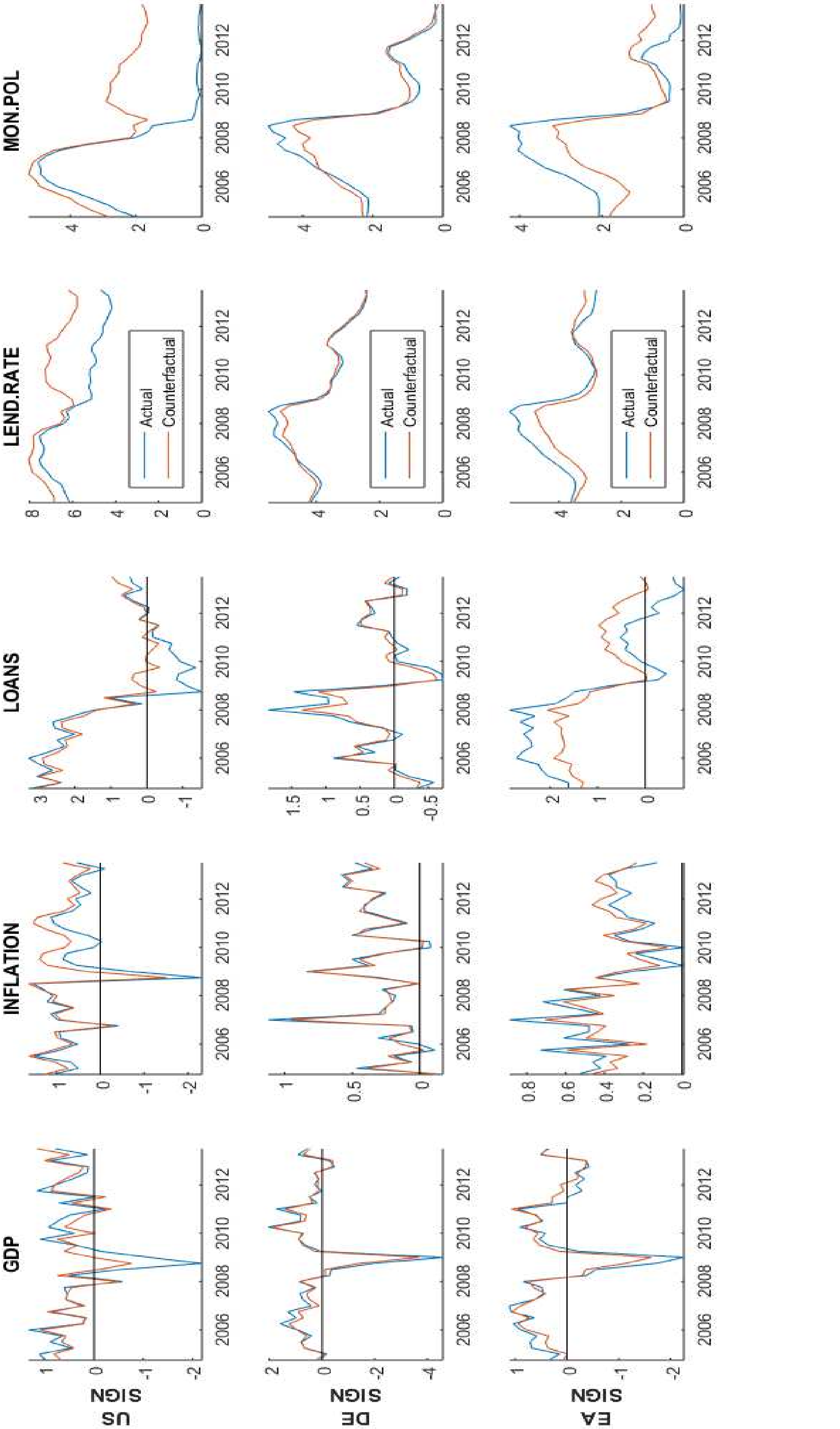
Notes: Median IRFs with 95% Confidence Interval (shaded area) for Recursive and Proxy SVARs, & with the space between the 16th and 84th percentiles (shaded area) for Sign Restrictions. Recursive VAR models have 7 variables, since the proxy variable is ordered after total loans. Plots are for the U.S., Germany and EA.
Source: Own visualization.

