

CREDIT-RELATED SHOCKS IN VAR MODELS: THE CASE OF LITHUANIA

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Abstract. *This article provides empirical evidence on the role played by credit-related shocks over the business cycle in Lithuania. To this end, we estimate a vector auto regression (VAR) with credit and housing variables and identify credit-related shocks. Using sign restriction, we identify credit supply shocks; while using zero restrictions, we identify credit spread shocks. We find evidence that credit-related shocks have a significant effect on housing and credit market variables, while the effect on GDP is less pronounced but still significant. While credit supply shocks weighed down on economic growth during the period from 2008 to 2014, the effect turned positive in 2014.*

Keywords: *credit related shocks, credit supply shocks, credit spread shocks.*

Introduction

During the so-called Great Moderation, there was a widespread belief among economists that credit and housing are not important in explaining business cycle fluctuations.¹ However, this view was shaken after the fall of the Lehman Brothers in 2008, which marked the onset of the global financial crisis, during which many advanced economies experienced serious financial turmoil and deep recessions. Now it is widely agreed that financial liberalization, monetary conditions and a buoyant credit market activity greatly contributed to the rise of the economic and financial imbalances prior to the crisis, whereas shocks originating specifically in credit markets were the actual trigger of the global financial crisis in 2008. The most advanced economies experienced sluggish, creditless recoveries² in the aftermath of the crisis. The recent financial cycle in Lithuania can be seen as a perfect example of the credit-driven housing bubble, followed by one of the largest GDP contractions in the EU and a typically sluggish economic recovery.³

¹ Most precrisis macromodels excluded housing and credit as largely irrelevant factors (see, e.g., Smets and Wouters 2003; Christiano et al. 2005), though there were notable exceptions (see Iacoviello 2005; Kiyotaki and Moore 1997).

² See, e.g., Abiad et al. (2012).

³ For a more detailed overview of the recent boom-and-bust cycle in Lithuania, see, e.g., Ramanauskas and Kuodis (2009).

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A constrained credit supply can be one explanation for deep downturns, though there possibly are other culprits, such as structural dislocations, sluggish external demand or fiscal austerity. In this article, we aim to investigate the relative importance of credit supply shocks in determining economic developments during the economic cycle in Lithuania. It is worth emphasizing that while there is little doubt that credit matters for economic developments, the role of specific *credit supply* shocks is not as clear. Banks' ability and willingness to provide credit depends on many factors, such as capital and liquidity positions, access to stable financing, profitability prospects and risk considerations etc. Some of the drivers behind credit supply change endogenously in line with changing economic conditions, but there is also an exogenous element signifying changes in exogenous bank risk preferences or the availability of external financing. Therefore, it is important to distinguish the exogenous credit supply shocks from the endogenous credit fluctuations. For this purpose, we build a VAR model and try to identify credit-related exogenous shocks using sign restrictions.

This article is structured as follows. Section No. 1 provides a brief overview of the related literature. The modeling framework is presented in Section No. 2. We discuss the main results in Section No. 3. Finally, we provide some concluding comments.

1. Related Literature

Prior to the global financial crisis, macroeconomists were typically interested in the macroeconomic impact of changes in a relatively small number of aggregate level shocks, such as aggregate demand, aggregate supply or monetary policy shocks. The problem is that these aggregate level shocks can be misleading, as they can be driven by many other factors. The crisis has particularly highlighted the need to take a deeper look at these shocks and of the direction that was to incorporate credit and housing markets (and the associated shocks) in otherwise standard models.

New-Keynesian DGSE models are the mainstay theoretical tool for economic policy analysis, though until recently, one of their shortcomings was the absence of the financial and housing markets. This area saw a strong increase in research in trying to incorporate these sectors, expanding on the early works of Kiyotaki and Moore (1997) and Iacoviello (2005). Now it is widely agreed that even small shocks to the economy might be amplified through the financial system and have a significant impact on output fluctuations; the financial system can also be a place where those shocks originate. It is important to distinguish financial shocks from the more "traditional" shocks.⁴ Iacoviello and Neri (2010) show that housing-related shocks are not non-negligible and explain a significant portion of economic volatility.

⁴ See Justiniano et al. 2010 for the discussion.

