Narodowy Bank Polski

NBP Working Paper No. 246

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Economic Institute
Warsaw, 2016

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Acknowledgements: We are grateful to an anonymous referee and the participants of the seminar held on 27 November 2015 at Narodowy Bank Polski for useful comments which improved the paper. The usual disclaimer applies.

Published by:
Narodowy Bank Polski
Education & Publishing Department
ul. Świętokrzyska 11/21
00-919 Warszawa, Poland
phone +48 22 185 23 35
www.nbp.pl

ISSN 2084-624X

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Abstract: We estimated a structural vector autoregressive (SVAR) model describing the links between a banking sector and a real economy. We proposed a new method to verify robustness of impulse-response functions in a SVAR model. This method applies permutations of the variable ordering in a structural model and uses the Cholesky decomposition of the error covariance matrix to identify parameters. Impulse response functions are computed for all permutations and are then combined. We explored the method in practice by analyzing the macro-financial linkages in the Polish economy. Our results indicate that the combined impulse response functions are more uncertain than those from a single specification ordering but some findings remain robust. It is evident that macroeconomic aggregate shocks and interest rate shocks have a significant impact on banking variables.

Key words: vector autoregression, Cholesky decomposition, combined impulse response, banking sector, real economy.

JEL codes: C32, C51, C52, C87, E44, E58.

Introduction

We analyze the linkages between the banking sector and the real economy within a structural vector autoregressive framework (SVAR). There is an ongoing debate on the appropriate structure of SVAR models containing banking and real variables. Various methods are used to identify shocks affecting the real economy through the credit channel as an alternative to the interest rate channel. These methods include zero short-term restrictions (e.g., Bernanke, 1986), long-term restrictions (e.g., Caporale et al., 2014), and sign restrictions (e.g., Meeks, 2012) – in SVAR models, long-term identifying restrictions in vector error correction models (VECM) (e.g., Iacoviello and Minetti, 2008), as well as shock variables identified outside the VAR (e.g. shocks estimated using lending survey data; Ciccarelli et al., 2015).

An application of the short-term zero restrictions is the most common approach due to its relative simplicity and mild assumptions on the contemporaneous relationships between the variables of the SVAR system. These mild restrictions leave large space for the effects driven by economic data. On the other hand, economic assumptions in such models introduce the risk of misspecified restrictions and assumption-driven results.

In this paper, we proposed a simple robustness analysis for SVAR models with short-term zero restrictions. A popular approach to deal with uncertainty surrounding economic structure of the model is to use the Cholesky decomposition of the error covariance matrix and to ortogonalize the structural shocks. This method depends on the ordering of variables in a VAR model. In the Cholesky decomposition, the variables placed first affect other variables immediately and the other variables affect those placed first only with a lag. Accordingly, the ordering of variables may have a crucial impact on the impulse-response functions in the estimated SVAR model. Indeed, the contemporaneous responses to shocks are usually the strongest and they tend to die out over time. Our approach is to account for the differences in effects of shocks depending on the ordering of variables. We proposed a method to mix impulse response functions from different model specifications and to build a 'combined' impulse-response function robust to the ordering of variables (cf., Koop, Pesaran, and Potter, 1996; Pesaran and Shin, 1998). Our empirical results reveal that some shock effects identified using the traditional recursive method or the generalized impulse response functions of Pesaran and Shin (1998) are based on strong assumptions and are not robust to changing model specifications. The 'combined' impulse response analysis identifies much fewer links between the real and financial sectors than do the standard approaches. The interest rate affects banking and real variables while the credit market conditions have no statistically significant impact on the macroeconomic variables.

There exist many identification methods for SVAR models. The methods include short and long-term restrictions, sign restrictions, and the identification-through-heteroscedasticity method among others. Each of these approaches has strengths and weaknesses (e.g., Fry and Pagan, 2011; Kilian, 2013). Focusing on just-identified recursive restrictions facilitates the analysis. For example, the total number of possible short-term zero restrictions for eight and more variables in a VAR model is so large that it prohibits investigating all of them. Therefore, we combine only recursive identification schemes and limit the number of investigated specifications in this way. The recursive method is also used when economic theory does not provide a clear view of a structural model. In this research, we assume no preference regarding the economic structure of our model of macro-financial linkages. Permuting the ordering of variables in the recursive method enables verifying robustness of dependencies between economic variables. This can be done by verifying some extreme restrictions (when linkages between the first and the last variable are analyzed) and milder restrictions (when linkages between two neighboring variables are analyzed). Moreover, combining recursive restrictions is a useful procedure when the aim is to search for significant linkages between economic variables rather than to identify specific economic shocks (e.g., Diebold and Yilmaz, 2009; Klößner and Wagner, 2014). In this paper, we do not identify any specific economic or financial shocks, but instead we search for linkages between banking and macroeconomic variables.

The paper is structured as follows. We explained the links between the banking and real sectors in Section 1. The econometric method is presented in Section 2. Section 3 contains empirical results. We end up with conclusions.

Section 1. Dependence between banking and real sectors

Banks provide various services to the financial and real sectors of the economy. Channeling financial resources between savers and borrowers through deposit and credit intermediation is its most important role and it rests in creating liquidity in the economy. Other major economic functions of banks include credit quality assessment and improvement, settlement of payments, and managing the maturity mismatch between assets and liabilities. All these functions generate wealth effects for households and corporations in the long run. The short-run effects are also intense, as the banking sector influences the economy through the interest rate and credit channels. These effects are managed by changing the interest rates or by adjusting the lending and borrowing volumes, respectively. Such adjustments affect both consumption and investment. In turn, the real sector also has a strong impact on financial sector activities through the aggregate growth and unemployment, as it affects the demand for loans and supply of deposits, the quality of loans, asset prices, and hence the value of collateral. It is evident that financial and real sectors are interconnected.

The most popular tool to analyze the linkages between business and financial cycles in the short and medium run is a vector autoregressive model (VAR). Most studies utilizing VARs aim at measuring the response of macroeconomic variables to shocks in the financial sector, including credit supply and demand shocks, interest rate shocks, and asset price shocks. The two prevailing tools used in these investigations are impulse-response analysis and forecast error variance decomposition. They are often accompanied by analyses of causality between the real and financial variables. A few studies present historical decompositions of macroeconomic aggregates, most importantly GDP, to observe the changing factors influencing these aggregates over time. Table 1 in Appendix presents selected research.

The typical variables used in these analyses are: (1) macroeconomic aggregates like GDP, price indices, and unemployment, (2) banking sector measures including credit or deposit aggregates, interest rate spreads, measures of loan quality and financial position of banks, (3) policy instruments, e.g. the exchange rate and the short-term market interest rate. The variables are either investigated in log-levels or log-differences.

Most research analyzes the impact of banking sectors on real sectors through two channels (apart from the analyses of interest rate channel not necessarily linked to the role of the banking sector), namely the bank lending channel (i.e., credit view) and the balance sheet channel (i.e., balance sheet view). The credit view assumes that credit supply shocks, directly affecting consumption and investment in the real economy, are caused by factors related to financial situation of banks. These factors include changes to lending policies of banks, adjustments in the regulatory framework, modifications of monetary policies, as well as funding shocks to banks, or even banking crises. In line with the balance sheet view, financial conditions of households and corporations affect their ability to borrow depending on the value of their eligible collateral, credit risk, monitoring costs for banks, price of loans, and other similar factors.

The economic identification of the above-mentioned shocks is of crucial importance in SVAR models. Economic theories are often suitable and enable researchers to impose short-term or long-term restrictions on parameters in VAR models. When well-established economic theories are unavailable, an ad-hoc approach is to use recursive restrictions. This is done by using the Cholesky decomposition of error covariance matrix to identify structural shocks in SVAR models (e.g., Bernanke, 1986; Gilchrist and Zakrajšek, 2012). Importantly, analysts often consider alternative restriction schemes to assess robustness of their results to different model specifications. Unfortunately, the choice of alternative identifying restrictions is arbitrary and the number of alternative models considered by practitioners is usually limited. Hence, this leaves some room for model misspecification. Other identification methods include sign restrictions in Bayesian VAR models, cointegrating restrictions in vector error correction models (VECM), and measures of shocks constructed outside the VAR model (e.g., by using financial instruments or survey data) (Chrystal and Mizen, 2002; Meeks, 2012; Bassett et al., 2014, and other research listed in Table 1).