Figure 9: Counterfactuals – Macro (Proxy)



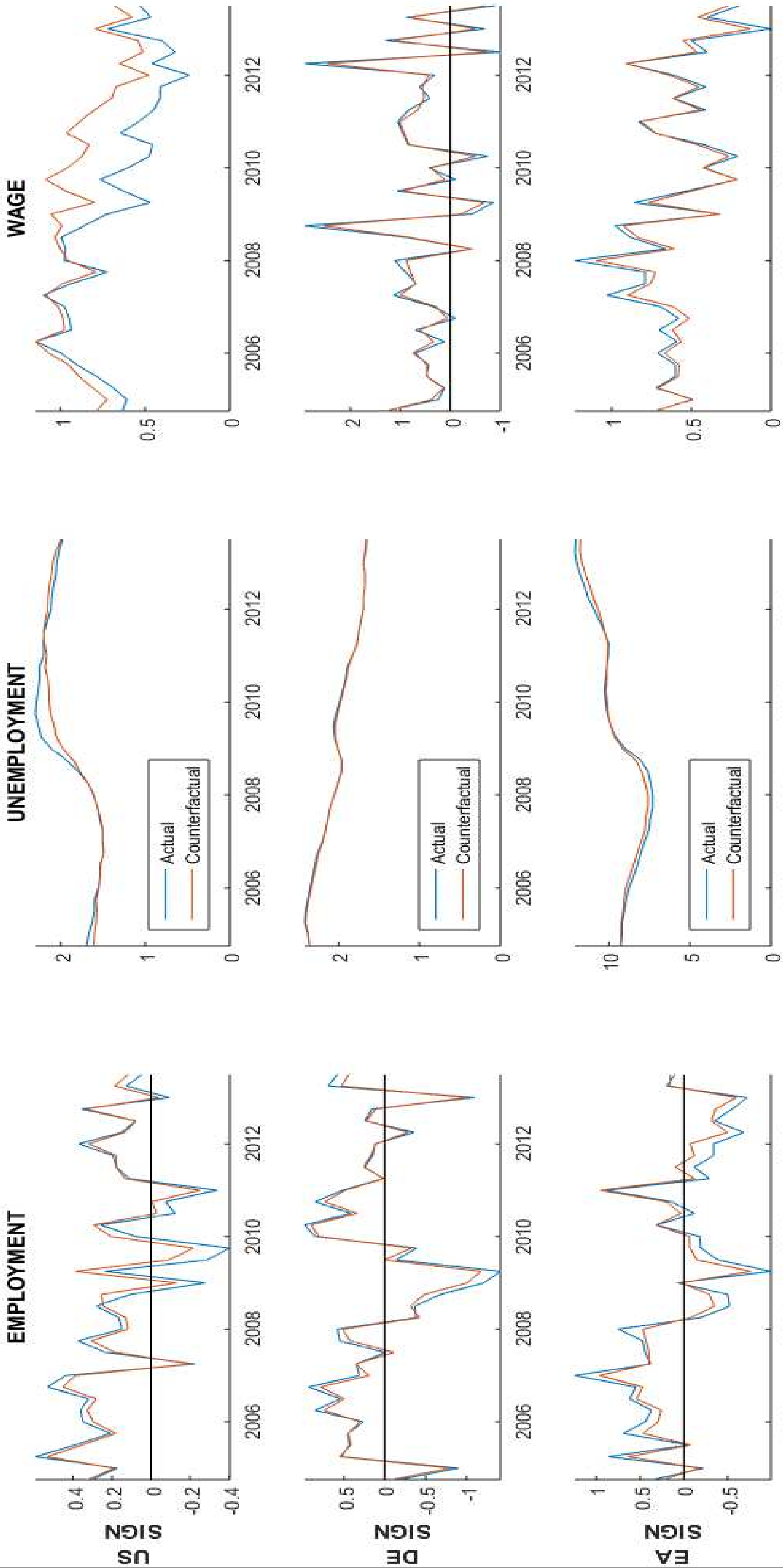
Notes: Counterfactuals for the extented VAR model. Recursive VAR models have 8 variables, since the proxy variable is ordered after total loans. Plots are for the U.S., Germany and Euro Area. NFCI is used in the U.S. estimations, whereas loan demand index in Germany and EA.
Source: Own visualization.

Figure 10: Counterfactuals – Macro (Sign)



Notes: Counterfactuals for the baseline VAR. Sign-restriction identification. Plots for Germany, EA & U.S.
Source: Own visualization.

Figure 11: Counterfactuals – Labor (Sign)



Notes: Counterfactuals for labor variables – Employment, Unemployment and Wages. Sign-restriction identification. Plots for Germany, EA & U.S.
Source: Own visualization.

References

Abildgren, K. (2012). FINANCIAL STRUCTURES AND THE REAL EFFECTS OF CREDIT-SUPPLY SHOCKS IN DENMARK 1922-2011. *ECB Working Paper Series, No 1460*.

Altavilla, C., Darracq Paries, M., & Nicoletti, G. (2015). Loan supply, credit markets and the euro area financial crisis. *ECB Working Paper Series, No 1861*.

Bassett, W. F., Chosak, M. B., Driscoll, J. C., & Zakrajsek, E. (2014). Changes in bank lending standards and the macroeconomy. *Journal of Monetary Economics, Elsevier, 62*(C), 23-40.