In a different strand of credit-related empirical research, a number of studies tried to include credit and housing variables in traditional structural vector autoregression (SVAR) models used in monetary policy analyses (see., e.g., Musso et al. 2011; Iacoviello and Minetti 2008; Elborne 2008). Incorporating the housing market is crucial for the identification of monetary policy shock transmission channels, since a large fraction of credit flows are directed specifically into the real estate and residential housing markets. Some authors explicitly identify exogenous financial and credit-related shocks, e.g., Walentin (2014) and Meeks (2012) show that exogenous shocks to lending spreads can be a source of economic volatility and can explain a significant fraction of variation in GDP.

Many authors try to specifically identify credit supply shocks using the SVAR framework (Duchi and Elbourne 2016; Furlanetto et al. 2014; Gambetti and Musso 2012; Hristov et al. 2011; Peersman 2011; Bijsterbosch and Falagiarda 2015; Barnett and Thomas 2013). They typically find that credit supply shocks matter and are a substantial source of macroeconomic fluctuations, though, naturally, the degree to which the credit supply had affected the economies during the recent economic cycle does differ. Duchi and Elbourne (2016) find that in the case of the Netherlands, about a half of the contraction in GDP growth during the crisis was attributable to credit supply shocks. Gambetti and Musso (2012) find that during 2008 and 2009, credit supply shocks can explain about one half of the decline in the annual real GDP growth in the euro area and in the United States as well as around three quarters of growth changes in the United Kingdom. Bijsterbosch and Falagiarda (2015) show that while credit supply shocks have a procyclical impact in the euro area, there is evidence of a strong rise in cross-country heterogeneity, reflecting the financial fragmentation in the euro area associated with the sovereign debt crisis and weaker banks' balance sheets. Hristov et al. (2011) show that in some EU countries, e.g. Austria, Finland or Italy, the dampening effects of loan supply shocks were particularly relevant in the course of 2008, while in other countries, e.g., Germany, Spain or France, they predominantly emerged during 2009 and 2010.

There are some examples of trying to further disentangle credit supply shocks. Notable examples can be seen in studies by Kanngiesser et al. (2016) and Furlanetto et al. (2014). Kanngiesser et al. (2016) tried to identify the impact of the shocks to banks' capital in the euro area. Furlanetto et al. (2014) disentangle shocks originating in the credit market, shocks originating in the housing market and uncertainty shocks. Such a more granular approach provides some benefits – in particular, the identification of more relevant shocks for the policymaker – however, the identification schemes in the literature are less established.

To our knowledge, there were *no attempts to specifically analyze credit supply shocks for the case of Lithuania*, though some authors include credit variables in their empirical

analyses. In particular, Stakėnas and Stasiukynaitė (2016) develop an SVAR model to analyze the effects of the euro area's monetary policy shocks on the Lithuanian economy. The authors include the credit margin as an exogenous variable to account for changes in the banks' risk preferences and willingness to extend loans. While this can be a suitable approach when trying to analyze (exogenous) monetary policy shocks, their framework is not intended to explain the drivers behind the fluctuations of credit margins. It is quite clear that credit margins are partly determined endogenously by the concurrent developments in the local economy. For example, the GDP growth, resulting from a positive aggregate demand or supply shock, positively affects the creditworthiness of households and firms, which, in turn, reduces credit risk and credit spreads. On the other hand, some of the variance in credit spreads can be directly related to credit markets (e.g., credit supply shocks).

Some authors include credit and housing markets in structural macroeconomic models (Ramanauskas 2012). Ramanauskas (2012) shows that easy credit conditions and active credit expansion contributed moderately to real economic growth but significantly added to overheating pressures. By applying a credit supply and demand disequilibrium model, Ramanauskas et al. (2015) finds that from 2002 to 2006, Lithuania experienced a period of excess credit demand, while 2009-2012 was a period of excessive credit supply.⁵

2. Methodology

VAR models proposed by Sims (1980) constitute a relatively agnostic class of models that allow the “data to speak,” as no tight cross-equation restrictions are imposed. We base our analysis on the VAR framework, which has become a standard tool to estimate how various macroeconomic variables are affected by exogenous shocks, such as monetary policy shocks (see, e.g., Stock and Watson 2001) or fiscal policy shocks (see, e.g., Caldara and Kamps 2008). First, we estimate a reduced-form VAR model, in which each dependent variable is regressed on its own lags and on the lags of other variables. We then impose specific restrictions on the errors of the reduced-form VAR to recover the structural shocks; thus, we develop a structural VAR model.⁶ There are a number of different approaches to recovering structural shocks, such as imposing zero, long-run and sign restrictions or combinations of those. In this article, we use two separate identification schemes, namely zero and sign restrictions, and then we compare the results.⁷

⁵ Qualitatively, similar results are provided by Everaert G. et al. (2015)

⁶ We use the Matlab SVAR toolbox provided by Ambrogio Cesa-Bianchi and available here: <<https://sites.google.com/site/ambropo/MatlabCodes>>

⁷ To see a detailed description of the methodology, see Duchi and Elbourne (2016).