Identified impulse responses demonstrate relationships between the endogenous variables in a VAR model. The results obtained so far in the literature suggest that credit shocks have a strong influence on real economic growth, especially during financial crises. Depending on the study, credit shocks were responsible for 10-20% of a decrease in GDP in the euro area, the UK and the US, 30-50% of production slowdown in Austria, Canada, and the UK, and up to 60% fall in real output in the US during the recent global financial crisis (Bernanke, 1986; Berkelmans, 2005; Gambetti and Musso, 2012; Meeks, 2012; Bezemer and Grydaki, 2014; Finlay and Jääskelä, 2014; Halvorsen and Jacobsen, 2014). Financial shocks caused up to 50% of volatility in GDP growth in the US and in the G7 countries (Jermann and Quadrini, 2012; Magkonis and Tsopanakis, 2014). The identification of banking channels responsible for real effects revealed that credit channel was active in Canada, Finland, the UK, and in the euro area. In turn, the balance sheet channel was found important in the US and Germany (Chrystal and Mizen, 2002; Safaei and Cameron, 2003; Lown and Morgan, 2006; Iacoviello and Minetti, 2008; Tamási and Világi, 2011; Musso et al., 2011; Ciccarelli et al., 2015).

It is important to precisely specify the banking variables to be considered. It was found that the measures of credit rationing better explained real output than credit spreads. On the other hand, default risk affected credit spreads and influenced the economy (Hall, 2011; Bassett et al., 2014; Caporalle et al., 2014). Several studies found lending market activity (measured with credit spread) to lead or to ’predict’ the real business cycle (Balke, 2000; Gilchrist et al., 2009; Gilchrist and Zakrajšek, 2012; Karfakis, 2013). The interactions between banking and real sectors in Poland have been rarely investigated with SVAR models (e.g., Wdowiński, 2013). Many investigations focused mainly on the role of monetary policy and its effects on the real economy, but the role of banking variables has remained unexplored (Brzoza-Brzezina, 2002; Waszkowski and Czech, 2012; Haug et al., 2013; Kapuściński et al., 2014; Bogusz et al., 2015). This further motivates our research.

Section 2. Combining results from SVAR models

A typical VAR model explaining the linkages between banking and real sectors in a small open economy contains three sets of variables. The first set includes aggregate macroeconomic variables, such as GDP or elements of final demand (e.g., consumption and investments), and price index. The second set is composed of financial variables like a monetary aggregate, a value of banking loans, an interest rate spread, and other measures of banking sector activity. The third set consists of financial market variables usually related to monetary policy instruments, e.g. the short-term interest rate and the exchange rate. This set may also consider instruments of macroprudential policy, e.g. regulatory capital buffers, liquidity measures, and leverage.

The identifying short-run restrictions are usually imposed in the form of zero restrictions under certain ordering of variables. The typical ordering is that the variables from the first set (macroeconomic aggregates) immediately affect all other variables in the model and the variables from the second set (banking sector variables) affect the variables from the third set (policy variables). However, the effects in the opposite direction are only possible with a lag. The identifying conditions are imposed by zero recursive restrictions in the form of Cholesky decomposition of the error covariance matrix.

Our aim is to assess robustness of a given SVAR specification by following two approaches. First, we consider all possible orderings of the endogenous variables that are specified in a given VAR model. Second, we fix the order of selected variables and consider all orderings of the remaining variables. In either case we identify the model by using the Cholesky decomposition and calculate impulse responses. The respective impulse responses from different permutations (variable orderings) are then combined into the augmented impulse response. In this approach, some variable orderings may seem economically implausible but they are observationally equivalent and as such are included in the augmented impulse response. This corresponds to the situation where a researcher has no prior knowledge of the dependencies between real and financial variables. The combination of impulse responses is then used to identify the most invincible links between the real and financial sectors. By using permutations of the variable ordering, we gather additional information on the robustness of the analyzed impulse responses.

We introduce our method below. Let us consider the vector autoregressive model (Lütkepohl, 2007, pp. 18-40):

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t, \qquad t = 1,2,\dots,T \tag{1}$$

where $\boldsymbol{y}_t = (\boldsymbol{w}'_t, \boldsymbol{x}'_t, \boldsymbol{z}'_t)'$ is a three-block vector $(m \times 1)$, where $\boldsymbol{w}_t$ is a vector of macroeconomic aggregates and prices, $\boldsymbol{x}_t$ is a vector of banking sector variables, and $\boldsymbol{z}_t$ is a vector of financial market variables, $\boldsymbol{\Phi}_i$ are fixed $(m \times m)$ coefficient matrices, $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \dots, \varepsilon_{mt})'$ is a Gaussian white noise process, $E(\boldsymbol{\varepsilon}_t) = 0$, $E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t) = \boldsymbol{\Sigma}_\varepsilon$, $E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_s) = 0$ for $t \neq s$, and $\boldsymbol{\Sigma}_\varepsilon$ is the covariance matrix of the error term.

Under the stability assumption of a VAR model (1), we can use the infinite moving average representation to describe that model:

$$\boldsymbol{y}_t = \boldsymbol{c} + \textstyle\sum_{i=0}^{\infty} \boldsymbol{A}_i \boldsymbol{\varepsilon}_{t-i} \tag{2}$$

The coefficient matrices $\boldsymbol{A}_i$ can be obtained from the following recursive formula:

$$\boldsymbol{A}_i = \textstyle\sum_{j=1}^{i} \boldsymbol{A}_{i-j} \boldsymbol{\Phi}_j, \qquad i = 1,2,\ldots \tag{3}$$

with $\boldsymbol{A}_0 = \boldsymbol{I}_m$ and $\boldsymbol{\Phi}_j = 0$ for $j > p$. The constant term can be obtained from $\boldsymbol{c} = \left(\boldsymbol{I}_m - \boldsymbol{A}_1 - \cdots - \boldsymbol{A}_p\right)^{-1} \boldsymbol{\mu}$.

The traditional approach to compute impulse-response functions has been suggested by Sims (1980). The impulse response function (IRF) of a one standard deviation shock to the ith variable in $\boldsymbol{y}_t$ on the jth variable in $\boldsymbol{y}_{t+n}$ is given by:

$$\psi_{ji}(n) = \boldsymbol{e}_j' \boldsymbol{A}_n \boldsymbol{P} \boldsymbol{e}_i, \qquad n = 0,1,2,\ldots \tag{4}$$

where $\boldsymbol{e}_i$ is a column selection vector with unity as the ith element and zeros otherwise, $\boldsymbol{P}$ is a lower triangular matrix obtained by decomposing the covariance matrix $\boldsymbol{\Sigma}_\varepsilon$ using the Cholesky method so that $\boldsymbol{P}\boldsymbol{P}' = \boldsymbol{\Sigma}_\varepsilon$.

In turn, the generalized impulse response function (GIRF) suggested by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) is given by:

$$\psi_{ji}^{g}(n) = \boldsymbol{e}_j' \sigma_{ii}^{-1/2} \boldsymbol{A}_n \boldsymbol{\Sigma}_\varepsilon \boldsymbol{e}_i, \qquad n = 0,1,2,\ldots \tag{5}$$

where σ_{ii} is the iith element of $\boldsymbol{\Sigma}_{\varepsilon}$. One problem with impulse response functions calculated using the Cholesky decomposition is that their values may heavily depend on the order of equations (and hence variables) in the SVAR model and in the covariance matrix $\boldsymbol{\Sigma}_{\varepsilon}$. An important advantage of GIRF over a standard impulse response function is that the former is invariant to the ordering of equations in the VAR. One disadvantage is that the method treats all the shock variables as if they were ordered first in a VAR. In practice, GIRFs generate responses that are larger and more frequently statistically significant than ordinary IRFs. Therefore, using GIRFs may result in misleading inferences caused by their extreme identification schemes (Kim, 2012).

We proposed an alternative approach to obtain impulse response functions invariant to the ordering of variables. In this approach we combine impulse response functions from all permutations of SVAR orderings. In a SVAR model with m endogenous variables, the number of all variable orderings is equal to the number of permutations, i.e. $m!$ (m factorial). The approach of combining impulse responses is similar to the one considered by Diebold and Yilmaz (2009) and Klößner and Wagner (2014) who computed average generalized forecast error variance decompositions to calculate spillover effects between economic variables, e.g. asset returns. Other algorithms to find the correct identification structure in a SVAR model include the automated general-to-specific model selection procedures and the graph-theoretic causal search algorithm (e.g., Krolzig, 2003; Hoover, 2005).