Bijsterbosch, M., & Falagiarda, M. (2014). Credit Supply Dynamics and Economic Activity in Euro Area Countries: A Time-Varying Parameter VAR Analysis. *ECB Working Paper Series, No 1714*.

Biovin, J., Giannoni, M., & Stevanovic, D. (2013). Dynamic Effects of Credit Shocks in a Data-rich Environment. *Staff Reports 615*. Federal Reserve Bank of New York, revised 01 October 2016.

Busch, U., Scharnagl, M., & Scheithauer, J. (2010). Loan supply in Germany during the financial crisis. *Deutsche Bundesbank Discussion Paper Series 1: Economic Studies, 2010*(05).

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

Carpenter, S. B., & Rodgers III, W. M. (2004). The disparate labor market impacts of monetary policy. *Journal of Policy Analysis and Management, 23*(4), 813-830.

Carriero, A., Mumtaz, H., Theodoridis, K., & Theophilopoulou, A. (2015). The Impact of Uncertainty Shocks under Measurement Error: A Proxy SVAR Approach. *Journal of Money, Credit and Banking, Blackwell Publishing, 47*(6), 1223-1238.

Ciccarelli, M., Maddaloni, A., & Peydro, J. L. (2010). Trusting the Bankers: A New Look at the Credit Channel of Monetary Policy. *ECB Working Paper Series, No 1228*.

De Bondt, G., Maddaloni, A., Peydro, J. L., & Scopel, S. (2010). The Euro area bank lending survey matters: Empirical evidence for credit and output growth. *ECB Working Paper Series, No 1160*.

Gambetti, L., & Musso, A. (2012). Loan Supply Shocks and the Business Cycle. *ECB Working Paper Series, No 1469*.

Gilchrist, S., & Mojon, B. (2018). Credit Risk in the Euro Area. *Economic Journal, Royal Economic Society, 128*(608), 118-158.

Gilchrist, S., & Zakrajsek, E. (2011). Monetary Policy and Credit Supply Shocks. *IMF Economic Review, 59*(2), 195-232.

Gilchrist, S., & Zakrajsek, E. (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review, 102*(4), 1692-1720.

Giovanni, F., Gilchrist, S., Lewis, K. F., & Zakrajsek, E. (2016, October 6). Updating the Recession Risk and the Excess Bond Premium. *FEDS Notes*. Washington: Board of Governors of the Federal Reserve System. doi:https://doi.org/10.17016/2380-7172.1836

Hristov, N., Hülsewig, O., & Wollmershäuser, T. (2012). Loan Supply Shocks during the Financial Crisis: Evidence for the Euro Area. *Journal of International Money and Finance, Elsevier, 31*(3), 569-592.

Jermann, U., & Quadrini, V. (2012). Macroeconomic Effects of Financial Shocks. *American Economic Review, 102*(1), 238-271.

Kilian, L., & Lee, T. K. (2014). Quantifying the Speculative Component in the Real Price of Oil: The Role of Global Oil Inventories. *Journal of International Money and Finance, 42*, 71-87.

Kilian, L., & Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis.* Cambridge: Cambridge University Press. Retrieved from https://sites.google.com/site/lkilian2019/textbook/preliminary-chapters

Lown, C., & Morgan, D. P. (2006). The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey. *Journal of Money, Credit and Banking, 38*(6), 1575-1597.

Mertens, K., & Ravn, M. O. (2013). The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States. *American Economic Review, 103*(4), 1212-47.

Mertens, K., & Ravn, M. O. (2014). A reconciliation of SVAR and narrative estimates of tax multipliers. *Journal of Monetary Economics, Elsevier, 68*(5), 1-19.

Metiu, N., Hilberg, B., & Grill, M. (2016). Credit constraints and the international propagation of US financial shocks. *Journal of Banking and Finance, Elsevier, 72*(C), 67-80.

Mumtaz, H., Pinter, G., & Theodoridis, K. (2018). What do VARs tell us about the impact of a credit supply shock? *International Economic Review, 59*(2), 625-646.

Peersman, G. (2011). Bank Lending Shocks and the Euro Area Business Cycle. *Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium, 11*(766).

Sales, M. (2016). Do Corporate Credit Conditions Alter Labor Market Dynamics? A SVAR Analysis in a Transatlantic Perspective. *<hal-01333025>*.

Stock, J. H., & Watson, M. W. (2008, July 15). What's New in Econometrics: Time Series. Lecture 7. *Recent Developments in Structural VAR Modeling*. National Bureau of Economic Research. Retrieved from https://www.nber.org/minicourse_2008.html

Stock, J. H., & Watson, M. W. (2012). Disentangling the Channels of the 2007-2009 Reccession. *Brookings Papers on Economic Activity, 43*(1), 81-156.