2.1. Model

In this section, we briefly present the used methodology. In vector notation, the VAR model can be expressed by:

$$y_t = c + \sum_{i=1}^p A_i y_{t-i} + u_t \quad (1)$$

where y_t is a $N \times 1$ vector containing all N endogenous variables, c is a $N \times 1$ vector of constants, A_i (for $i = 1, \dots, P$) are $N \times N$ parameter matrices, and u_t is the $N \times 1$ one-step ahead prediction error with $u_t \sim N(0, \sigma)$, where σ is the $N \times N$ variance-covariance matrix. The vector of y_t contains the endogenous variables – the GDP deflator, GDP growth, credit spreads, growth of MFI loans to non-financial sector and housing price growth. The correlation of the residuals (u_t) reflects a contemporaneous relation between the variables. Therefore, we cannot interpret the reduced-form error terms as structural shocks.

Regarding the identification procedure, the prediction error u_t can be written as a linear combination of structural innovations:

$$u_t = B e_t \quad (2)$$

with $e_t \sim N(0, I_N)$, where I_N is an ($N \times N$) identity matrix and where B is a non-singular parameter matrix. The variance-covariance matrix has thus the following structure: $\Sigma = BB'$. Given the fact that the variance-covariance matrix is symmetric, $N(N - 1)/2$ further restrictions are needed to derive B from this relationship.

Data and estimation. To estimate our model, we use quarterly data for Lithuania spanning from Q1 2002 to Q3 2016. A model is comprised of five endogenous variables – the GDP deflator, GDP growth, credit spreads, MFI loans to households and housing prices. With the exception of the credit spread variable, the variables are expressed as the year-on-year growth rates. Detailed data sources and data descriptions are provided in Annex B. We estimate the model using the ordinary least squares.

2.2. Identification – Zero-Restrictions

The most common restrictions to recover structural shocks are the so-called zero restrictions (following Sims 1980). A most commonly used identification scheme is the Cholesky decomposition, which assumes B (in Eq. 2) to be a lower triangular matrix. This identification scheme utilizes a recursive contemporaneous ordering of variables, based on the assumption that it is possible to determine the variables that are not affected by contemporaneous changes in other variables and only respond to those that change with a lag. Yet, economic theory is quite often silent about the specific zero restrictions in SVAR models, and, for some applications, the assumption of the causal ordering (i.e., which variable affects which) is problematic, since in reality, variables can be jointly de-

terminated. Nevertheless, this method is often applied in practice to identify credit-related shocks and, more specifically, credit margin shocks.

In this article, the identifying zero restriction is that credit spread shocks do not affect GDP growth or the GDP deflator on impact, but they are allowed to contemporaneously (within the quarter) affect the loan growth and house price growth. This is a standard identification scheme in the related literature.⁸ We do not identify other shocks beside credit spread; thus, the ordering of other variables does not matter.

2.3. Identification – Sign Restrictions

It is typically more natural to have *a priori* expectations about the sign of a variable's response to a shock rather than the length of time it will take for a variable to respond to a shock. The identification procedure of using sign restrictions was first proposed by Uhlig (2005) in an application for the identification of monetary policy shocks. This identification procedure is now widely used to identify credit-related shocks (see Duchi and Elbourne 2016 for a literature review).

As was mentioned, sign restrictions are based on the expected comovement of economic variables following a structural shock. For instance, in response to a positive aggregate demand shock, prices and output should both increase, whereas a favorable aggregate supply shock should boost output but weigh down on output prices. In this regard, an SVAR model can help disentangle the aggregate demand and supply shocks using this information. In a similar vein, it is possible to identify other more specific shocks, such as monetary policy, housing price etc. In this note, we are interested in identifying a credit supply shock. We interpret a credit supply shock as a shock that moves credit spreads and credit growth in opposite directions.

A credit supply shock identified this way can be associated with various events, such as unexpected changes in bank capital buffers (e.g., due to a change in regulatory capital ratio requirements), unanticipated changes in bank funding (e.g., due to bank runs or, conversely, the introduction of credible deposit insurance schemes), banks' risk perceptions (e.g., following changes in key bank managerial positions or innovations in risk monitoring technology) or the degree of competition in the banking sector (which might change loan supply schedules).