Let $\{k\}$ denote the kth variable ordering in the m-variable SVAR ($k = 1,2,\dots,m!$) and $\psi_{ji}^{\{k\}}(n)$ be the impulse response function of a one standard deviation shock to the ith element $\boldsymbol{y}_t$ on the jth element of $\boldsymbol{y}_{t+n}$. The combined impulse response function is defined as:

$$\bar{\psi}_{ji}(n) = \frac{1}{m!}\sum_{k=1}^{m!}\psi_{ji}^{\{k\}}(n), \qquad n = 0,1,2,\dots \tag{6}$$

Since we assume no prior knowledge on the ordering of variables in a given SVAR model, we can only use the statistical inference about the likelihood of different specifications of the model. However, for the just-identified SVAR model, i.e. under the Cholesky decomposition, the likelihood function has the same value under each permutation since all orderings are observationally equivalent. Therefore, each impulse response function $\psi_{ji}^{\{k\}}(n)$ has weight equal to $\frac{1}{m!}$ in equation (6).

When in fact we use some prior knowledge and recognize that some orderings have no economic interpretation, we can rule out certain permutations. For example, we can assume that real shocks to $\boldsymbol{w}_t$ may affect all other variables instantaneously, and banking and financial variables in $\boldsymbol{x}_t$ and in $\boldsymbol{z}_t$ can affect $\boldsymbol{w}_t$ only with a lag. In such case the number of Cholesky decompositions is significantly reduced and equals $m^* = (m_x + m_z)!$, where m_w, m_x, m_z are the numbers of variables in vectors $\boldsymbol{w}_t$, $\boldsymbol{x}_t$, and $\boldsymbol{z}_t$, respectively. Then the combined impulse response function is given by:

$$\bar{\psi}_{ji}^{wxz}(n) = \frac{1}{m^*}\sum_{k=1}^{m^*}\psi_{ji}^{\{k\}}(n), \qquad n = 0,1,2,\dots \tag{7}$$

where $\{k\}$ denotes the kth ordering of variables in the m-variable SVAR with variables in $\boldsymbol{w}_t$ always preceding variables in $\boldsymbol{x}_t$ and $\boldsymbol{z}_t$.

In practice, coefficients in matrices $\boldsymbol{\Phi}_i$ and elements of the covariance matrix $\boldsymbol{\Sigma}_\varepsilon$ are unknown and have to be estimated. Therefore the values of the impulse response functions need to be estimated as well. Lütkepohl (1990) provides asymptotic distributions of impulse response function estimates under the assumption of normal disturbances in a VAR. Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) present asymptotic distributions of GIRF estimates.

Let $\mu_{ji}^{\{k\}}(n)$ be the mean estimate of the impulse-response function $\psi_{ji}^{\{k\}}(n)$ in the kth variable ordering and $\sigma_{ji}^{\{k\}}(n)$ be its estimated variance. We can obtain a mean estimate of the combined impulse-response function $\bar{\psi}_{ji}(n)$ defined in (6) by considering a mixture of normally distributed estimates of $\psi_{ji}^{\{k\}}(n)$ for all $k = 1,2,\dots,m!$. The mean of the normal mixture equals:

$$\bar{\mu}_{ji}(n) = \frac{1}{m!}\sum_{k=1}^{m!}\mu_{ji}^{\{k\}}(n), \qquad n = 0,1,2,\dots \tag{8}$$

The variance is given by:

$$\bar{\sigma}_{ji}(n) = \frac{1}{m!}\sum_{k=1}^{m!}\sigma_{ji}^{\{k\}}(n) + \frac{1}{m!}\sum_{k=1}^{m!}\left(\mu_{ji}^{\{k\}}(n) - \bar{\mu}_{ji}(n)\right)^2, \qquad n = 0,1,2,\dots \tag{9}$$

Similarly, $\bar{\psi}_{ji}^{wxz}(n)$ can be approximated with a mixture of normally distributed estimates of $\psi_{ji}^{\{k\}}(n)$ for these permutations $(k = 1,2,\dots,m^*)$ where variables in $\boldsymbol{w}_t$ precede those in $\boldsymbol{x}_t$ and variables in $\boldsymbol{x}_t$ precede those in $\boldsymbol{z}_t$. The mean of this mixture equals:

$$\bar{\mu}_{ji}^{wxz}(n) = \frac{1}{m^*}\sum_{k=1}^{m^*}\mu_{ji}^{\{k\}}(n), \qquad n = 0,1,2,\dots \tag{10}$$

The variance is given by:

$$\bar{\sigma}_{ji}^{wxz}(n) = \frac{1}{m^*}\sum_{k=1}^{m^*} \sigma_{ji}^{\{k\}}(n) + \frac{1}{m^*}\sum_{k=1}^{m^*}\left(\mu_{ji}^{\{k\}}(n) - \bar{\mu}_{ji}(n)\right)^2,\ n = 0,1,2,\dots \tag{11}$$

After combining impulse responses we can proceed with two results. Firstly, we decompose the joint uncertainty $\bar{\sigma}_{ji}(n)$ of the combined impulse response into two components presented in equation (9). The first component $\frac{1}{m!}\sum_{k=1}^{m!} \sigma_{ji}^{\{k\}}(n)$ describes the mean uncertainty of estimated model parameters. The second component $\frac{1}{m!}\sum_{k=1}^{m!}\left(\mu_{ji}^{\{k\}}(n) - \bar{\mu}_{ji}(n)\right)^2$ is related to the dispersion of individual impulse responses in different variable orderings (i.e., permutations). The same interpretation applies to the variance defined in equation (11).

Secondly, the joint uncertainty makes it possible to assess statistically significant impulse responses to orthogonal shocks. We verify the statistical significance of combined impulse response functions. For a normal distribution, the two-sigma confidence interval $\langle\bar{\mu} - 2\bar{\sigma}; \bar{\mu} + 2\bar{\sigma}\rangle$ includes 95.5% of observations. Even if the distribution is not known, at least 75% observations lie inside this interval according to Chebyshev’s inequality. In our empirical analysis, we used the two-sigma interval for the estimated combined impulse-response functions to assess their uncertainty.

Section 3. Empirical results

In this section, we presented results from our empirical analysis. We estimated SVAR models describing the linkages between the banking and real sectors in Poland. The Polish banking sector is interesting to investigate because of its moderate size and simple structure, typical for emerging and less developed economies. It contains around 70 commercial banks and branches of foreign banks. Banking assets account for 86% of GDP and they have been growing rapidly in recent years (PFSA, 2014). The analysis of the banking sector in Poland is facilitated by the fact that banking activities are traditional. The banks concentrate mainly on lending to local companies and households. This may indicate that links between borrowing and lending of banks is much more straightforward than in other developed banking sectors. Another important characteristic of the Polish banking sector over the past 15 years has been its unique robustness against financial crises and bank defaults. Therefore, we may avoid the risk of major structural shocks and nonlinearities caused by crises and other turbulences in the banking sectors of more developed economies by analyzing the Polish economy.

3.1 Data

We have utilized eight variables describing real and financial processes in the Polish economy. Real output (seasonally adjusted GDP) and real housing prices (seasonally adjusted HPI, deflated with consumer price index) describe the developments in the non-financial sector. The variables representing activity of the banking sector include aggregate loan supply to the non-financial sector (LOANS, deflated with the consumer price index), return on bank assets (ROA), capital adequacy ratio (CAR) aggregated over the whole sector, and spread between the lending and deposit rates (SPREAD). The short-term money market rate (RATE), and the real effective exchange rate (REER) control for the monetary policy and external shocks, respectively.

We have used quarterly data in the period Q4, 1997 - Q2, 2014 from Eurostat (GDP), Narodowy Bank Polski (loan aggregate, return on assets, capital adequacy ratio, interest rate spread, money market rate, housing price index, and consumer price index), and from Bank for International Settlements (real effective exchange rate). GDP, loans, housing prices, and the exchange rate are expressed in natural logarithms, and all other variables (the interest rate, spread, bank return on assets, and capital adequacy ratio) are in levels.

3.2 Estimation

We estimated several VAR models for lags up to four and selected the optimal lag-length based on the Schwarz information criterion and the model stability condition. We also calculated probabilities based on Schwarz and Akaike weights, measuring the degree of belief that a certain model is the true data generating model (e.g., Wagenmakers and Farrell, 2004). Table 2 presents main results from different specifications of the VAR model. We decided to use VAR(1), i.e. the model with one lag, and we called it an optimal VAR model.

In the next step, we considered structural identification of impulse responses in the optimal VAR model. Hence, we identified the model by using the Cholesky decomposition of the error covariance matrix. The initial order of variables in the model determined the sequence of structural shocks and their effects on other endogenous variables. This initial order was the following: $\log(GDP)$, $\log(HPI)$, $\log(REER)$, ROA, CAR, $\log(LOANS)$, and $RATE$. The VAR model also included dummies as exogenous variables, adjusting for any remaining seasonal effects and outliers. Dummies were included to control those outlier observations where errors exceeded two standard deviations.