APPENDIX A - Data

The following paragraphs comprise details about data sources for the U.S., Germany and EA.

United States

3-m Tbill	3-month Treasury Bill rate is a monthly data. Quarterly version of the data that is calculated with an arithmetic average of the corresponding months. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: TB3MS
Comp. Lending Rate	Composite Lending Rate is constructed in the light of Appendix B of Gambetti & Musso (2012). I calculate the data as a weighted average of lending rate to households and lending rate to non-financial corporations. Lending rate to non-financial corporations is the arithmetic average of 'Commercial and Industrial Loans Rate' (see Board of Governors of the Federal Reserve System Survey of Terms of Business Lending – E2., see https://www.federalreserve.gov/releases/e2/e2chart.htm) and 'Bank Prime Loan Rate for short-term business loans' (see Federal Reserve Bank of St. Louis with the code: MPRIME). C & I Loan Rate covers the period from Q3-1986 to Q2-2017, thus extended backwards and onwards using MPRIME first differentials. Lending rate to households weighted average of personal loan rate and mortgage rate (see Federal Reserve Bank of St. Louis with the code: MORTGAGE30US). Personal loan rate is the arithmetic average of '24-month Personal Loans' 'Interest Rates on Credit Card Plans' and '48-month New Auto Loans' (see Federal Reserve Bank of St. Louis with the codes: TERMCBPER24NS, TERMCBCCALLNS, TERMCBAUTO48NS, respectively). Interest Rates on Credit Card Plans extended backwards from Q4-1994 using the changes in the average of the other two loan rates. The weight for 'Household Total Mortgage Liability' (HHMSDODNS) and for personal loan rate – 'Consumer Credit Liability' (HCCSDODNS) are taken from the Federal Reserve Bank of St. Louis with the codes in the parentheses.

	The weights for loans to non-financial organizations and households are the outstanding amount of loans that are explained broadly in the part for Total Loans, below. Federal Reserve Bank of St. Louis's webpage is: https://fred.stlouisfed.org/.
Consumption	Real Personal Consumption Expenditures is a quarterly data for the period from Q1-1972 to Q3-2018. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: PCECC96
CPI	Consumer Price Index is a quarterly data for all urban consumers. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: CPIAUCSL
EBP	Excess Bond Premium is a monthly data for the period from January-1973 to December-2018. I took the average of the corresponding months and turned it to the quarterly data. The original data is the 07-January-2019 version that is downloaded from: www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html
Employment	Civilian Labor Force, Thousands of Persons, Quarterly, Seasonally Adjusted. Federal Reserve Bank of St. Louis with the code: CLF16OV
GDP	Real Gross Domestic Product is a is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: GDPC1
Investment	Real Gross Private Domestic Investment is a quarterly data for the period from Q1-1972 to Q3-2018. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: GPDIC1
NFCI	Chicago Fed's National Financial Conditions index is a weekly data. Quarterly version is calculated as an arithmetic average of the corresponding weeks. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: NFCI

ROA	Return On Average Assets for all US banks is a quarterly data for the period from Q2-1990 to Q3-2018. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: USROA.
SLOOS	Senior Loan Officer Opinion Survey on Bank Lending Practices is a quarterly data for the period Q2-1990 to Q3-2018. The original data is the October-2018 release that is downloaded from: https://www.federalreserve.gov/data/sloos/sloos-201810-chart-data.htm From the original data I use the series on Panel 1 which is the Net Percentage of Domestic Respondents Tightening Standards for Commercial and Industrial Loans, with subsection Large and Medium firms.
Total Loans	– is the sum of nominal amounts (millions of dollars) of loans to households and non-financial organizations. I construct the series in the light of Appendix B of Gambetti & Musso (2012). The ingredients of the addends and their codes are given below: HH and NFC loans are 'Households and nonprofit organizations; loans; liability' (FL154123005.Q) and 'Nonfinancial business; loans; liability' (FL144123005.Q). The series are 6-December-2018 release that is downloaded from: https://www.federalreserve.gov/releases/z1/current/default.htm The original data is not seasonally adjusted. Therefore, I calculate the seasonal adjustment index using the seasonal (CMDEBT) and non-seasonal (TCMILBSHNO) data for HHs Credit Market Instruments Liability . For NFCs seasonal (BCNSDODNS) and non-seasonal (TCMILBSNNCB) Nonfinancial Corporate Business; Credit Market Instruments; Liability are exploited. The data is available in the webpage of Federal Reserve Bank of St. Louis with the given codes in the parentheses. Federal Reserve Bank of St. Louis's webpage is: https://fred.stlouisfed.org/.
UNRATE	Civilian Unemployment Rate, Percent, Quarterly, Seasonally Adjusted. Federal Reserve Bank of St. Louis with the code: UNRATE

