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Credit Supply or Demand? The Changing Role of Structural Market Forces in Bank Lending

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Credit Supply or Demand? The Changing Role of Structural Market Forces in Bank Lending*

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Abstract

The Global Financial Crisis, the European Debt Crisis, and the recent COVID-19 Crisis have repeatedly demonstrated that disruptions in credit markets can have serious macroeconomic consequences. This paper aims to assess the structural drivers of the NFCs bank lending market, as bank lending dominates the credit markets in the euro area, and to determine its macroeconomic consequences. To study these effects, we use structural VAR methodology with a modified identification scheme and modified variable selection compared to what is usually found in the literature. As an empirical illustration, we analyze the importance of the bank lending market in a small, open and bank-based euro area economy - Slovakia. The results show that loan demand shocks (loans demanded by firms) are at least as important as credit supply shocks (loans supplied by banks) in the lending market and that this importance changes over the cycle. These findings have important policy implications, as responding to these shocks may require different policy measures. Contributions to the literature are (i) new empirical evidence on the macroeconomic importance of loan demand shocks compared to credit supply shocks and (ii) new country-specific modification of structural VAR methodology.

Keywords: Credit supply; Loan demand; Non-financial corporations; Structural VAR models; Sign restrictions; Zero restrictions
JEL-Codes: C32, E51, G01

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Nontechnical Summary

After the Global Financial Crisis, the European Debt Crisis, and to some extent during the COVID-19 Crisis, it has become clear that the importance of credit supply shocks as a source of business cycle fluctuations is not negligible. But the credit supply shocks are only one part of the story. After numerous crises related to bank credit, an unexpected contraction/expansion in the supply of bank credit and unexpected changes in the demand for credit have become important sources of macroeconomic fluctuations.

The standard methodology for studying the source of macroeconomic fluctuations is structural VAR models. Many studies with sign and zero restrictions identify bank lending and other macroeconomic shocks and study their effects across countries. The drawback of these studies is that while some of them identify loan demand shocks, they focus only on the impact of credit supply shocks on GDP and do not examine the broader macroeconomic importance of this shock as well as a loan demand shock.

In this paper, we assess the impact of supply-side (banks) and demand-side (firms) shocks in the NFC bank lending market (both in terms of the quantity of credit and the price of credit), their broader macroeconomic implications (feedback loops from lending shocks to the real economy and vice versa), and their changing importance over the business cycle. We estimate the impact of these structural drivers using the structural VAR methodology. In addition, we enrich the standard modelling framework to make it suitable for other EA countries.

The results show that both the credit supply shock and the loan demand shock are important drivers of the NFCs bank lending market with spillovers to the broader economy. The importance of these shocks changes over the business cycle. Moreover, there is evidence that these lending shocks affect the real economy and vice versa. These results have important *policy implications*:

- Credit supply shocks were more important for the lending market in the stressed periods, while loan demand shocks were more important in the calmer periods. This result has implications for the conduct of monetary and macroprudential policies, as adverse (positive) credit supply shocks require a different policy response than negative (positive) loan demand shocks.
- Credit supply and demand shocks had a limited, but not negligible, impact on the real economy. However, this limited impact was not unexpected and is likely to be country-specific. The Slovak banking sector was relatively healthy and strong during the recent crises. The limited impact of credit shocks, especially in adverse scenarios, was to be expected. After all, real economy shocks, as opposed to credit market shocks, are very broad categories of structural shocks, and one could expect them to play a dominant role.

- We find empirical evidence that the ECB's monetary policy is transmitted through the banking sector, which further underscores the importance of bank lending shocks in our model, variable selection, and identification scheme.

The contributions to the literature are (i) new empirical evidence on the changing role of structural loan demand factors relative to structural credit supply factors over the business cycle, and (ii) a new country-specific modification of the structural VAR methodology to account for modeling specifics of Slovakia as a member of the Monetary Union.

1. Introduction

Since the Global Financial Crisis, the European Debt Crisis, and to some extent during the recent COVID-19 Crisis, it has been widely believed that disruptions in credit markets can have far-reaching macroeconomic consequences (Peersman (2011), Park and Shin (2021)). Credit markets in the euro area are dominated by the banking sector, which was initially considered only as part of the transmission mechanism amplifying shocks originating elsewhere (monetary policy shocks, real economy shocks etc.). However, after numerous crises related to bank credit, an unexpected contraction/expansion in the supply of bank credit and unexpected changes in the demand for credit have become important sources of macroeconomic fluctuations.

In the literature, the standard methodology to study the source of macroeconomic fluctuations is structural VAR models. Barnett and Thomas (2013) is one of the first studies to analyze the macroeconomic importance of bank credit shocks using zero and sign-restricted structural VAR analysis. Many other studies, such as Hristov et al. (2012), Bijsterbosch and Falagiarda (2015), Duchi and Elbourne (2016), Gambetti and Musso (2017), or Vacca et al. (2021) identify bank lending shocks and other macroeconomic shocks and study their effects across countries. However, the drawback of these studies is that while some of them identify loan demand shocks, they focus only on the impact of credit supply shocks on GDP and do not examine the broader macroeconomic importance of these shocks as well as of a loan demand shock.

In this paper, we assess the impact of supply-side (banks) and demand-side (firms) shocks in the NFC bank lending market (both in terms of the quantity of credit and the price of credit), their broader macroeconomic implications (feedback loops from lending shocks to the real economy and vice versa), and their changing importance over the business cycle. We estimate the impact of these structural drivers using the structural VAR methodology. In addition, we enrich the standard modeling framework to make it suitable for other EA countries.