In line with the majority of empirical studies, we assumed that shocks to GDP impact all other variables instantaneously. Shocks to housing prices affect immediately all variables except GDP. We also assumed that the real exchange rate affects immediately the value of loans (a large portion of loans in Poland is indexed to foreign currencies, mainly CHF and EUR), the values of ROA and CAR (through the balance sheet value of assets), and the value of interest rate spread. We further assumed that shocks to bank returns, loans, capital ratio, and spread, respectively, affect the market interest rate directly. Hence, by assumption the financial market variables responded to news more rapidly than the other macroeconomic variables and they influenced the economic aggregates only with a lag.

In Figures 1-4 we presented an inter-sectoral 'map' of statistically significant impulse responses in the model. The green cells (denoted with a '+' sign) represent positive shock reactions, the red cells (denoted with a '–' sign) denote negative reactions, and the grey cells represent a combination of positive and negative reactions. The integers in the cells represent numbers of periods when the reaction to the shock was statistically significant, i.e., the mean response function was at least two standard deviations above or below zero. The fractional number represents the share of observations with statistically significant reaction values. The idea of this map is to visualize all combinations of reactions to shocks in a single figure.

The results we have obtained may seem plausible (cf., Figure 1). A positive macroeconomic output shock gives raise to housing prices (through increased demand for housing), increases the value of loans and bank returns (e.g. through improved financial situation of borrowers), and decreases interest rate spreads (e.g. through the channel of diminishing credit risk and increased collateral value). Similarly, growing housing prices give rise to loans (due to increased values of mortgages and collateral) and boost aggregate demand. The values of ROA and CAR are reduced by the housing shock, most likely due to an increase in total assets (the denominator part of CAR and ROA). In turn, a shock strengthening the currency reduces the value of loans and improves ROA.

We also observed some interesting effects of shocks to banking variables. A positive shock to aggregate loans had a negative impact on bank returns and on the interest rate spread, but surprisingly it had a positive effect on the bank capital ratio. As we discuss in due course, the latter effect is not robust to model specification. There was also no reaction of macroeconomic variables to increased loan supply. As expected, a shock increasing CAR reduced the amount of loans and increased the interest rate spread. However, a shock to increase ROA reduced the value of supplied loans and capital ratio in subsequent periods and it caused housing prices to increase. Again, these above-mentioned effects are not robust to model specification. An increase in ROA had also a positive short-lived effect on the market interest rate. Finally, a shock to the interest rate spread had a negative effect on housing prices, reflecting the working channel of loan supply.

We should notice that the market interest rate turned out to be one of the most important variables in the model as it affected all other variables. A positive shock to the market interest rate reduced output, housing prices, as well as aggregate loans. It also influenced currency depreciation and increased spread in the short-run.

As a further robustness check, we computed generalized impulse responses using the formula (5) as an alternative to traditional impulse responses given in (4) (cf., Figure 2). Nevertheless, the new results are similar to those presented above. For example, the results are the same for shocks to GDP and HPI, which suggests that macroeconomic shocks generate responses robust to model specifications. For the exchange rate, the only additional significant effect in comparison to the traditional impulse responses was the negative reaction of GDP to currency appreciation, possibly due to weakening terms-of-trade conditions and a drop in exports.

In case of banking variables, a positive shock to loans had a positive impact on the GDP and on the interest rate, and a negative effect on the exchange rate (zloty depreciation), the spread, as well as CAR and ROA. The contradicting reactions of the market rate and the spread seem implausible but they could suggest a strong correlation of deposit rate and market rate after shocks in the loan market. In comparison to the results of traditional impulse responses, the generalized responses to shocks in CAR indicate an additional negative reaction of the market rate, and the generalized impulses to shocks in ROA indicate a positive reaction of GDP instead of HPI and no reaction of CAR. A positive shock to spread had a negative effect on the GDP and loan supply. It also had a positive effect on REER but no effect on HPI.

Surprisingly, the effects of market rate shocks are not as widespread under generalized impulse responses as they are under traditional responses. The difference is the lack of significant reactions of REER, CAR, and spread, as well as a short-lived positive reaction of ROA.

Economic theory on macro-financial linkages does not provide any clear view on the momentum of specific shock effects. Therefore, looking for the variable ordering in a VAR is crucial to understand the nature of responses to shocks. The proposed robustness check with combined impulse responses may help assess vulnerability of main results to different model specifications. Figures 3 and 4 contain results concerning combined impulse responses calculated by using all permutations of variable orderings ($m! = 8! = 40320$) and using only permutations of selected variables ($m^* = 6! = 720$), respectively. In the latter case, the permuted variables are $\log(REER)$, CAR, ROA, $\log(LOANS)$, $SPREAD$, and $RATE$, respectively, while the variables $\log(GDP)$ and $\log(HPI)$ are kept at their fixed positions (they are not permuted) and they precede the other variables in the VAR.

The main difference between Figures 3 and 4, and the previously described Figures 1 and 2 are much less evident reactions to shocks in banking sector variables. A shock to loans had only a negative effect on ROA and a shock to CAR had a positive impact on the interest rate spread. GDP and HPI did not react to banking variables and they only reacted to interest rate shocks. GDP influenced ROA and loans with a positive sign. A shock to housing prices increased the value of loans and decreased ROA. The appreciating currency had a negative impact on ROA, which is at odds with the evidence concerning this relationship from traditional impulse response and generalized impulse response analyses. The impact of REER shocks on the value of loans was not statistically significant. The impact of interest rate shocks on macroeconomic variables and loans was again significant and negative. In Figure 3, there is also evidence of interest rate shocks affecting ROA negatively. In Figure 4, interest rate shocks affect all variables except REER.

In our opinion, Figure 4 provides the most reliable results because it accounts for possible misspecification (e.g., in the ordering of variables) among banking sector variables and assumes the leading role of aggregate macroeconomic shocks in line with the literature. Therefore, we also present more detailed results from this analysis, namely the graphs of all impulse response functions in Figures 5a to 5h. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size up to two standard deviations around the mean, and the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines is related to the dispersion of individual impulse responses over different variable orderings (permutations). It is clear that there is no dispersion of impulse responses depending on model permutations in Figures 5a and 5b, because the shock variables GDP and HPI are not permuted in this exercise (i.e., GDP and HPI always precede other variables in the VAR model). In Figures 5c to 5h, the dispersions of impulse responses depending on model permutations play a more significant role. Additional uncertainty generated by permutations reduces the number of significant response values, especially in the first periods after a shock. For example, the shock to loans has no statistically significant effect on REER, CAR, or the spread due to increased dispersion of responses in the initial periods after the shock in Figure 5f. This result is caused by the uncertainty associated with a correct model specification since the dispersion caused by the parameter uncertainty is relatively low.

In general, we confirm the strong positive impact of macroeconomic conditions and housing prices on the performance of the loan market in Poland. In contrast to earlier studies relying on single specifications, we find that the credit channel has no unequivocal effect on output growth since the banking variables do not cause any statistically significant reactions of macroeconomic variables. In turn, the interest rate channel drives developments in both the real and banking sectors.

Conclusions

This research offers a new method to verify robustness of impulse-response functions in a structural VAR model under Cholesky decomposition of the error covariance matrix. The method applies permutations of variables' ordering in a structural model. For all permutations, impulse response functions are computed and averaged accordingly. In order to explore the method in practice, we estimated a VAR model describing the linkages between the banking sector and the real economy of Poland. Our results indicate that the combined impulse responses are more uncertain than those from a single specification, but some findings remain robust. For example, macroeconomic aggregate shocks and interest rate shocks have a significant impact on banking variables. This result is further confirmed by the outcomes from generalized impulse responses proposed by Pesaran and Shin (1998).

Future studies may further explore this idea by combining other important statistics in SVAR models, including forecast error variance decompositions and historical decompositions. The idea of combining impulse-response functions seems to be particularly interesting for SVAR models where the number of dependent variables is limited and analyzing all permutations is not computationally intensive. Extending the number of combined specifications is also worth considering, should just-identifying restrictions, other than Cholesky decomposition or over-identifying restrictions prove relevant.