Wage Hourly Earnings: Private Sector for the United States, Index 2015=100, Quarterly, Seasonally Adjusted. Federal Reserve Bank of St. Louis with the code: LCEAPR01USQ661S

Germany

BLS Bank Lending Survey is a quarterly data. Pure supply is the average of the 12 given series below:

1) BLS.Q.DE.ALL.NBC.E.Z.B3.ST.S.FNET – Credit standards-Impact of non-bank competition-Enterprise.
2) BLS.Q.DE.ALL.MFC.E.Z.B3.ST.S.FNET – Credit standards-Impact of market financing competition-Enterprise.
3) BLS.Q.DE.ALL.MF.E.Z.B3.ST.S.FNET – Credit standards-Impact of ability to access market financing-Enterprise.
4) BLS.Q.DE.ALL.LP.E.Z.B3.ST.S.FNET – Credit standards-Impact of liquidity position-Enterprise.
5) BLS.Q.DE.ALL.CP.E.Z.B3.ST.S.FNET – Credit standards-Impact of capital position-Enterprise.
6) BLS.Q.DE.ALL.BC.E.Z.B3.ST.S.FNET – Credit standards-Impact of bank competition-Enterprise.
7) BLS.Q.DE.ALL.NBC.H.H.B3.ST.S.FNET – Credit standards-Impact of non-bank competition-Household.
8) BLS.Q.DE.ALL.BSC.H.H.B3.ST.S.FNET – Credit standards-Impact of cost of funds and balance sheet constraints-Household.
9) BLS.Q.DE.ALL.BC.H.H.B3.ST.S.FNET – Credit standards-Impact of bank competition-Household.
10) BLS.Q.DE.ALL.NBC.H.C.B3.ST.S.FNET – Credit standards-Impact of non-bank competition-Household.
11) BLS.Q.DE.ALL.BSC.H.C.B3.ST.S.FNET – Credit standards-Impact of cost of funds and balance sheet constraints-Household.
12) BLS.Q.DE.ALL.BC.H.C.B3.ST.S.FNET – Credit standards-Impact of bank competition-Household.

The data can be downloaded from the page of Statistical Data Warehouse of ECB: https://sdw.ecb.europa.eu/home.do

CLR Composite Lending Rate is constructed in the light of Appendix B of Bijsterbosch & Falagiarda (2014). I calculate the data as a weighted average of lending rate to households for house purchase and lending rate to non-financial corporations. The interest rates and the corresponding weights are the quarterly average of the monthly data and can be downloaded from the page of Statistical Data Warehouse of ECB.

The interest rates for HHs: MIR.M.DE.B.A2C.A.R.A.2250.EUR.N & the weights for HHs: BSI.M.DE.N.A.A22.A.1.U2.2250.Z01.E. The interest rates for NFCs: MIR.M.DE.B.A2A.A.R.A.2240.EUR.N & the weights for NFCs: BSI.M.DE.N.A.A20.A.1.U2.2240.Z01.E

The webpage: https://sdw.ecb.europa.eu/home.do

Deflator Prices are given with quarterly GDP Implicit Price Deflator. The data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: DEUGDPDEFQISMEI

Employment Total employment - Total - All activities, Hours worked. Quarterly data taken from Statistical Data Warehouse of ECB: https://sdw.ecb.europa.eu/home.do Code: ENA.Q.Y.DE.W2.S1.S1._Z.EMP._Z._T._Z.HW._Z.N

FIBOR Germany 3-month Interbank Rate is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: IR3TIB01DEQ156N

Federal Reserve Bank of St. Louis's webpage is: https://fred.stlouisfed.org/.

GDP Real Gross Domestic Product – GDP at market prices is taken from Statistical Data Warehouse page of ECB. The code for the real GDP: MNA.Q.Y.DE.W2.S1.S1.B.B1GQ._Z._Z._Z.EUR.LR.N

The webpage: https://sdw.ecb.europa.eu/home.do

Loan Demand – is a quarterly data constructed from the bank lending survey of ECB. The index is the average of the 9 given series below:

1) BLS.Q.DE.ALL.DR.E.Z.B3.ZZ.D.FNET – Impact of debt refinancing/ restructuring/ renegotiation-Enterprise.
2) BLS.Q.DE.ALL.DSI.E.Z.B3.ZZ.D.FNET – Impact of debt securities issuance-Enterprise.
3) BLS.Q.DE.ALL.FIX.E.Z.B3.ZZ.D.FNET – Impact of fixed investment-Enterprise.
4) BLS.Q.DE.ALL.IF.E.Z.B3.ZZ.D.FNET – Impact of internal financing-Enterprise.
5) BLS.Q.DE.ALL.INV.E.Z.B3.ZZ.D.FNET – Impact of inventories and working capital-Enterprise.
6) BLS.Q.DE.ALL.CCF.H.H.B3.ZZ.D.FNET – Impact of consumer confidence -Household.
7) BLS.Q.DE.ALL.HMP.H.H.B3.ZZ.D.FNET – Impact of housing market prospects-Household.
8) BLS.Q.DE.ALL.CCF.H.C.B3.ZZ.D.FNET – Impact of consumer confidence -Household.
9) BLS.Q.DE.ALL.SDC.H.C.B3.ZZ.D.FNET – Impact of spending on durable consumer goods-Household.