The contributions to the literature are (i) new empirical evidence on the changing role of structural loan demand factors relative to structural credit supply factors over the business cycle, and (ii) a new country-specific modification of the structural VAR methodology to account for modeling specifics of Slovakia as a member of the Monetary Union. The results show that credit supply shocks are not the only driver of the NFC bank lending market, loan demand shocks are at least as important. Interestingly, the macroeconomic importance of these shocks changes over the business cycle. Credit supply shocks are more important in times of economic or financial stress, while loan demand shocks are more relevant in normal times. Moreover, the identified structural shocks to bank lending are consistent with economic theory, historical perspectives, and the results of the ECB's Bank Lending Survey. Furthermore, there is evidence that credit shocks affect the real economy and vice versa. These findings have important policy implications, as these shocks may require different policy responses.

The paper is organized as follows. Section 2 reviews the relevant literature and places our study in context. Section 3 explains the SVAR methodology, estimation algorithm, data selection, and identification scheme. Section 4 presents our main results in terms of impulse response functions, historical decomposition, and structural shocks themselves. Section 5 computes and explains selected robustness checks. Finally, Section 6 concludes and offers some areas for future research.

2. Related Literature

Early work on the importance of credit markets for business cycle fluctuations focused on their role as part of the propagation mechanism that amplifies shocks originating elsewhere (monetary policy shocks, real economy shocks, productivity shocks, etc.)[1].

Past (The Global Financial Crisis, The European Debt Crisis) and recent (COVID-19 Crisis) crises have shown the macroeconomic importance of the (un)availability of bank credit. Barnett and Thomas (2013), Hristov et al. (2012), Bijsterbosch and Falagiarda (2015), Duchi and Elbourne (2016), Gambetti and Musso (2017), Vacca et al. (2021) find that an unexpected contraction/expansion in the provision of bank credit has a significant effect on bank credit markets and economic activity, and identify this type of shock as an important source of macroeconomic fluctuations. On the other hand, a similarly detailed and thorough analysis of unexpected changes in demand for credit as a source of macroeconomic fluctuations is lacking.

The authors use several methods to estimate or assess the macroeconomic importance of bank lending shocks. In the first approach, Del Giovane et al. (2011) or Ciccarelli et al. (2015) estimate the impact of credit supply shocks on the macroeconomy using the reduced-form regressions and the results from the ECB's Bank Lending Survey. This approach has limitations, such as the presence of endogeneity in large macroeconomic systems and the reliability of the survey results. The second approach attempts to overcome these problems and uses DSGE models to study the effects of bank lending shocks. For example, Gerali et al. (2010) find that the contribution of these shocks to the 2006-2007 expansion and subsequent recession was significant. The problem with this approach is that it requires strong modeling assumptions. The third approach, structural VAR models, overcomes the problem of endogeneity of macroeconomic variables while not requiring strong modeling assumptions.

Structural VAR models are a standard methodology for identifying the macroeconomic significance of structural shocks. From the reduced form VAR, it is not possible to directly identify the underlying structural model of the economy, so an econometrician must apply restrictions to the reduced form VAR model - identification. Peersman (2011), Barnett and Thomas (2013), Barnett and Thomas (2013), Hristov et al. (2012), Bijsterbosch and Falagiarda (2015), Duchi and Elbourne (2016), Gambetti and Musso (2017), Vacca et al. (2021) use a combination of zero and sign restriction to identify and assess the macroeconomic importance of bank lending shocks in several countries.

[1]The prevailing view among macroeconomists can be summarized by Bernanke and Gertler (1995) as follows: *"Except in rare circumstances, credit is not a primitive driving force; rather credit conditions (. . .) are an endogenous factor that help shape the dynamic response of the economy to shifts in monetary policy"*. In the euro area, credit markets are dominated by the banking sector as the main source of external finance for the private sector (Altavilla et al. (2019)).

The problem with zero- and signed-identified SVARs is that, unlike zero-restricted SVARs, they are only set-identified. This means that the observed data are potentially consistent with a wide range of structural models, all of which are admissible in the sense that they satisfy the identifying (inequality) restrictions. A good explanation of the methodological aspects of zero and sign-identified SVARs is Arias et al. (2018), where the authors review the drawbacks of current econometric methods and propose an improved algorithm that ensures that no unwanted sign restrictions are imposed on the data[2].

Our paper builds on previous work done in the following papers. Barnett and Thomas (2013) examines the role of credit supply shocks in driving the weakness in UK bank lending and economic activity during both the global financial crisis and the various UK financial crises since 1966. They find that credit supply shocks can account for most of the weakness in bank lending and a significant part of the fall in GDP since the onset of the crisis. They also identify a loan demand shock but do not examine this shock. Duchi and Elbourne (2016) investigate the role of credit supply shocks in the Netherlands using the Barnett and Thomas (2013) identification scheme. Their results show that positive credit supply shocks boosted growth before 2007, and negative credit supply shocks depressed GDP growth between 2008 and 2012 and were negligible thereafter. The authors identify a loan demand shock but do not investigate its broader macroeconomic implications or its behavior over the cycle. In addition, since the Netherlands is part of the monetary union, we modify their modeling framework to better capture the nuances of modeling monetary policy in the monetary union. Gambetti and Musso (2017) study the effects of credit supply shocks over the cycle in the euro area, the UK, and the US using the time-varying structural VAR model with stochastic volatility. Their evidence suggests that credit supply shocks have a significant effect, especially during recessions. They do not identify a loan demand shock. Finally, Vacca et al. (2021) assesses the impact of a credit supply shock on GDP for Austria, Germany, Spain, and Italy. They find evidence of a negative impact of (adverse) credit supply shocks, but only with a significant degree of uncertainty. Moreover, the uncertainty increases when the authors include the COVID-19 period in their estimation sample. Loan demand shocks are identified, but their broader macroeconomic importance is not explored.

Some studies analyze similar issues in the Central European region. The first application uses a SVAR model to analyze the effects of two types of credit supply shocks for the Hungarian economy: a shock stemming from (i) the risk assessment of financial intermediaries and (ii) variations in the regulatory environment. Tamási et al. (2011) find that the first shock mainly affects the quantity of loans, while the second shock affects both the price and the quantity. Both shocks contributed to the decline in economic activity during the GFC, but they were not dominant. The second is the application of VECM to the Czech Republic to disentangle credit supply and credit demand in the long-run relationship of the model. Plašil et al. (2012) find a dominant role for credit demand in driving credit growth. However, this is only true in normal times, while in times of crisis (in their case, only the GFC), credit dynamics were influenced by credit

[2] In Breitenlechner et al. (2019) the authors provide the algorithm implementation of Arias et al. (2018) in MATLAB.

restrictions imposed by banks.