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Appendix

Table 1. Analyzing the linkages between banking and real sectors with VAR models

Study	Model	Causa-lity	Identifying restrictions	Cointegrating relations	Impulse-response analysis	Forecast error variance decom-position	Histo-rical decom-position	Other issues
Barnett, Thomas (2013)	SVAR		identifying shocks	+	+		+	
Bassett et al. (2014)	SVAR		economic identification		+			stationary variables
Berkelmans (2005)	SVAR		economic restrictions		+	+		variables in levels (nonstationary)
Bernanke (1986)	SVAR		economic identification		+	+		variables in levels (nonstationary) (log) and growth rates
Bezemer, Grydaki (2014)	VAR	+			+			stationary variables
Caporale et al. (2014)	SVAR	+	long-run restrictions	+	+			stationary variables
Chrystal, Mizen (2002)	SVECM			+				variables in levels (nonstationary) (log)
Ciccarelli et al. (2015)	BVAR		recursive restrictions, alternative specifications		+			
Elbourne (2008)	SVAR		testing overidentifying restrictions	+	+	+		variables in levels (nonstationary), analyses of alternative scenarios
Finlay, Jääskelä (2014)	BVAR		sign restrictions		+		+	variables: mainly growth rates, demand and supply credit shocks identified
Gambetti, Musso (2012)	TVP-VAR		sign restrictions		+			alternative scenarios
Gilchrist, Zakrajšek (2012)	SVAR		recursive restrictions		+	+		growth rate variables
Halvorsen, Jacobsen (2014)	SVAR		sign restrictions, alternative specifications		+			stationary variables
Iacoviello, Minetti (2008)	VAR		recursive restrictions, short- and long-run restrictions		+			
Karfakis (2013)	VAR	+			+			stationary variables
Kim, Rousseau (2012)	VAR, VECM	+		+	+			
Lown, Morgan (2006)	VAR	+			+	+		variables in levels (nonstationary)
Magkonis, Tsopanakis (2014)	SVAR		recursive restrictions, sign restrictions, testing overidentifying restrictions		+		+	
Meeks (2012)	BVAR		sign restrictions	+		+	+	variables in levels (nonstationary) (log)
Milcheva (2013)	SVAR			+		+		variables in levels (nonstationary),

								model simulations
Mumtaz et al. (2015)	SVAR, DSGE		recursive restrictions, sign restrictions, moment equations		+			variables in levels (nonstationary), simulating VAR and DSGE models
Musso, Neri, Stracca (2011)	SVAR		recursive restrictions		+	+		variables in levels (nonstationary) (log)
Safaei, Cameron (2003)	SVAR		economic identification		+			stationary variables
Tamási, Világi (2011)	BSVAR		sign restrictions and zero restrictions		+	+	+	
Walentin (2014)	SVAR				+	+		variables in levels (nonstationary)

Note: Respective studies are presented in separate rows. The '+' sign indicates that a given analysis has been considered in the respective study.

Table 2. Summary statistics of VAR models

Model	VAR(1)	VAR(2)	VAR(3)	VAR(4)
LogL	678.00	754.54	829.61	949.04
AIC	-17.15	-17.80	-18.43	-20.48
SIC	-13.44	-11.91	-10.33	-10.14
w(AIC)	0.08	0.14	0.21	0.57
w(SIC)	0.54	0.25	0.11	0.10
Stability	yes	yes	yes	no

Note: LogL is the value of the likelihood function in the estimated VAR model. AIC and SIC are Akaike and Schwarz information criteria, respectively. w(AIC) and w(SIC) denote the relative probabilities that given specifications are the correct ones. These probabilities were computed with so called Akaike and Schwarz weights, respectively (Wagenmakers and Farrell, 2004). ‘Stability’ is set to ‘yes’ if the VAR model is stable and ‘no’ otherwise.

Figure 1. Impulse-response of endogenous variables to orthogonal shocks under single Cholesky decomposition

	log(*GDP*)	log(*HPI*)	log(*REER*)	*CAR*	*ROA*	log(*LOANS*)	*SPREAD*	*RATE*
log(*GDP*)	(+) ; 18 ; 0.9	(+) ; 3 ; 0.15						(-) ; 18 ; 0.9
log(*HPI*)	(+) ; 9 ; 0.45	(+) ; 8 ; 0.4			(+) ; 6 ; 0.3		(-) ; 3 ; 0.15	(-) ; 15 ; 0.75
log(*REER*)	(-) ; 1 ; 0.05		(+) ; 4 ; 0.2					(-) ; 2 ; 0.1
CAR		(-) ; 7 ; 0.35		(+) ; 3 ; 0.15	(-) ; 11 ; 0.55	(+) ; 3 ; 0.15		(+) ; 8 ; 0.4
ROA	(+) ; 9 ; 0.45	(-) ; 2 ; 0.1	(+) ; 3 ; 0.15		(+) ; 6 ; 0.3	(-) ; 8 ; 0.4		(+);1 ; 0.05; (-) ; 7 ; 0.35
log(*LOANS*)	(+) ; 20 ; 1	(+) ; 9 ; 0.45	(-) ; 2 ; 0.1	(-) ; 3 ; 0.15	(-) ; 4 ; 0.2	(+) ; 5 ; 0.25		(-) ; 11 ; 0.55
SPREAD	(-) ; 5 ; 0.25		(+) ; 3 ; 0.15	(+) ; 3 ; 0.15		(-) ; 4 ; 0.2	(+) ; 3 ; 0.15	(+) ; 1 ; 0.05
RATE		(-) ; 1 ; 0.05	(-) ; 6 ; 0.3		(+) ; 1 ; 0.05			(+) ; 8 ; 0.4

Note: The names in columns denote 'shocking' variables and the shocked variables are presented in rows. The respective symbols are separated with semicolons in colored cells. (+) denotes a statistically significant positive effect of a one unit positive shock and (-) denotes a negative effect. An integer next to the (+), (-) signs denotes the number of periods for which the reaction to a shock is statistically significantly different from zero. The fractional numbers next to integers denote the fraction of the horizon where the reaction to a shock is statistically significant. Positive statistically significant reactions are also identified with graded green color, negative reactions are identified with graded red color, and mixed (positive and negative) reactions are identified with graded grey color. A white empty cell denotes no significant reaction to a shock.

Figure 2. Generalized impulse-response of endogenous variables

	log(*GDP*)	log(*HPI*)	log(*REER*)	*CAR*	*ROA*	log(*LOANS*)	*SPREAD*	*RATE*
log(*GDP*)	(+) ; 18 ; 0.9	(+) ; 3 ; 0.15	(-) ; 6 ; 0.3		(+) ; 2 ; 0.1	(+) ; 5 ; 0.25	(-) ; 2 ; 0.1	(-) ; 16 ; 0.8
log(*HPI*)	(+) ; 9 ; 0.45	(+) ; 8 ; 0.4						(-) ; 4 ; 0.2
log(*REER*)	(-) ; 1 ; 0.05		(+) ; 4 ; 0.2			(-) ; 4 ; 0.2	(+) ; 2 ; 0.1	
CAR		(-) ; 7 ; 0.35		(+) ; 3 ; 0.15		(-) ; 2 ; 0.1		
ROA	(+) ; 9 ; 0.45	(-) ; 3 ; 0.15	(+) ; 2 ; 0.1		(+) ; 6 ; 0.3	(-) ; 4 ; 0.2		(+) ; 2 ; 0.1
log(*LOANS*)	(+) ; 20 ; 1	(+) ; 11 ; 0.55	(-) ; 2 ; 0.1	(-) ; 4 ; 0.2	(-) ; 2 ; 0.1	(+) ; 5 ; 0.25	(-) ; 3 ; 0.15	(-) ; 8 ; 0.4
SPREAD	(-) ; 5 ; 0.25		(+) ; 3 ; 0.15	(+) ; 4 ; 0.2		(-) ; 4 ; 0.2	(+) ; 4 ; 0.2	
RATE		(-) ; 1 ; 0.05	(-) ; 7 ; 0.35	(-) ; 5 ; 0.25	(+) ; 1 ; 0.05	(+) ; 7 ; 0.35		(+) ; 6 ; 0.3

Note: The names in columns denote 'shocking' variables and the shocked variables are presented in rows. The respective symbols are separated with semicolons in colored cells. (+) denotes a statistically significant positive effect of a one unit positive shock and (-) denotes a negative effect. An integer next to the (+), (-) signs denotes the number of periods for which the reaction to a shock is statistically significantly different from zero. The fractional numbers next to integers denote the fraction of the horizon where the reaction to a shock is statistically significant. Positive statistically significant reactions are also identified with graded green color, negative reactions are identified with graded red color, and mixed (positive and negative) reactions are identified with graded grey color. A white empty cell denotes no significant reaction to a shock.