The data can be downloaded from the page of Statistical Data Warehouse of ECB: https://sdw.ecb.europa.eu/home.do

ROA — Return On Assets for German banks is a yearly data for the period from 2003 to 2015. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis via the code: DDEI05DEA156NWDB.

Total Loans – is the sum of the outstanding amounts (millions of dollars) of loans at the end of the period to households and non-financial corporations. The series are adjusted to sales and securitizations.

I construct the series in the light of Appendix B of Gambetti & Musso (2012). The data is seasonally adjusted and can be downloaded from the page of Statistical Data Warehouse of ECB: https://sdw.ecb.europa.eu/home.do

The code for HHs: BSI.M.DE.Y.A.A20T.A.1.U2.2250.Z01.E. The code for NFCs: BSI.M.DE.Y.A.A20T.A.1.U2.2240.Z01.E

UNRATE Harmonized Unemployment Rate: Total: All Persons for the Euro Area, Percent, Quarterly, Seasonally Adjusted. Federal Reserve Bank of St. Louis with the code: LRHUTTTTDEQ156S

Wage Hourly Earnings: Private Sector for the Euro Area, Index 2015=100, Quarterly, Seasonally Adjusted. Federal Reserve Bank of St. Louis with the code: LCEAPR01DEQ661S

Euro Area

BLS Bank Lending Survey is a quarterly data. Pure supply is the average of the 12 given series below:

1) BLS.Q.U2.ALL.NBC.E.Z.B3.ST.S.BWFNET – Credit standards-Impact of non-bank competition-Enterprise
2) BLS.Q.U2.ALL.MFC.E.Z.B3.ST.S.BWFNET – Credit standards-Impact of market financing competition-Enterprise
3) BLS.Q.U2.ALL.MF.E.Z.B3.ST.S.BWFNET – Credit standards-Impact of ability to access market financing-Enterprise
4) BLS.Q.U2.ALL.LP.E.Z.B3.ST.S.BWFNET – Credit standards-Impact of liquidity position-Enterprise
5) BLS.Q.U2.ALL.CP.E.Z.B3.ST.S.BWFNET – Credit standards-Impact of capital position-Enterprise
6) BLS.Q.U2.ALL.BC.E.Z.B3.ST.S.BWFNET – Credit standards-Impact of bank competition-Enterprise
7) BLS.Q.U2.ALL.NBC.H.H.B3.ST.S.BWFNET – Credit standards-Impact of non-bank competition-Household
8) BLS.Q.U2.ALL.NBC.H.C.B3.ST.S.BWFNET – Credit standards-Impact of non-bank competition-Household
9) BLS.Q.U2.ALL.BSC.H.H.B3.ST.S.BWFNET – Credit standards-Impact of cost of funds and balance sheet constraints-Household
10) BLS.Q.U2.ALL.BSC.H.C.B3.ST.S.BWFNET – Credit standards-Impact of cost of funds and balance sheet constraints-Household
11) BLS.Q.U2.ALL.BC.H.H.B3.ST.S.BWFNET – Credit standards-Impact of bank competition-Household

12) BLS.Q.U2.ALL.BC.H.C.B3.ST.S.BWFNET – Credit standards-Impact of bank competition-Household

The data can be downloaded from the page of Statistical Data Warehouse of ECB: https://sdw.ecb.europa.eu/home.do

CLR Composite Lending Rate is constructed in the light of Appendix B of Bijsterbosch & Falagiarda (2014). I calculate the data as a weighted average of lending rate to households for house purchase and lending rate to non-financial corporations. The interest rates and the corresponding weigths are the quarterly average of the monthly data and can be downloaded from the page of Statistical Data Warehouse of ECB.