All these papers have in common that, although some of them identify loan demand shocks, they focus only on the impact of credit supply shocks on GDP and do not examine the broader macroeconomic importance of this shock as well as of a loan demand shock. In our paper, we focus equally on the impact of credit supply and loan demand shocks in the NFC bank lending market (both in terms of the quantity of loans and the price of loans), their broader macroeconomic implications, and their changing importance over the business cycle. In addition, we enrich the standard modeling framework to make it suitable for EA countries.

3. Methodology, Data, and Model

The most common approach to tracing the macroeconomic importance of structural shocks is the SVAR methodology, which arises from the work of Sims (1980).

3.1. Structural VAR Models and Estimation Algorithm

Standard VAR analysis[3] starts with the reduced form, where each endogenous variable is regressed on its lags and lags of other variables and possibly other deterministic terms (constant, time trend, or seasonal dummy variables). In matrix notation:

$$\mathbf{y_t} = \mathbf{c} + A_1\mathbf{y_{t-1}} + A_2\mathbf{y_{t-2}} + \cdots + A_p\mathbf{y_{t-p}} + \mathbf{u_t} \tag{1}$$

where $\mathbf{y_t}$ is an $n \times 1$ vector of endogenous variables at quarter t, $\mathbf{c}$ is in this case a vector of constants, A_p are $n \times 1$ matrices of coefficients, $\mathbf{u_t}$ are the reduced-form residuals with zero mean and covariance matrix $E[\mathbf{u_t}\mathbf{u_t'}] = \Sigma_\mathbf{u}$ such that $u_t \sim \mathcal{N}(0, \Sigma_\mathbf{u})$.

The problem with the reduced form VAR (1) is that residuals cannot be used for structural analysis because they are cross-correlated. In other words, reduced form residuals are a linear combination of structural shocks. To recover the structure of the economy (and the evolution of structural shocks) as the main goal of the structural analysis, we assume the following structural model:

$$A_0\mathbf{y_t} = k + A_1^*\mathbf{y_{t-1}} + A_2^*\mathbf{y_{t-2}} + \cdots + A_p^*\mathbf{y_{t-p}} + \epsilon_\mathbf{t} \tag{2}$$

where A_0 is an $n \times n$ matrix containing the contemporaneous reactions of the variables to the structural shocks, A_p^* are $n \times n$ matrices of structural coefficients for the system (1), and $\epsilon_\mathbf{t}$ is an $n \times 1$ vector of mean zero serially uncorrelated structural shocks with $E[\epsilon_\mathbf{t}\epsilon_\mathbf{t}'] = \Sigma_\epsilon = \mathbf{I}$, $\epsilon_\mathbf{t} \sim \mathcal{N}(0, \mathbf{I})$ respectively[4]. The equations of a structural VAR define

[3] More detailed explanation of VAR models can be found in Lütkepohl (2007) and structural VAR models in Kilian and Lütkepohl (2017).

[4] From the technical point of view (Kilian and Lütkepohl (2017)), (i) there are as many structural shocks as variables in the VAR model; (ii) structural shocks are mutually uncorrelated ($\Sigma_\epsilon = \mathbf{I}$ is diagonal); and (iii) the variance of all structural shocks is normalized to unity. In an economic sense, these shocks must be economically interpretable since they do not correspond to particular model variables.

the true structure of the economy.

Usually, we can estimate, with standard econometric methods, the reduced form (1) with the covariance matrix $\Sigma_{\mathbf{u}}$. Then we can check the statistical validity of the model with the reduced form residuals diagnostics (stability, normality, autocorrelation, homoskedasticity). However, we are not able to directly recover the structural form (2). This is done by pre-multiplying the structural form (2) by A_0^{-1}(1)[5] and establishing a relationship with the reduced form residuals as

$$\mathbf{u_t} = A_0^{-1}\epsilon_\mathbf{t}. \tag{3}$$

From the estimated covariance matrix $\Sigma_{\mathbf{u}}$ we construct a system of equations $\Sigma_{\mathbf{u}} = E[\mathbf{u_t}\mathbf{u_t'}] = (A_0^{-1})(A_0^{-1})'$[6] which can be used to solve for the unknown parameters in $(A_0^{-1})(A_0^{-1})'$. Since the matrix $\Sigma_{\mathbf{u}}$ is symmetrical it has only $(n(n+1))/2$ estimated parameters, whereas $(A_0^{-1})(A_0^{-1})'$ has n^2 parameters, which means we need to impose additional $(n(n-1))/2$ restrictions on matrix A_0^{-1} in a process called identification[7].

In this paper we use the combination of zero and sign restrictions. Combining these two approaches we reduce drawbacks and accentuate advantages, but the estimation algorithm needs to be modified accordingly. Early types of algorithms dealing with sign restrictions were proposed by Uhlig (2005) and Mountford and Uhlig (2009). These algorithms used a penalty function approach where a single value of the structural parameters is selected by minimizing the loss function. Arias et al. (2018) showed a number of drawbacks of this algorithm and provide an alternative algorithm which is now accepted in the literature (Duchi and Elbourne (2016), Bobeica et al. (2019), Baumeister and Hamilton (2020), and many others)[8].

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[5] $\mathbf{c} = A_0^{-1}\mathbf{k}$, $A_1 = A_0^{-1}A_1^*$, $A_2 = A_0^{-1}A_2^*$, $\ldots$, $A_p = A_0^{-1}A_p^*$.