Figure 3. Combined impulse response of endogenous variables to orthogonal shocks under Cholesky decompositions of all permuted variables

	log(*GDP*)	log(*HPI*)	log(*REER*)	*CAR*	*ROA*	log(*LOANS*)	*SPREAD*	*RATE*
log(*GDP*)	(+) ; 20 ; 1							(-) ; 17 ; 0.85
log(*HPI*)		(+) ; 8 ; 0.4						(-) ; 10 ; 0.5
log(*REER*)			(+) ; 4 ; 0.2					
CAR		(-) ; 8 ; 0.4		(+) ; 3 ; 0.15				
ROA	(+) ; 5 ; 0.25	(-) ; 4 ; 0.2	(-) ; 2 ; 0.1		(+) ; 2 ; 0.1	(-) ; 3 ; 0.15		(-) ; 2 ; 0.1
log(*LOANS*)	(+) ; 15 ; 0.75	(+) ; 10 ; 0.5				(+) ; 4 ; 0.2		(-) ; 9 ; 0.45
SPREAD				(+) ; 3 ; 0.15			(+) ; 3 ; 0.15	
RATE			(-) ; 5 ; 0.25					(+) ; 7 ; 0.35

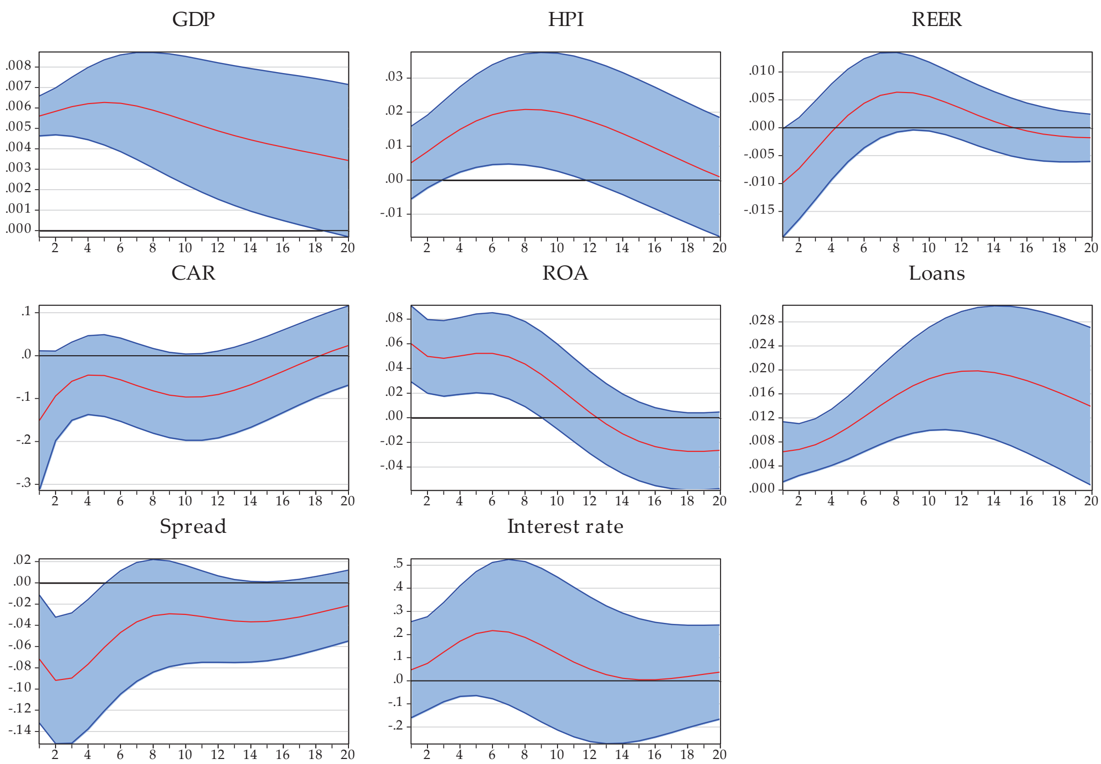
Note: The names in columns denote 'shocking' variables and the shocked variables are presented in rows. The respective symbols are separated with semicolons in colored cells. (+) denotes a statistically significant positive effect of a one unit positive shock and (-) denotes a negative effect. An integer next to the (+), (-) signs denotes the number of periods for which the reaction to a shock is statistically significantly different from zero. The fractional numbers next to integers denote the fraction of the horizon where the reaction to a shock is statistically significant. Positive statistically significant reactions are also identified with graded green color, negative reactions are identified with graded red color, and mixed (positive and negative) reactions are identified with graded grey color. A white empty cell denotes no significant reaction to a shock.

Figure 4. Combined impulse response of endogenous variables to orthogonal shocks under Cholesky decompositions of selected permuted variables

	log(*GDP*)	log(*HPI*)	log(*REER*)	*CAR*	*ROA*	log(*LOANS*)	*SPREAD*	*RATE*
log(*GDP*)	(+) ; 18 ; 0.9	(+) ; 3 ; 0.15						(-) ; 19 ; 0.95
log(*HPI*)	(+) ; 9 ; 0.45	(+) ; 8 ; 0.4						(-) ; 12 ; 0.6
log(*REER*)	(-) ; 1 ; 0.05		(+) ; 4 ; 0.2					
CAR		(-) ; 7 ; 0.35		(+) ; 3 ; 0.15				(+) ; 6 ; 0.3
ROA	(+) ; 9 ; 0.45	(-) ; 2 ; 0.1	(-) ; 3 ; 0.15		(+) ; 2 ; 0.1	(-) ; 4 ; 0.2		(-) ; 6 ; 0.3
log(*LOANS*)	(+) ; 20 ; 1	(+) ; 9 ; 0.45				(+) ; 3 ; 0.15		(-) ; 10 ; 0.5
SPREAD	(-) ; 5 ; 0.25			(+) ; 3 ; 0.15			(+) ; 3 ; 0.15	(+) ; 1 ; 0.05
RATE		(-) ; 1 ; 0.05	(-) ; 5 ; 0.25					(+) ; 8 ; 0.4

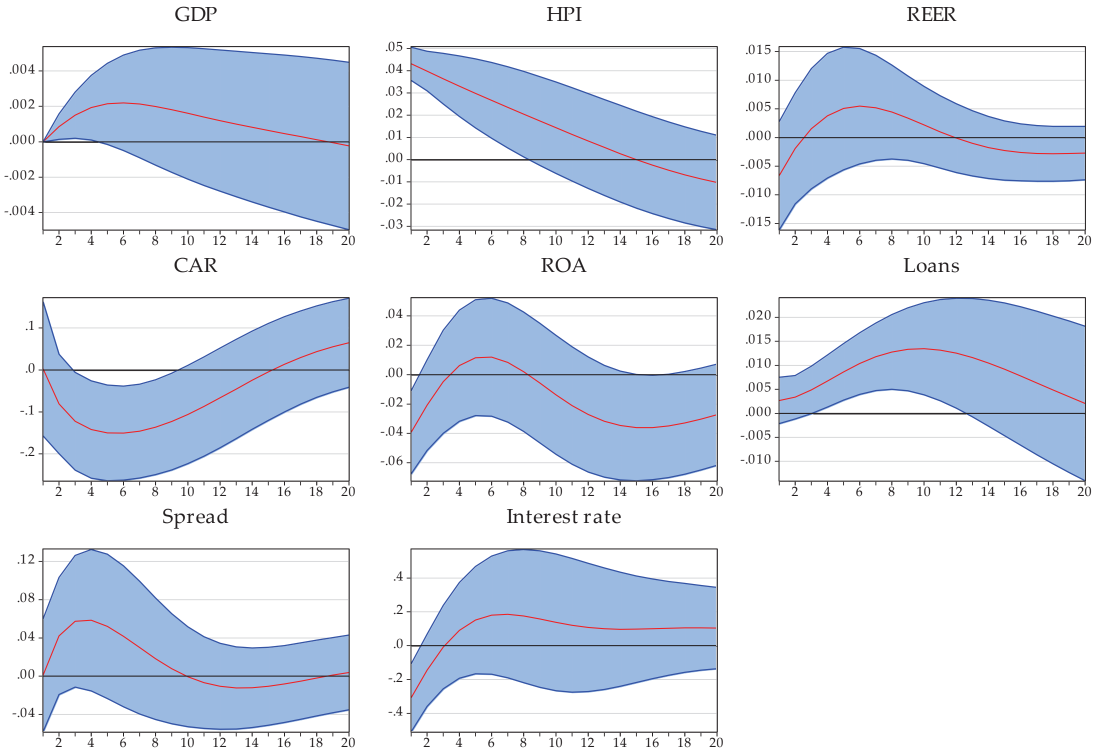
Note: The names in columns denote 'shocking' variables and the shocked variables are presented in rows. The respective symbols are separated with semicolons in colored cells. (+) denotes a statistically significant positive effect of a one unit positive shock and (-) denotes a negative effect. An integer next to the (+), (-) signs denotes the number of periods for which the reaction to a shock is statistically significantly different from zero. The fractional numbers next to integers denote the fraction of the horizon where the reaction to a shock is statistically significant. Positive statistically significant reactions are also identified with graded green color, negative reactions are identified with graded red color, and mixed (positive and negative) reactions are identified with graded grey color. A white empty cell denotes no significant reaction to a shock.