The interest rates for HHs: MIR.M.U2.B.A2C.A.R.A.2250.EUR.N & the weights for HHs: BSI.M.U2.N.A.A22.A.1.U2.2250.Z01.E. The interest rates for NFCs: MIR.M.U2.B.A2A.A.R.A.2240.EUR.N & the weights for NFCs: BSI.M.U2.N.A.A20.A.1.U2.2240.Z01.E

The webpage: https://sdw.ecb.europa.eu/home.do

Deflator Prices are given with quarterly GDP Price Deflator. The data is accessible in the webpage of Federal Reserve Bank of St. Louis with the code: NAGIGP01EZQ661S

Employment Total employment - Total - All activities, Hours worked. Quarterly data taken from Statistical Data Warehouse of ECB: https://sdw.ecb.europa.eu/home.do Code: ENA.Q.Y.U2.W2.S1.S1._Z.EMP._Z._T._Z.HW._Z.N

EONIA Euro Overnight Index Average is used as a short-term interest rate. It is accessible in the webpage of Statistical Data Warehouse of ECB via the code: FM.Q.U2.EUR.4F.MM.EONIA.HSTA

Federal Reserve Bank of St. Louis's webpage is: https://fred.stlouisfed.org/

GDP Real Gross Domestic Product (CLVMNACSCAB1GQEA) is downloaded from the page of Federal Reserve Bank of St. Louis with the given.

The webpage: https://fred.stlouisfed.org/

Loan Demand – is a quarterly data constructed from the bank lending survey of ECB. The index is the average of the 9 given series below:

1) BLS.Q.U2.ALL.DR.E.Z.B3.ZZ.D.BWFNET – Impact of debt refinancing/ restructuring/ renegotiation-Enterprise.
2) BLS.Q.U2.ALL.DSI.E.Z.B3.ZZ.D.BWFNET – Impact of debt securities issuance-Enterprise.
3) BLS.Q.U2.ALL.FIX.E.Z.B3.ZZ.D.BWFNET – Impact of fixed investment-Enterprise.
4) BLS.Q.U2.ALL.IF.E.Z.B3.ZZ.D.BWFNET – Impact of internal financing-Enterprise.
5) BLS.Q.U2.ALL.INV.E.Z.B3.ZZ.D.BWFNET – Impact of inventories and working capital-Enterprise.
6) BLS.Q.U2.ALL.CCF.H.C.B3.ZZ.D.BWFNET – Impact of consumer confidence -Household.
7) BLS.Q.U2.ALL.HMP.H.H.B3.ZZ.D.BWFNET – Impact of housing market prospects-Household.
8) BLS.Q.U2.ALL.CCF.H.H.B3.ZZ.D.BWFNET – Impact of consumer confidence -Household.
9) BLS.Q.U2.ALL.SDC.H.C.B3.ZZ.D.BWFNET – Impact of spending on durable consumer goods-Household.

The data can be downloaded from the page of Statistical Data Warehouse of ECB: https://sdw.ecb.europa.eu/home.do

ROA Return On Assets for Euro Area banks is a yearly data for the period from 2003 to 2015. The original data is accessible in the webpage of Federal Reserve Bank of St. Louis via the code: DDEI05EZA156NWDB.

Total Loans – is the sum of the outstanding amounts (millions of dollars) of loans at the end of the period to households and non-financial corporations. The series are adjusted to sales and securitizations.

I construct the series in the light of Appendix B of Gambetti & Musso (2012). The data is seasonally adjusted and can be downloaded from the page of Statistical Data Warehouse of ECB.

	The code for HHs: BSI.M.U2.Y.U.A20T.A.1.U2.2250.Z01.E. The code for NFCs: BSI.M.U2.Y.U.A20T.A.1.U2.2240.Z01.E The webpage: https://sdw.ecb.europa.eu/home.do
UNRATE	Harmonized Unemployment Rate: Total: All Persons for the Euro Area, Percent, Quarterly, Seasonally Adjusted. Federal Reserve Bank of St. Louis with the code: LRHUTTTTEZQ156S
Wage	Hourly Earnings: Private Sector for the Euro Area, Index 2015=100, Quarterly, Seasonally Adjusted. Federal Reserve Bank of St. Louis with the code: LCEAPR01EZQ661S

APPENDIX B - Equations

Appendix B incorporates an extended version of equations that are shortly shown in the body of the paper.

Equation 6

$E(Z_t\, u_t') = E(Z_t\, (H\, e_t)') =$ $\qquad$ $u_t' = (H\, e_t)' = e_t'\, H'$

$= E(Z_t\, e_t'\, H') = [Z_t\, e_t^c \quad Z_t\, e_t^r]_{1x2} \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}_{2x2}' =$ $\qquad$ since $e_t = [e_t^c \quad e_t^r]'$

$= [\phi \quad 0]_{1x2} \begin{bmatrix} H_{11} & H_{21} \\ H_{12} & H_{22} \end{bmatrix}_{2x2} =$ $\qquad$ because of equation 4 & 5

$= [\phi\, H_{11} \quad \phi\, H_{21}]_{1x2} = \phi\, [H_{11} \quad H_{21}]_{1x2}$