[6] $\Sigma_{\mathbf{u}} = E[\mathbf{u_t}\mathbf{u_t'}] = E[A_0^{-1}\epsilon_\mathbf{t}(A_0^{-1}\epsilon_\mathbf{t})'] = A_0^{-1}\Sigma_\epsilon(A_0^{-1})' = (A_0^{-1})(A_0^{-1})'$ since $\Sigma_\epsilon = \mathbf{I}$.

[7] There are quite a few approaches for structural VAR identification. The most popular are restrictions based on the economic theory implemented through short-run restrictions, long-run restrictions, sign restrictions, or identification based on other external data not included in the VAR model. Other methods are based on the statistical properties of the data for identification.

[8] In the paper we use the we use the *ZeroSignVAR* Matlab toolbox developed by Breitenlechner et al. (2019). Source for *ZeroSignVAR* Matlab toolbox: https://eeecon.uibk.ac.at/ breitenlechner/research.html. When the econometrician is interested only in studying one structural shock at a time (partial identification), it is possible to use Eviews Add-ins *ARW* or *srvar*: *https://www.eviews.com/Addins/addins.shtml*. The algorithm is based on generating and then accepting or discarding candidates for A_0^{-1}. For more details on the algorithm see appendix A.

[9] In the paper we use the *ZeroSignVAR* Matlab toolbox developed by Breitenlechner et al. (2019).

3.2. Data Used for Structural VAR Analysis

As an empirical illustration, we study the importance of bank lending shocks for the Slovak economy. This example may be interesting for several reasons. First, Slovakia is a European country, and bank lending is a crucial source of funding in the economy. Second, during the period analyzed, Slovakia entered the monetary union, and therefore it is possible to test the proposed methodology in this specific economic environment. Next, the Slovak economy experienced the effects of the Global Financial Crisis in 2008/2009, the European Debt Crisis in 2010-2012, the COVID-19 Recession, the high inflation environment, but also the effects of the adoption of the Euro and ECB's non-standard monetary policy measures, while all these shocks manifest themselves through the bank lending market. Furthermore, the application on Slovakia can serve as a template for other CESEE countries. Finally, Vacca et al. (2021)'s results for Austria, Germany, Spain, and Italy are not satisfactory. Authors in their factor-augmented VAR model use data beginning only in 2014, which is somewhat short for this type of analysis (George et al. (2008)), and may cause large (and possibly growing) confidence intervals for estimated IRFs.

To evaluate the macroeconomic relevance of credit supply and loan demand structural shocks, the literature[10] usually employs the following macroeconomic variables: CPI inflation as a measure of price pressures, GDP growth as a measure of economic activity, 10-year government bond yield as a measure of monetary policy stance, lending margins on loans to non-financial corporations, and banks' loans to non-financial corporations[11].

Before structural VAR analysis, we need to check the stationarity of the variables and the possible cointegration between them. In Appendix B we present a series of unit root tests for variables in levels and first differences. Firstly, the CPI is not stationary in level or differences. The economic explanation is the current surge in inflation, which started in early 2021 and shows no signs of slowing down until the end of the sample (2022Q4). Using the ADF breakpoint unit root test, we can conclude that CPI inflation (in first differences) is only stationary with a breakpoint in 2021Q1. Therefore, in this paper, we have to use an adjusted version of this series[12], which will be stationary. Secondly, GDP growth, the quarterly change in the government bond spread, and the growth of NFC loans are stationary in their first differences. Finally, lending margins are stationary at their levels, so no further transformation is needed. Regarding cointegration, the Johansen cointegration test for all variables in levels (except lending margins) from

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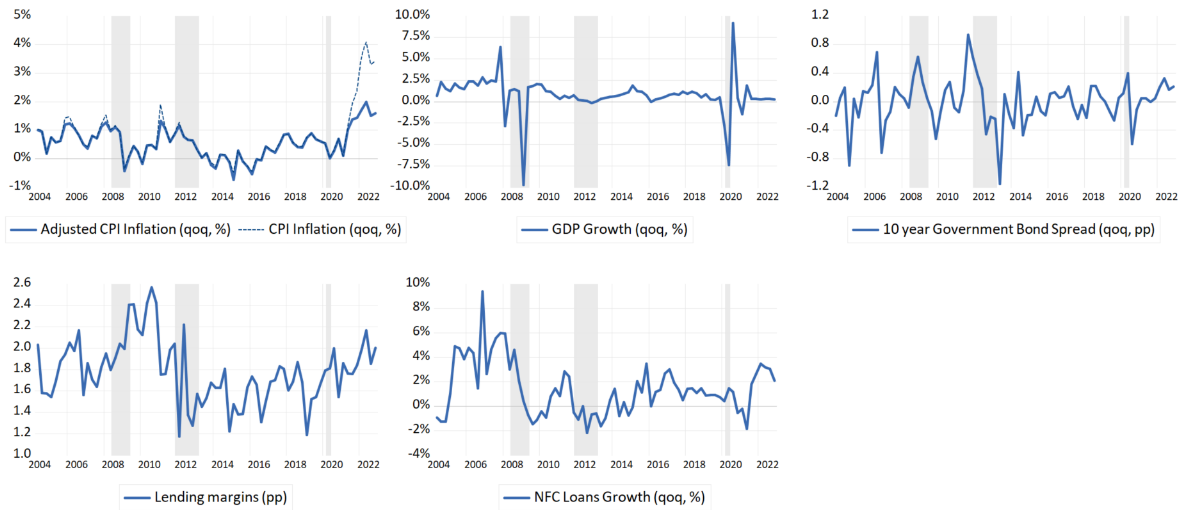
Source for *ZeroSignVAR* Matlab toolbox: https://eeecon.uibk.ac.at/ breitenlechner/research.html. If the econometrician is interested in studying only one structural shock at a time (partial identification), it is possible to use Eviews add-ins *ARW* or *srvar*: *https://www.eviews.com/Addins/addins.shtml*. The algorithm is based on generating and then accepting or discarding candidates for A_0^{-1}. For more details on the algorithm, see the A appendix.