Figure 5a. Reactions to shocks in GDP



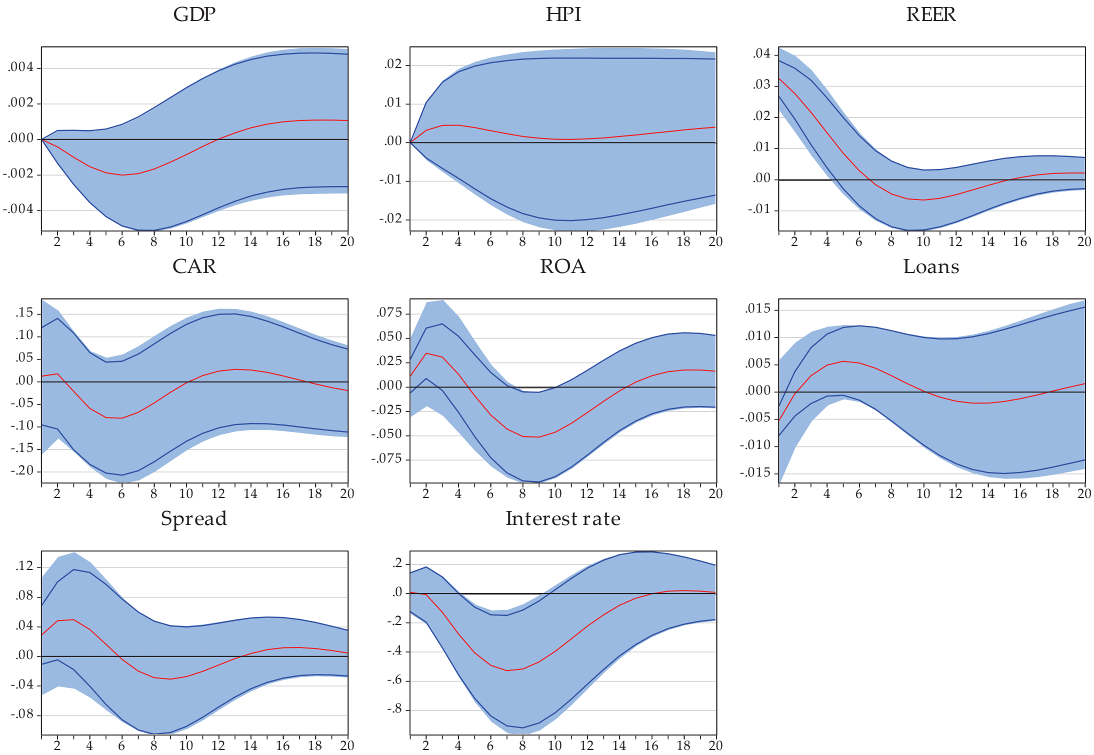
Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

Figure 5b. Reactions to shocks in HPI



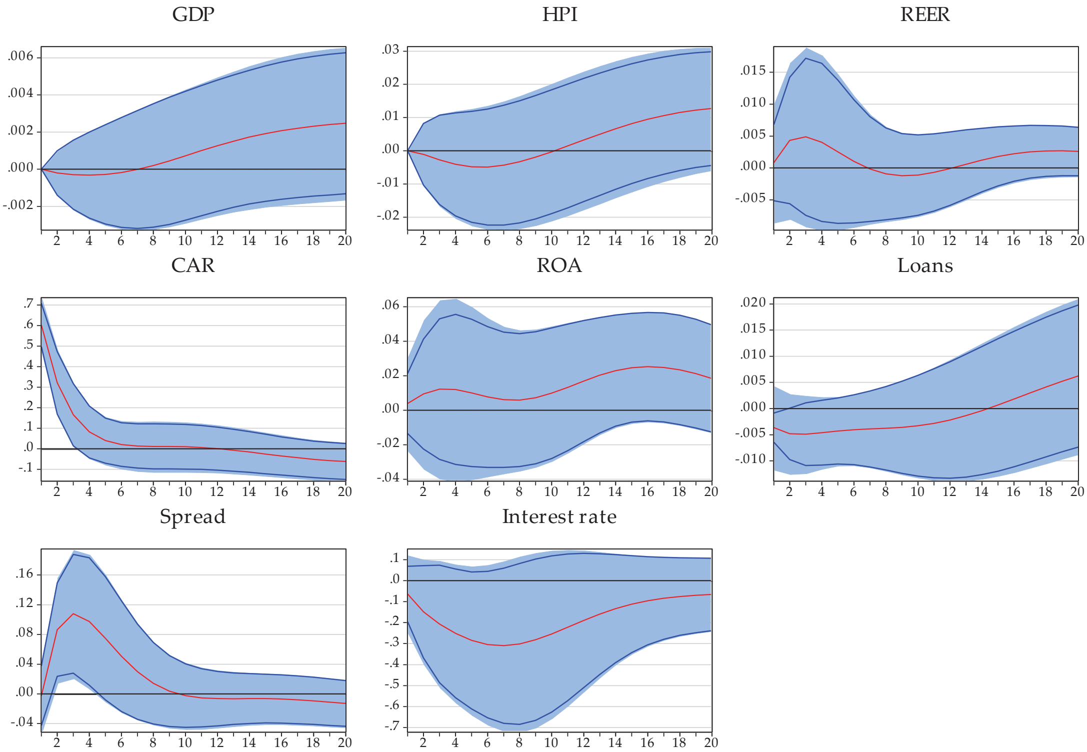
Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

Figure 5c. Reactions to shocks in REER



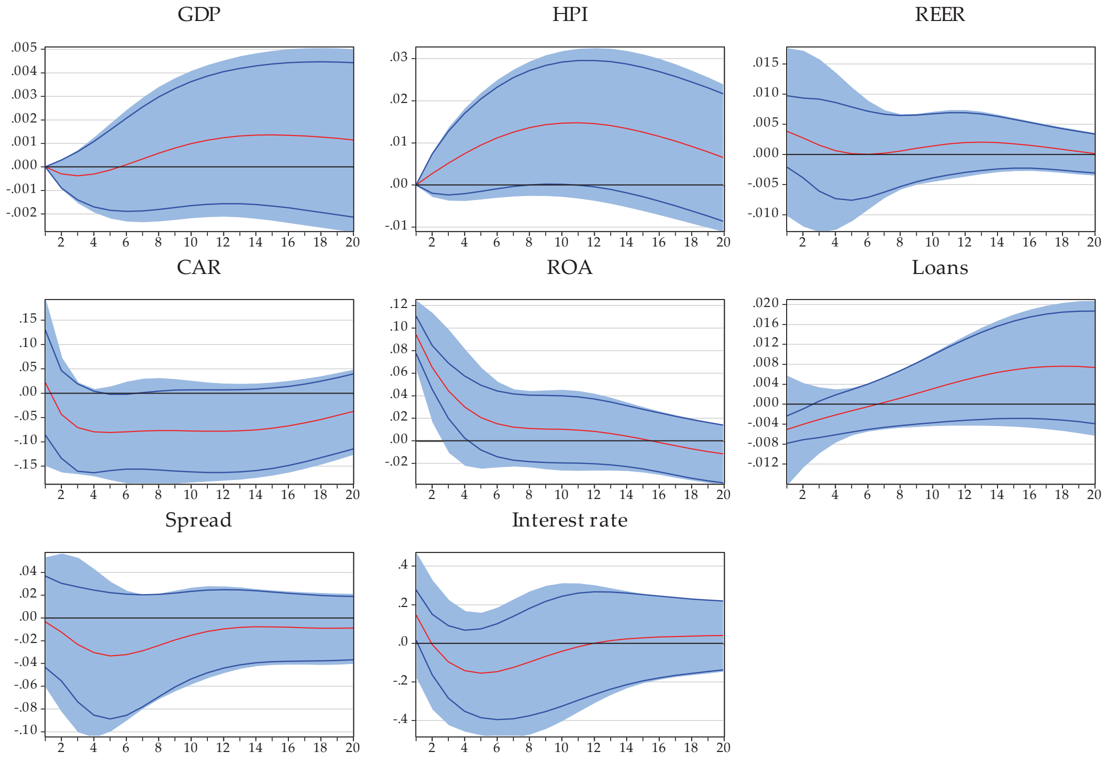
Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