The standard technique for imposing sign restrictions is to randomly draw orthogonal matrices, Q , such that $BQQ'B' = \Sigma$. By replacing B in equation (2) with BQ , we have a new model that is observationally equivalent to the reduced form; however, it comes with different impulse response functions. We generate the IRF and check if they are in line with the contemporaneous and next period's sign restriction. If the responses from the new model satisfy the sign restrictions, the matrix is kept – it is discarded otherwise. This process is repeated until a sufficient number (in our case, 100) of matrixes are accepted.

⁸ See Walentin K. (2014)

Each of these models have their own set of identified shock series, impulse response functions and historical decompositions. To summarize, the results of these 100 models are that we follow convention and display median values across all accepted models. For the impulse response functions, this means that the solid line in Figure No. 3 depicts the median response at each horizon across all accepted models, while the dashed lines represent the middle 76% of the models.

3. Results

3.1. Identification Using Zero-Restrictions

Impulse responses to (one standard deviation) shocks in credit spread innovations are provided in Figure No. 1. The credit spread shock leads to a temporary reduction in GDP, loan and housing price growth rates. Only the price variable exhibits a short-term rise in response to the credit spread shock, but the impact also turns negative over the medium term. This is qualitatively in line with our intuition about the impact credit supply shock and suggests that credit spread innovations can be interpreted as a credit supply shock. We find that a single standard deviation (0.35 p.p.) shock to the credit spread results in a decline in GDP, loan and house price growth rate by, respectively, 0.9, 4.2 and 3.9 p.p. The largest effect on the GDP and house price growth occurs after three quarters, while the loan growth reacts more slowly – the maximum effect is reached after four quarters.

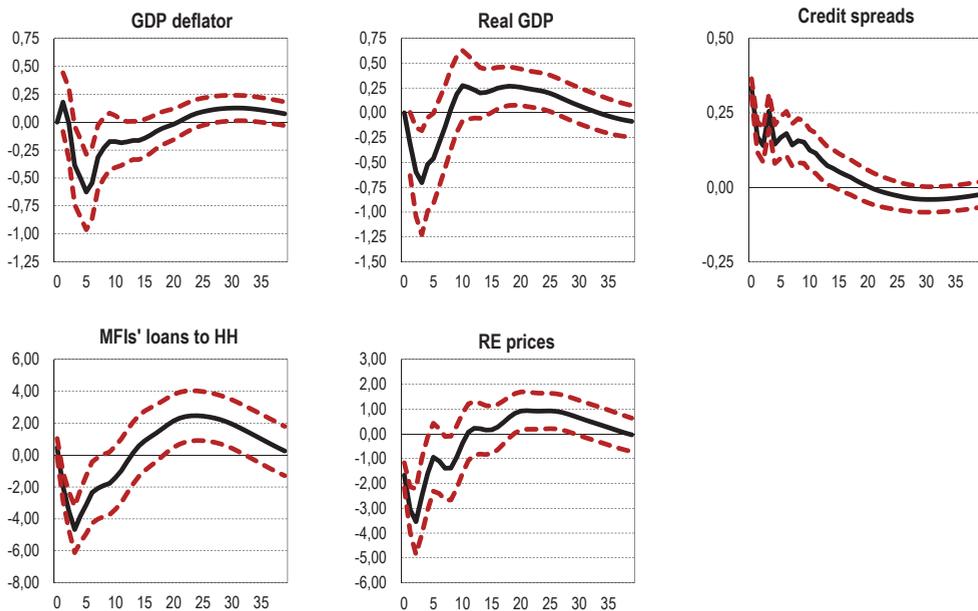


FIG. No. 1. Impulse responses to a one standard deviation shock in credit spreads.

Note: Units are in percent point deviation, except the credit spreads which are in terms of percentages. Dashed lines provide 68% confidence interval.

The VAR methodology allows us to discern the cumulative impact of credit margin shocks and other factors on the dynamics of the model's endogenous variables (see Fig. No. 2). The brown bars in the figure denote the cumulative effect of credit spread shocks. In the boom phase from 2004 to 2008, in the absence of credit spread shocks, the growth of GDP, housing prices and credit would have been considerably lower, while during the downturn, credit spread shocks negatively affected the growth figures of these variables. In quantitative terms, credit spread shocks accounted for about 9 p.p. of credit growth and about 7 p.p. of housing price growth in 2007.