[10] Barnett and Thomas (2013), Duchi and Elbourne (2016), Vacca et al. (2021) among others.

[11] Some studies, such as Barnett and Thomas (2013) or Duchi and Elbourne (2016), use equity prices as an endogenous variable in the VAR system. Since this variable does not help to identify any structural shocks, we do not include it in the system.

[12] Since there is only one problematic variable in our model, we use van der Waerden's method (see Boudt et al. (2012)) to deal with the outliers in CPI inflation related to the energy shock at the end of the sample. See the solid and the dotted lines in Figure 1.

Figure 1: Data used in SVAR anaylsis



Notes: Shaded areas represent EA recessions according to Euro Area Business Cycle Network.
Source: NBS, SOSR, ECB, Eurostat.

2004Q1 to 2020Q4 shows that there is no cointegration among the variables (Appendix B) and that a structural VAR analysis in first differences is appropriate (see Figure 1).

CPI inflation (%, qoq)

The seasonally adjusted quarterly rate of CPI inflation. This variable attempts to capture broad price pressures in the economy (source: Statistical Office of the Slovak Republic - SOSR). Apart from the stationarity issues related to the sudden spike in energy prices at the end of the sample, Kupkovič (2020) finds that the historical evolution of inflation has been quite stable. There is only one breakpoint at the beginning of 2004, which coincides with the official adoption of the inflation targeting regime and the commitment to the adoption of the euro. Since the ECB does not specifically target inflation in Slovakia, the baseline inflation rate can be estimated.

GDP growth (%, qoq)

The seasonally adjusted quarterly growth rate of real GDP. This is a standard measure of economic activity (source: Eurostat/SOSR).

The measure of aggregate funding in the economy (pp, qoq)

Quarterly change in the spread between Slovakian and German 10-year government bond yield (Source: Eurostat, NBS). This measure is conceptually related to conventional and unconventional monetary policy, as well as country-specific factors, and has many dimensions[13]:

- To assess the effects of monetary policy in normal times, the literature (Walsh (2017)) usually recommends using the policy rate, the interbank rate, or some

[13]These are also reasons why we prefer this measure compared to deposit rates or (shadow) policy rates. Nevertheless, in the robustness checks section, we analyze the results concerning different measures of monetary policy.

kind of short-term interest rate. These are then translated to the longer rates such as the 10-year government bond yield and the broader economy[14].

- In the environment of the zero lower bound (ZLB) on short-term interest rates, short-term interest rates are no longer indicative of the stance of monetary policy. The central bank uses non-standard monetary policy tools (quantitative easing/tightening, forward guidance, and others[15]) to alter borrowing costs through their impact on 10-year government bond yields.
- We are not only interested in the level of Slovak long-term interest rates[16], but also in the spread over its German counterpart, as this spread also captures additional country-specific risks. These risks are related to country-specific macroeconomic stabilization policies, reforms undertaken, and the like.
- 10-year government bond yield in Slovakia works as a reference rate for other retail bank rates.

While the nature of country-specific factors is intuitive, when it comes to Slovakia and its monetary policy stance, we need to make assumptions similar to Duchi and Elbourne (2016) for the Netherlands. Since 2009, Slovakia has been part of the euro area and does not have its own monetary policy[17]. The ECB gives almost no weight to the evolution of the Slovak economy when adjusting its monetary policy stance, as it focuses on euro area-wide developments. Our assumption of an endogenous monetary policy stance is only valid if there is a reasonably high degree of correlation between macroeconomic performance (in our SVAR model in terms of GDP growth and CPI inflation) between Slovakia and the euro area. Slovakia is a small and highly open economy integrated into European global value chains[18]. Therefore, the Slovak economy can be expected to move in tandem with the euro area economy. In our sample (2004-2022), the correlation between GDP growth and CPI inflation in Slovakia and the euro area is 0.74^{***} and 0.87^{***}, respectively. Before the adoption of the euro, but during the inflation targeting regime of ERM II (2004-2008), the correlation was 0.35 for GDP and 0.63^{***} for inflation. After adoption, the correlation was 0.82^{***} and 0.91^{***}, respectively. To conclude, if there was a rationale for monetary tightening (loosening) in the euro area, it was also reasonable to assume monetary tightening (loosening) for Slovakia.

Lending margins (pp)

As a measure of the price of credit risk, we use seasonally adjusted lending margins of MFIs′ (banks′) on loans to non-financial corporations. Lending margins are measured

[14]Standard transmission channels of monetary policy as in Ireland (2010).

[15]See, for example, Fratzscher et al. (2016).

[16]Here we can see the downward trend that is observed globally. Rachel and Smith (2017) and many others explained this trend by declining natural real interest rates around the world.

[17]The monetary policy of the NBS was in line with the ECB even before 2009. In May 2004 Slovakia joined the EU and the NBS was integrated into the European System of Central Banks. In September 2004, the authorities approved the euro adoption strategy. The monetary policy regime during this period was characterized by inflation targeting under ERM II. Monetary policy was conducted by setting interest rates and managing inflation expectations in line with the ECB.

[18]Most notable is Central European integration in the German supply chains (Augustyniak et al. (2013)).

as the difference between MFI′ (banks′) interest rates on new business loans and a weighted average interest rate on new deposits from NFCs (Source: Risk assessment indicators of ECB).

NFCs loans growth (%, qoq)

The seasonally adjusted quarterly growth rate of total outstanding loans of MFIs′ (banks′) to NFCs. This variable corresponds to the volume element of bank loans to NFCs (Source: NBS, ECB)[19]. Our focus on bank lending to NFCs has several motivations. Firstly, bank lending is crucial in the euro area and its members, as it is the main source of financing and plays a leading role in the transmission of monetary policy. Secondly, according to Vacca et al. (2021), bank lending to NFCs has implications for the broader economy: (i) firms are one of the main sources of investment, employment, value-added and foreign trade within an economy; (ii) NFCs are borrowers whose risk assessment tends to be difficult and where banks can add the most value; (iii) unlike lending to NFCs, lending to households (both for housing and consumption) can be more easily substituted by other banks. Finally, looking at bank lending to NFCs in Slovakia, (i) it is one of the most important sources of finance compared to other sources, whether resident or non-resident; and (ii) it is the source most related to the business cycle.