Figure 5d. Reactions to shocks in CAR



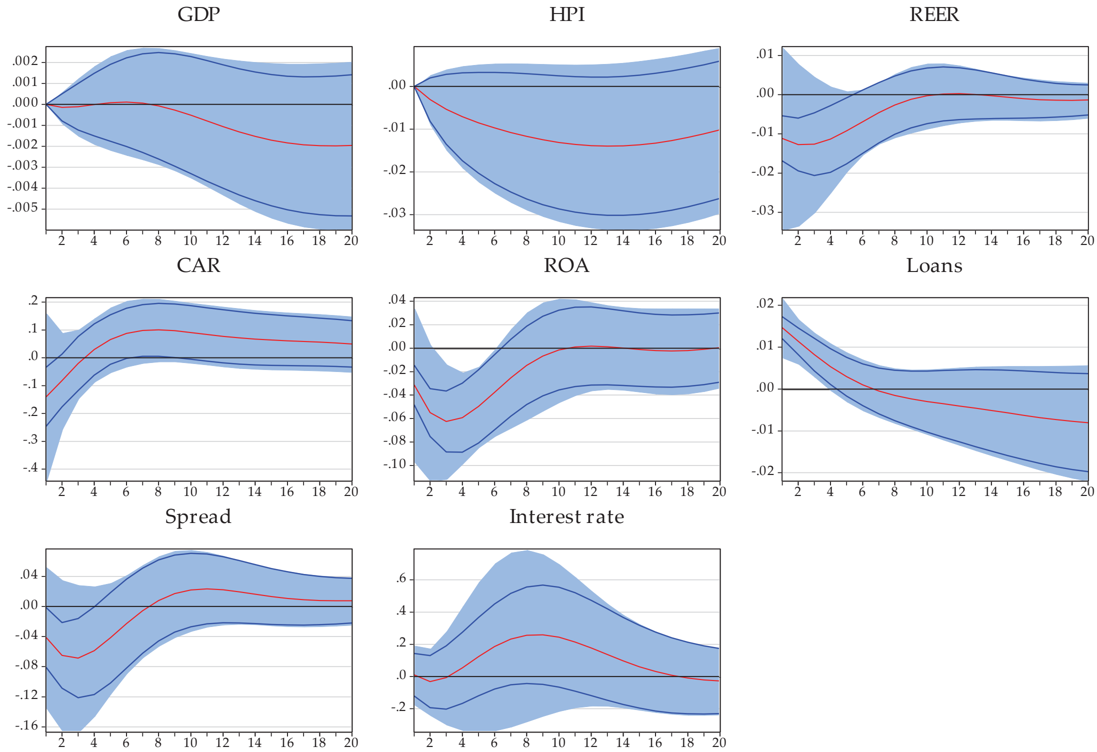
Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

Figure 5e. Reactions to shocks in ROA



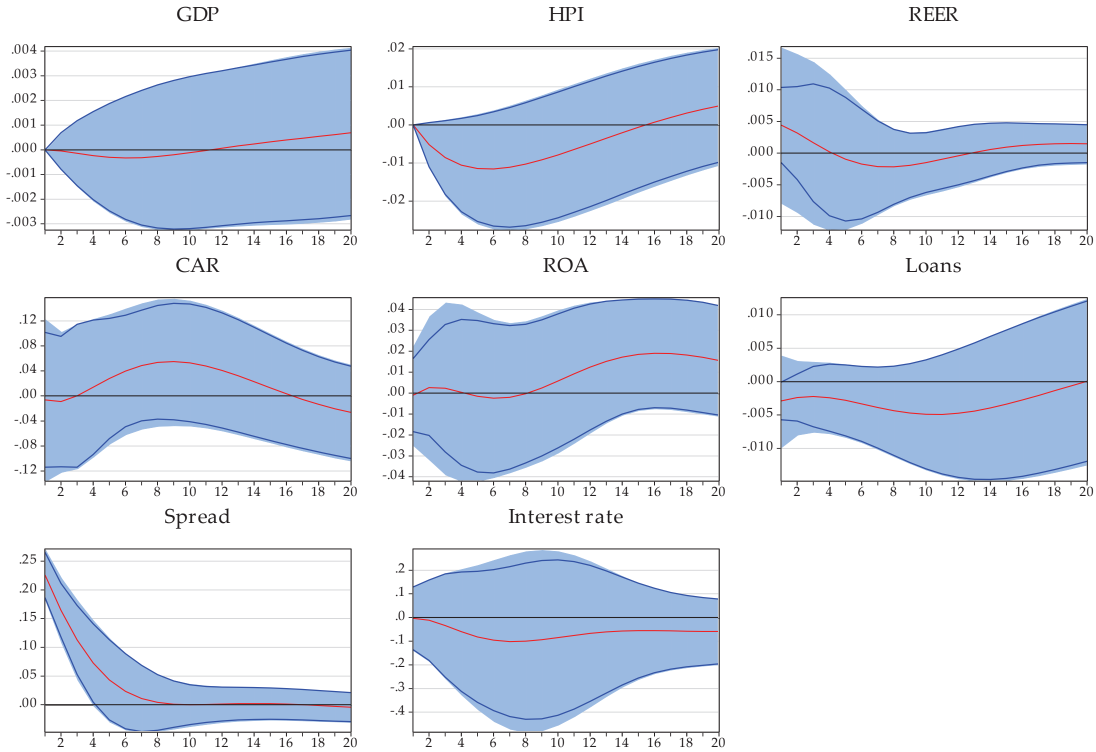
Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

Figure 5f. Reactions to shocks in LOANS



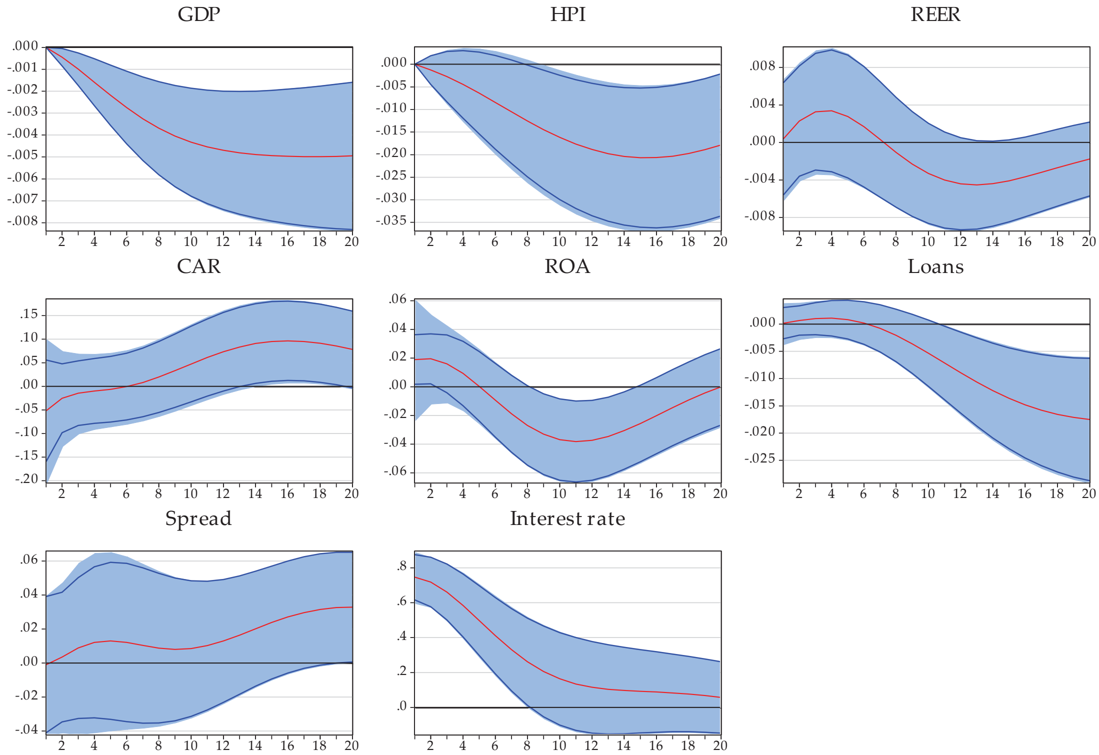
Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

Figure 5g. Reactions to shocks in SPREAD



Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

Figure 5h. Reactions to shocks in RATE



Note: The titles of graphs indicate variables reacting to the shock. In each graph, the red line represents the mean reaction function, the blue-shaded area is the confidence region of the size equal to two standard deviations around the mean, the darker blue border lines represent the size of response uncertainty associated solely with the parameter estimation errors. In turn, the shaded area beyond the dark lines (if present) is related to the dispersion of individual impulse responses in different variable orderings (permutations).

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