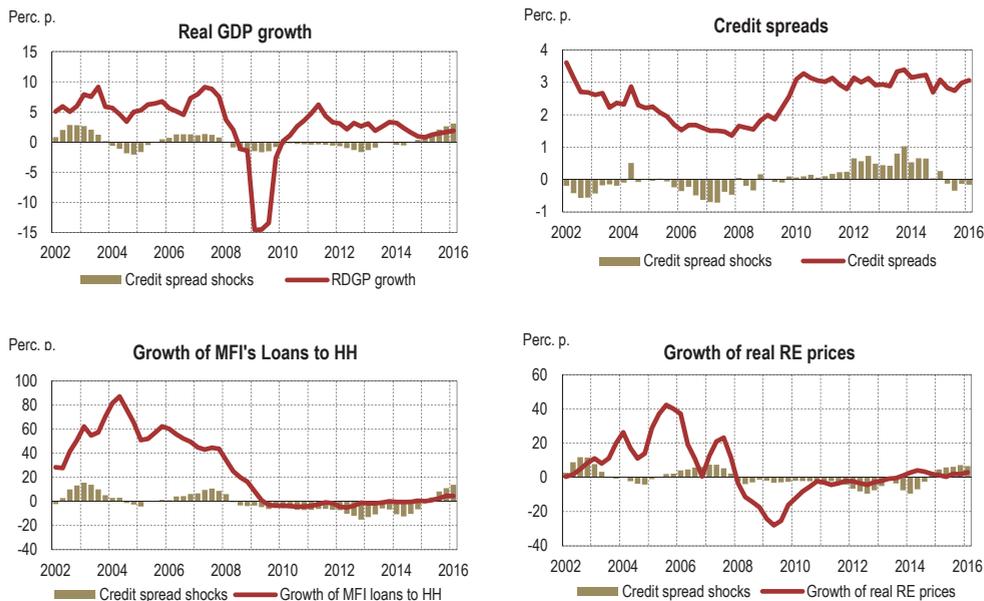


FIG. No. 2. The historical decomposition of endogenous variable dynamics in the zero-restrictions model.

Note: the red lines depict the actual dynamics. The brown bars represent the accumulated contribution of credit spread shocks to the endogenous variables. A positive (negative) bar at each period captures how the change in the endogenous variable would have been lesser (greater) in the absence of the shock.

3.2. Identification Using Sign Restrictions

Impulse responses of the model's endogenous variables to a one standard deviation of an adverse credit supply shock are presented in Figure No. 3. A typical adverse credit supply shock reduces lending growth by about 1.2 p.p. on the impact, while the impact peaks at 5.1 p.p. after 4 quarters. The dampening impact on lending growth and housing price growth is quite persistent, as the median response is still below zero six years after the shock. The credit spread also rises by 0.1 p.p. on the impact before slowly returning to the baseline. After the credit supply shock, GDP growth falls by about 0.6 p.p. in the first few quarters following the shock. The immediate reaction of the GDP deflator

growth to the credit supply shock is positive but it temporarily falls by about 0.6 p.p. with roughly a one year lag. Note, however, that the impact on the GDP deflator growth is surrounded by high uncertainty, as we do not impose a specific sign restriction on this response.