Equation 7

$E(Z_t\, u_t') = \Sigma_{Zu'} = [\Sigma_{Zu_1} \quad \Sigma_{Zu_2}]_{1x2} = [\phi\, H_{11} \quad \phi\, H_{21}]_{1x2},$ $\qquad$ see equation 6 above,

i) $\quad \Sigma_{Zu_1} = \phi\, H_{11}$

ii) $\quad \Sigma_{Zu_2} = \phi\, H_{21},$ $\qquad$ consequently,

$H_{11} = \left(\Sigma_{Zu_2}^{-1}\, \Sigma_{Zu_1}\right) H_{21}$

Equation 9

$\Pi u_t = E(Z_t\, u_t')\ [E(\mathrm{u}_t\, u_t')]^{-1}\, u_t =$ $\qquad$ from $u_t = H\, e_t$, we get

$= E(Z_t\, (H\, e_t)')\, [E(H\, e_t\, (H\, e_t)')]^{-1}\, u_t =$ $\qquad$ $(H\, e_t)' = e_t'\, H'$, thus

$= E(Z_t\, e_t'\, H')\ [E(H\, e_t\, e_t'\, H')]^{-1}\, u_t =$ $\qquad$ equation 6 & 8 yield then

$= \phi\, [H_{11} \quad H_{21}]_{1x2}\, [H\, D\, H']^{-1}\, u_t =$

$= \phi\ [H_{11} \quad H_{21}]_{1x2}\ (H')^{-1} D^{-1} H^{-1}\ u_t =$ $\qquad H^{-1}\ u_t = e_t$

$= \phi\ \begin{bmatrix} H_{11} \\ H_{21} \end{bmatrix}'\ (H')^{-1}\ D^{-1}\ e_t =$ $\qquad A'(B')^{-1} = (B^{-1}\ A)'$, so

$$= \phi\ (H^{-1} \begin{bmatrix} H_{11} \\ H_{21} \end{bmatrix})'\ D^{-1}\ e_t = \phi\ (\begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}^{-1} \begin{bmatrix} H_{11} \\ H_{21} \end{bmatrix})'\ D^{-1}\ e_t =$$

$$= \phi\ (\frac{1}{H_{11}\ H_{22} - H_{12}\ H_{21}} \begin{bmatrix} H_{22} & -H_{12} \\ -H_{21} & H_{11} \end{bmatrix} \begin{bmatrix} H_{11} \\ H_{21} \end{bmatrix})'\ D^{-1}\ e_t =$$

$= \phi\ \begin{bmatrix} 1 \\ 0 \end{bmatrix}'\ D^{-1}\ e_t = \phi\ [1 \quad 0]\ D^{-1}\ e_t =$ $\qquad$ comprise D from eq. 8,

$$= \phi\ [1 \quad 0] \begin{bmatrix} \sigma_{e_c}^2 & 0 \\ 0 & \sigma_{e_r}^2 \end{bmatrix}^{-1} e_t = \phi\ [1 \quad 0] \begin{bmatrix} \frac{1}{\sigma_{e_c}^2} & 0 \\ 0 & \frac{1}{\sigma_{e_r}^2} \end{bmatrix} e_t =$$

$= \phi\ \begin{bmatrix} \frac{1}{\sigma_{e_c}^2} & 0 \end{bmatrix}\ e_t = \phi\ \begin{bmatrix} \frac{1}{\sigma_{e_c}^2} & 0 \end{bmatrix}_{1x2} \begin{bmatrix} e_t^c \\ e_t^r \end{bmatrix}_{2x1}$ $\qquad$ remember $e_t = [e_t^c \quad e_t^r]'$

$$= \left(\frac{\phi}{\sigma_{e_c}^2} \right) e_t^c$$

Equation 10

$\Pi e_t = \mathrm{E}(\mathrm{Z_t\ e_t'})\ \ [\mathrm{E}(\mathrm{e_t\ e_t'})]^{-1}\ e_t =$ $\qquad$ from equations 4, 5 & 8,

$$= [\phi \quad 0]_{1x2}\ [D]^{-1}\ e_t =$$

$$= [\phi \quad 0] \begin{bmatrix} \sigma_{e_c}^2 & 0 \\ 0 & \sigma_{e_r}^2 \end{bmatrix}^{-1} e_t = [\phi \quad 0] \begin{bmatrix} \frac{1}{\sigma_{e_c}^2} & 0 \\ 0 & \frac{1}{\sigma_{e_r}^2} \end{bmatrix} e_t =$$

$$= \begin{bmatrix} \frac{\phi}{\sigma_{e_c}^2} & 0 \end{bmatrix}_{1x2} \begin{bmatrix} e_t^c \\ e_t^r \end{bmatrix}_{2x1}$$

$$= \left(\frac{\phi}{\sigma_{e_c}^2} \right) e_t^c$$