3.3. Structural Model - Identification

As has been discussed in the literature (Barnett and Thomas (2013) or Bobeica et al. (2019)), our purpose serves the best combination of short-run zero restrictions and sign restrictions on the matrix $A_0^{-1}(A_0)$. The main advantage of zero restrictions[20] is that, in line with economic theory, they allow us to specify the response of a variable to a structural shock with a lag(s). This is extremely helpful when economic theory assumes a lagged effect, as is the case with financial shocks. Financial shocks originating from credit institutions usually take some time to work their way through the economy and affect aggregate macroeconomic variables. On the other hand, it is difficult to economically justify too many zero restrictions in large VAR systems.

Sign restrictions have become popular in SVAR analysis as an alternative to traditional approaches based on exclusion restrictions. The literature began with the pioneering work on robust monetary policy identification by Faust (1998), which was followed by a popular model by Uhlig (2005) for identifying a structural monetary policy shock. The main advantage of this approach is that it can be used in situations where economic theory provides information about the expected sign of a variable's response to the given structural shock. In addition, sign restrictions can capture the expected co-movement of variables following a structural shock. It is useful when we model demand and supply

[19] The growth rate of outstanding loans (source: NBS, ECB) is almost identical to the growth rate of loans based on a notional stock index (source: ECB). Therefore, in this paper, we only use the growth rate of outstanding amounts of loans, for which we have a longer time series.

[20] Sims (1980), Christiano et al. (1998), or Stock and Watson (2001) are prominent examples of using zero restrictions, in this case, a recursive structure, to identify structural shocks that drive the US economy. Another example is Kilian (2009)'s model of the global crude oil market to disentangle the role of demand and supply shocks.

shocks in the classical market (aggregate demand vs. supply shocks, credit supply vs. credit demand shocks, etc.). In a standard market model, a demand shock moves price and quantity in the same direction, while a supply shock moves price and quantity in the opposite direction. The main drawback of this approach is that SVAR models identified with sign restrictions are not point identified (one structural model that satisfies the structural restrictions), but only set identified (there may be many structural models that satisfy the structural restrictions). This makes estimation and statistical inference very difficult.

Our identification stems from several studies: Peersman (2011), Hristov et al. (2012), Barnett and Thomas (2013), Bijsterbosch and Falagiarda (2015), Duchi and Elbourne (2016), Gambetti and Musso (2017), Bobeica et al. (2019), or Vacca et al. (2021). The restrictions are imposed on the quarter when the shock occurs and in the case of lending shocks also in the next quarter. In early SVAR models identified with zero and sign restrictions authors usually identified only one structural shock (for example monetary policy shock as in Uhlig (2005)) or a small subset of all possible structural shocks - partial identification. Paustian et al. (2007) recommends the identification of as many structural shocks as economically possible to improve the recovery of true structural shocks. In this paper, we identify all possible structural shocks - full identification. Structural shocks (Table 1) can be divided into two broad categories: *NFCs credit shocks* and *aggregate macroeconomic shocks*.

Table 1: Identification scheme

Structural shocks → Endogenous Variables ↓	Credit Supply (CS)	Loan Demand (LD)	Aggregate Supply (AS)	Aggregate Demand (AD)	Monetary Policy (MP)
CPI Inflation	0	0	+	-	-
GDP Growth	0/-	0/-	-	-	-
10y Bond Spread	0	0	?	-	+
Lending Margins	+	-	?	?	?
NFCs Loans Growth	-	-	?	?	?

Notes: (+/-) sign restrictions, (0) zero restrictions, (?) parameters are not restricted, (0/-) or (0/+) mean a zero restriction in the impact period and a sign restriction in the next period.
Source: Duchi and Elbourne (2016) among others.

The three aggregate shocks are the most important factors driving economic fluctuations (Brand and Mazelis (2006)). They ensure that the structural shocks in the lending market are truly exogenous rather than endogenous responses to general economic activity. The two NFCs' bank lending shocks represent shocks originating from banks (credit supply shocks) or firms (loan demand shocks). Credit supply and loan demand shocks are disentangled from macroeconomic shocks by the time restriction and among themselves by the sign restriction. These shocks need at least one quarter to affect the real economy. For example, a contraction in the supply of credit (lower demand for loans by firms) means lower availability of finance, fewer investment opportunities, lower output, and ultimately lower overall economic activity. The sign restrictions for these shocks are defined as:

- A *credit supply shock* usually leads to opposite movements in the price of credit (lending margins) and in the volume of credit[21]. This shock could reflect an unexpected contraction in bank capital, a decline in bank assets or a change in the pricing of default risk by financial institutions. We experienced real-life examples of these shocks (negative) during the global financial crisis and the European debt crisis, or (positive) in the mid/late 2000s as a loosening of credit standards. The key point is that these shocks originate from financial institutions and are exogenous to other macroeconomic shocks.
- A *loan demand shock* characterizes agents′ preferences. In our case, these are exogenous shifts in firms′ preferences for bank loans. These shifts can be the result of shifts in firms′s macroeconomic perceptions, shifts in expectations, or the availability of alternative forms of finance. A shock to the demand for credit moves the price (lending margins) and the volume of credit in the same direction.

In addition, we impose a sign restriction on the response of GDP to credit supply and loan demand shocks for the next quarter. Loan demand shocks lead to additional lending, and we assume that this lending will translate into higher GDP growth in the next quarter. We apply the same economic intuition to credit supply shocks, as the lack of additional lending will translate into lower GDP growth in the following quarter[22]. Other parameters remain unrestricted.