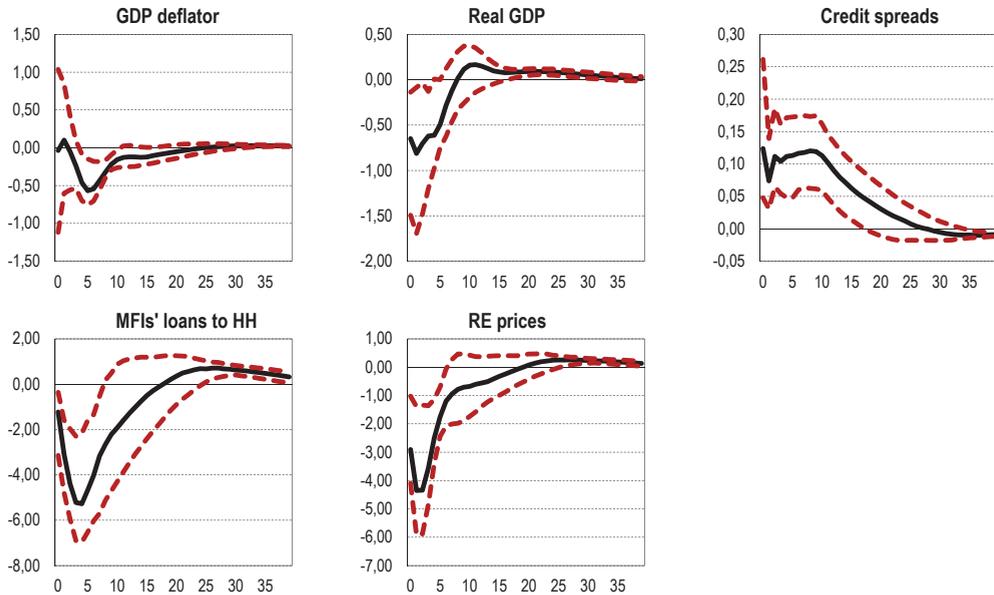


FIG. No. 3. Impulse responses to a standard credit supply shock.

Note: Units are in percent point deviation, except for the credit spreads, which are in terms of percentages. The solid line depicts the median response at each horizon across all accepted specifications, while the dashed lines represent the 12 and 88 percentiles.

The historical decomposition of credit supply and other drivers behind the dynamics of endogenous variables are reported in Figure No. 4. Similarly to credit spread shocks, credit supply shocks had a procyclical effect during the recent business cycle. Figure No. 4 indicates that during the boom episode between 2004 and 2008, in the absence of credit supply shocks, credit spreads would have been higher, while GDP, housing prices and credit growth would have been considerably lower. In contrast, during the economic downturn of 2008 and 2009, real GDP growth would have stayed higher in the absence of credit supply shocks. Housing price and credit growth variables were affected in a similar fashion, though in quantitative terms, they were more affected than the real economy during the crisis. In general, as one would expect, credit supply shocks had a procyclical and somewhat destabilizing effect on the Lithuanian economy during the recent cycle.

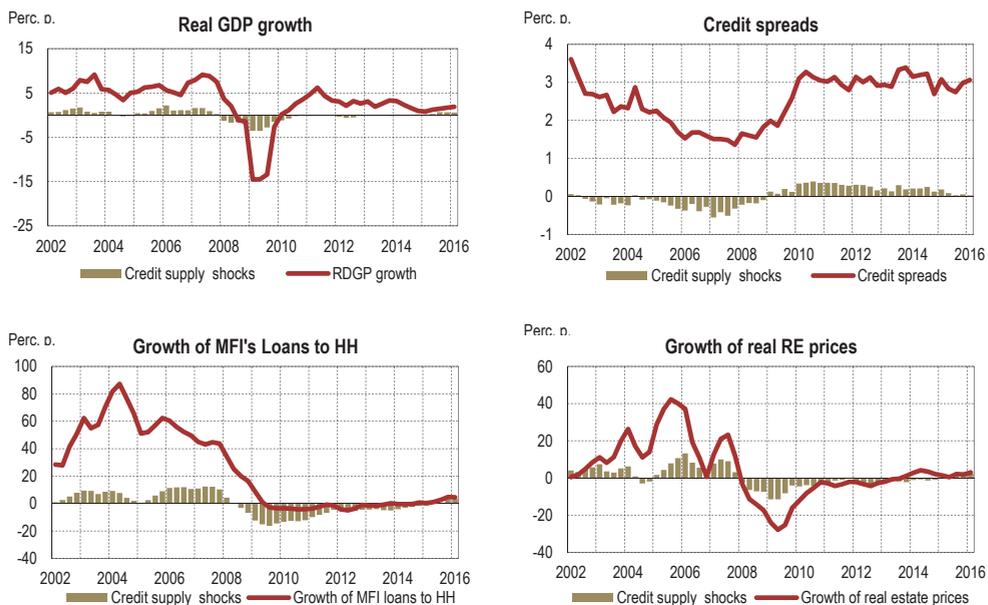


FIG. No. 4. The historical decomposition of endogenous variable dynamics in the sign-restrictions model.

Note: the red lines depict the actual dynamics. The brown bars represent the accumulated contribution to the endogenous variables of credit supply shocks. A positive (negative) bar at each period captures how the change in the endogenous variable would have been lesser (greater) in the absence of the shock.