To distinguish between aggregate shocks themselves, we use only sign restrictions:

- An *aggregate supply shock* is identified as a structural shock that moves inflation and GDP in opposite directions and can be internally or externally generated (e.g., commodity shocks, technology shocks, labor supply shocks, COVID-19 supply shocks, etc.).
- An *aggregate demand shock* and a *monetary policy shock* move GDP and inflation in the same direction and are distinguished by the sign of the policy rate response (10y Gov Bond). A *aggregate demand shock* has a positive sign because the positive demand shock (e.g., consumption/investment shocks, government spending/tax shocks, external demand shocks, COVID-19 demand shocks, etc.) creates an inflationary environment and the inflation-targeting central bank tries to contain inflation by raising policy rates. More recently, Kanngiesser et al. (2017) left this parameter unrestricted in their sign-restricted SVAR model for the EA and provide

[21] This logic follows a standard market model. It is also important to note that when identifying structural shocks with sign restrictions, it is the relative sign restrictions between shocks that are of interest. For example, a demand shock can be defined with either all plus or all minus signs, while a supply shock must be defined with plus (minus) and minus (plus) signs. Structural shocks in Table 1 can be equivalently identified as ”negative” or ”positive” regarding their expected effect on economic activity. In this paper, we identify shocks according to their expected negative effect on GDP.

[22] Barnett and Thomas (2013) used restrictions only in the impact period, Duchi and Elbourne (2016) added additional restrictions in the next period only for credit demand shocks. We added the additional restriction for credit supply shocks because we expect a credit crunch to reduce economic growth, and we wanted to discipline the erratic behavior of Slovak quarterly GDP growth (see Figure 1). In the robustness checks section, we present the main results without these additional restrictions.

empirical evidence to support this claim. On the other hand, it has a negative sign in the case of a *monetary policy shock*, as a lower policy rate leads to higher GDP growth and CPI inflation (e.g. transmission channels of standard monetary policy (Ireland (2010)) and/or unconventional monetary policy (Fratzscher et al. (2016))). To be consistent with the literature, we will interpret this shock as a monetary policy shock, but the reader should keep in mind that this shock captures rather the aggregate level of (or change in) financing in the economy, where monetary policy is one of many factors.

4. Results and Discussion

In this paper, we estimate a SVAR model of the Slovak economy, using quarterly data for five endogenous variables (CPI inflation, GDP growth, 10y Government bond spread, lending margins, and NFCs loans growth) for the period 2004Q2-2022Q4. The reduced form (1) is estimated with two lags[23] and has a constant term for all equations. Breitenlechner et al. (2019) algorithm with Bayesian estimation is then used to generate a set of admissible structural models (10000) that satisfies our identification scheme. To summarise the set, we compute the median response at each horizon across all accepted models, the middle 68% of accepted models, and the one specific model that is closest to the median model.

The macroeconomic significance of structural shocks in the NFC bank lending market is evaluated according to a standard VAR format. In the first section, we check the consistency of the transmission channels of the identified structural shocks via the impulse response functions (IRFs) to a typical (one st. dev.) shock. This ensures that the identified shocks and the estimated IRFs have the intended economic interpretation. In the second section, we assess the economic importance of credit shocks in terms of their effect on the variability of endogenous variables (forecast error variance decomposition - FEVD) and explain their changing role over the business cycle (historical decomposition - HD). In the final section, we compare the estimated structural shocks with the results of the bank lending survey to assess their possible drivers.

4.1. Transmission channels of structural shocks

In the absence of structural shocks, the endogenous variables in the model grow at their baseline rate. For quarterly CPI inflation, this means 0.6%, for quarterly GDP growth 0.8%, for quarterly NFCs loans growth 1.6%, while the baseline level of lending spread is 1.8 pp[24]. This section evaluates the effect of a typical (one standard deviation) structural shock on the endogenous variables starting from their baseline levels. The structural shock of this magnitude is typically considered in economic modeling because

[23] Standard lag length criteria suggested one lag, which was also sufficient to control for possible autocorrelation in the reduced-form residuals (see Appendix C). However, to better capture the business cycle characteristics of the data, we chose two lags. This number of lags was also used in Barnett and Thomas (2013) or Duchi and Elbourne (2016), where they used data at a quarterly frequency. In the robustness check section, we also show the main results for one lag.

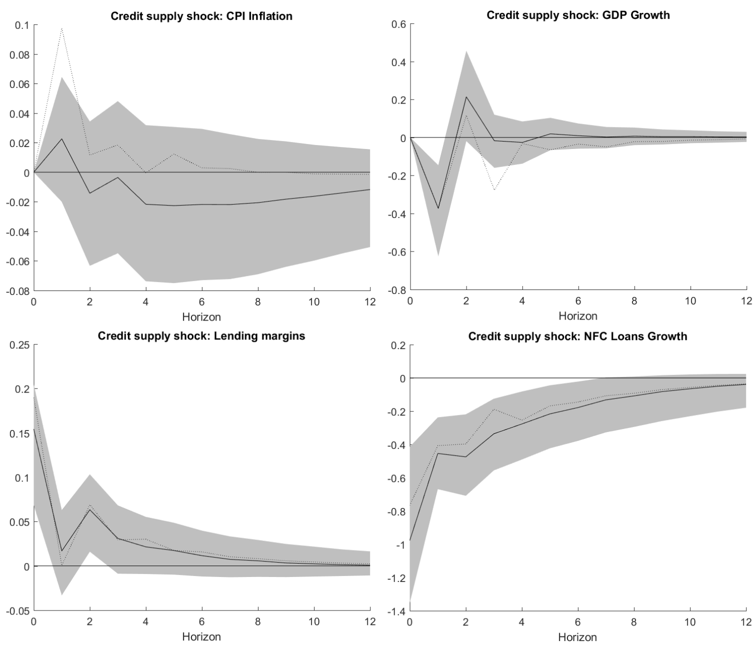
[24] Baseline change in 10y Gov Bond spread is zero.

it reflects the average fluctuations in economic variables.