Our findings suggest that credit supply shocks have played an important role in the recent business cycle in Lithuania. Credit supply shocks contributed positively to output growth in the precrisis phase and negatively during the downturn in 2008–2009. While in the post-crisis period the credit-related shocks weighed down on the economic, credit and real estate price growth, the effect turned positive in 2014. In general, the significance of credit supply (or credit spread) shocks in explaining economic activity was somewhat lower as compared to the results in other studies for EU countries (e.g., results of Duchi and Elbourne 2016; Gambetti and Musso 2012). This could be, at least to some extent, attributed to the low private sector indebtedness and, therefore, the importance of credit in Lithuania. However, our results must be taken with caution, as we use quite short data series. In addition, quantitative results are quite sensitive to different model specifications and different shock identification schemes.

Concluding remarks

In this article, we use an SVAR model identified by using two approaches – sign restrictions and zero restrictions – to analyze the role of credit supply shocks for the Lithuanian economy. We provide some evidence that credit-related shocks played a nontrivial role during the last boom-and-bust cycle. However, the importance of credit-related supply

shocks is found to be less significant as compared to similar studies of other countries, which can be at least partly attributed to a low credit to GDP ratio.

From the policy perspective, it is important to follow the dynamics of credit margins as a measure of banks' willingness to lend. While some of the observed variation in credit spreads is determined by the endogenous response to other fluctuations, some of it can be attributable to exogenous shifts in credit supply. Nevertheless, an exogenous shift is quite important – a 1 p.p. exogenous decline in the credit spread would cause a maximum decrease in the growth rates of GDP, household loans portfolio and housing price of, respectively, 3 p.p., 13.7 p.p. and 11.2 p.p. This would imply that the QE or the macroprudential policies that affect the credit spread should be expected to have sizable effects on the business cycle. It is also important to note that while credit supply-related shocks weighed down on economic growth during the period from 2008 to 2014, the effect turned positive in 2014.

LITERATURE

Abiad A., Dell'Ariccia G., Li B. 2012: *What Have We Learned about Creditless Recoveries?* IMF, <https://www.imf.org/external/np/seminars/eng/2012/fincrisis/pdf/ch10.pdf>

Altavilla, C., Darracq-Paries, M., Nicoletti, G. 2015: *Loan supply, credit markets and the euro area financial crisis*. European Central Bank, Working Paper Series No. 1861.

Barnett, A., Thomas, R. 2013: *Has weak lending and activity in the United Kingdom been driven by credit supply shocks?* Bank of England, Working Paper No. 482.

Bijsterbosch, M., Falagiarda, M. 2015: The macroeconomic impact of financial fragmentation in the euro area: which role for credit supply? – *Journal of International Money and Finance*, 54 (C), 93–115.

Bondt, G. d., Maddaloni, A., Peydró, J. L., Scopel, S. 2010: *The euro area bank lending survey matters: Empirical evidence for credit and output growth*. European Central Bank, Working Paper No. 1160.

Caldara D., Kamps C., 2008: *What are the effects of fiscal policy shocks? A VAR-based comparative analysis*. European Central Bank, Working paper No. 877.

Cappiello, L., Kadareja, A., Sørensen, C. K., Protopapa, M. 2010: *Do bank loans and credit standards have an effect on output? A panel approach for the euro area*. European Central Bank, Working Paper No. 1150.

Christiano J. L., Eichenbaum M., Evans L. C. 2005: Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy – *Journal of Political Economy* 113, no. 1, 1-45.

Duchi F, Elbourne A., 2016: Credit supply shocks in the Netherlands. – *Journal of Macroeconomics* Vol. 50, 51–71

Elbourne, A., 2008: The UK housing market and the monetary policy transmission mechanism: An SVAR approach. – *Journal of Housing Economics*, Vol. 17(1), 65–87.

Everaert G., Che N., Geng N., Gruss B., Impavido G., Lu Y., Saborowski C., Vandebussche J., Zeng L. 2015: *Does supply or demand drive the credit cycle? Evidence from Central, Eastern, and Southeastern Europe*. International Monetary Fund Working Paper WP/15/15

- Furlanetto F., Ravazzolo F., Sarferaz S., 2014: *Identification of financial factors in economic fluctuations*. Norges Bank, Working paper No. 2014/09
- Gambetti, L., Musso, A., 2012. *Loan supply shocks and the business cycle*. European Central Bank, Working Paper Series No. 1469.
- Ginters B., 2015 Financial frictions in a DSGE model for Latvia, Dynare working paper No 42, <http://www.dynare.org/wp-repo/dynarewp042.pdf>
- Hristov, N., Hulsewig, O., Wollmershauser, T. 2011: *Loan Supply Shocks During the Financial Crisis: Evidence for the Euro Area*. CESifo Working Paper Series No. 3395.
- Iacoviello M. 2005: House Prices, Borrowing Constraints and Monetary Policy in the Business Cycle. – *American Economic Review*, Vol. 95, No. 3, 739-764.
- Iacoviello, M., Neri, S. 2010. Housing market spillovers: evidence from an estimated DSGE model. – *American Economic Journal*, Vol 2, 125–164.
- Iacoviello, Matteo, and Raoul Minetti 2008: *The Credit Channel of Monetary Policy: Evidence from the Housing Market*. – *Journal of Macroeconomics*, Vol. 30, No. 1 69-96.
- Justiniano, A., Primiceri, G., Tambalotti, A. 2010: Investment shocks and business cycles. – *Journal of Monetary Economics* Vol. 57, 132-145.
- Kanngiesser D, Martin A., Maurin L., Moccero D., 2016: *Estimating the Impact of Shocks to Bank Capital in the Euro Area*. European Central Bank mimeo.
- Kiyotaki N., Moore J. 1997: Credit Cycles. *Journal of Political Economy*. Vol. 105 (2) 211–248.
- Kuodis R., Ramanauskas T., 2009 From Boom To Bust: Lessons From Lithuania. – *Pinigų studijos* 2009/1
- Meeks R. 2012: Do credit market shocks drive output fluctuations? Evidence from corporate spreads and defaults. – *Journal of Economic Dynamics & Control* Vol. 36 568-584.
- Musso A., Neri, S., Stracca L. 2011: Housing, consumption and monetary policy: How different are the US and the euro area? – *Journal of Banking & Finance*, Vol. 35(11), 3019-3041.
- Peersman, G., 2011. *Bank lending shocks and the Euro area business cycle*. Working Papers of Faculty of Economics and Business Administration. Ghent University, Belgium.
- Ramanauskas T. 2011a: A Macroeconometric Model with the Financial Sector for the Case of the Lithuanian Economy. – *Pinigų studijos* 1, 5–30.
- Ramanauskas T. 2011b: Analysis of Determinants of the Boom-And-Bust Cycle in Lithuania Using a Macroeconometric Model. – *Pinigų studijos* 2, 5-23
- Sims A. C., 1980. Macroeconomics and reality. – *Econometrica* 48 (1), 1–48.
- Smets, F., Wouters R. 2003: An estimated dynamic stochastic general equilibrium model of the euro area – *Journal of the European Economic Association*, 1:5, 1123-1175.
- Stakėnas J. and Stasiukynaitė R. 2016: *Monetary policy transmission: the case of Lithuania*, Bank of Lithuania, Working Paper Series No. 24.
- Stock H. J., Watson W. M. 2001: Vector Autoregressions. – *The Journal of Economic Perspectives*, Vol 15. No 4. 101–115.
- Uhlig, Harald, 2005: What are the effects of monetary policy on output? Results from an agnostic identification procedure, – *Journal of Monetary Economics*, Vol. 52(2), 381-419.
- Walentin K. 2014: Business cycle implications of mortgage spreads. – *Journal of Monetary Economics*, Vol 67, 62–77.

Data description and sources.

Variable	Source	Transformations	Description
<i>Inflation</i>	Eurostat	Seasonally adjusted; Y-o-Y growth rate	Lithuanian GDP deflator.
Output growth:	Eurostat	Seasonally adjusted and adjusted by working days; Y-o-Y growth rate	Lithuanian gross domestic product at market prices; Chain linked volumes, index 2005=100; GDP values prior to 2005Q1 extrapolated using quarterly changes in GDP according to ESA95.
Credit spread:	Bank of Lithuania; author's calculations		As in a study by Stakėnas and Stasiukynaitė (2016), credit margins are calculated as follows: $\text{credit margin} = \text{laon interest} \left(\frac{\text{new laons in euros}}{\text{total new laons}} \right)$ $* \text{Euribor}_{3m} + \frac{\text{new laons in litas}}{\text{total new laons}} + \text{Viliber}_{3m}$ where the loan interest contains the average interest rates on new loans (both in litai and in euros) to households.
Lending growth:	MFI balance sheet data	Y-o-Y growth rate	MFI loans to non-households in Lithuania; Adjusted for reclassifications and technical changes.
Housing price growth	State Enterprise Centre of Registers	Y-o-Y growth rate	House price index in Lithuania (total territory).