A credit supply shock

An adverse credit supply shock (Figure 2) originating from banks causes margins to rise and NFC lending to fall. Credit growth slows by 1 percentage point on impact and remains depressed for two years. Lending margins increase by 15 bps on impact before returning to baseline after half a year. The real economy reacts with a lag due to the restrictions. GDP growth slows by 40 bps in the first quarter and returns to baseline after one year. The short-run impact on CPI inflation is ambiguous. The median model suggests a persistent slowdown in inflation that peaks between the fourth and sixth quarters and slowly fades out after three years. In general, however, the impact is limited. The 10-year government bond spread responds to these adverse real and financial developments by narrowing (monetary easing). This is an oversimplification of a more complicated transmission mechanism. Credit supply shocks originate in banks (e.g. an unexpected contraction in bank capital), and all Slovak banks are owned by banks from other larger EA countries (e.g. Italy), so it is reasonable to assume that these credit shocks are related, or may even originate in larger owner countries. The ECB is forced to react to these developments (either conventionally or unconventionally), which is later transmitted to government bond spreads.

Figure 2: Transmission of an adverse CS shock

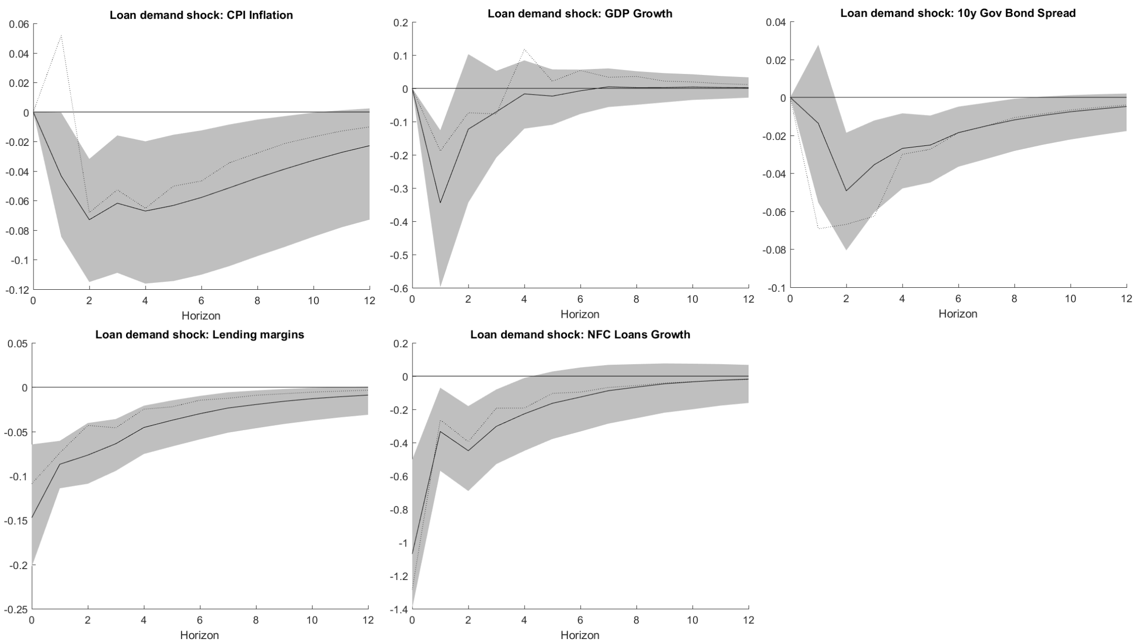


Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

A loan demand shock

Figure 3 shows the responses to the fall in corporate demand for credit, which is characterized by a simultaneous fall in NFC lending and lending margins. Loan growth is immediately lower by 1 percentage point, while margins fall by 15 basis points on impact. This negative impact lasts for about one and a half years. The credit contraction slows economic activity, and GDP growth in the first quarter falls by 35 basis points. Noteworthy is the persistent negative impact on inflation, which peaks at 8 basis points after two quarters. The negative credit demand shock contracts the economy and inflation and is followed by an easing of monetary policy (the 10-year government bond spread falls). Again, Slovak companies in particular, and the Slovak economy in general, are among the most open economies trading with EA (EU) countries. Declining economic activity or the prospect of low economic activity in this trading bloc may lead to low credit demand in Slovakia as well (also a decline in GDP growth and inflation). The ECB is responding with policy easing and government bond spreads are narrowing across the region.

Figure 3: Transmission of a negative LD shock



Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

An aggregate supply shock

Figure 14 in Appendix D shows the responses to the negative aggregate supply shock, defined as a shock that raises inflation and lowers GDP growth. GDP growth returns to baseline after three quarters, and inflation only after two years. The response of GDP growth never goes much above baseline, implying that aggregate supply shocks have a permanent effect on the level of GDP. This shock is larger in magnitude than either CS or LD shocks. The response of MP is insignificant. In theory, a central bank should not respond to this type of shock. The transmission of this shock to the financial sector is insignificant.

An aggregate demand shock

Figure 15 in Appendix D shows the responses to the negative aggregate demand shock. In this scenario, inflation and GDP growth fall simultaneously. Monetary policy is expected to react immediately, so that the 10-year government bond spread also falls. Inflation initially falls by 20 basis points, and this negative effect lasts for almost a year. The negative impact on economic growth is short-lived. The initial decline is followed by growth above the baseline. During the impact period, monetary policy responds with an easing that mirrors the response of inflation in terms of duration. Since we model the Slovak economy, which is part of the monetary union, we assume that aggregate demand shocks are sufficiently correlated across euro area countries. The negative demand shock is transmitted through the real economy to the financial sector and is similar to the negative credit demand shock, but of smaller magnitude. This highlights the importance of including other macroeconomic shocks in the system in order to better isolate the effects of credit supply and credit demand shocks.

A monetary policy shock

Finally, Figure 16 in Appendix D shows the responses to the negative monetary policy (or general financing) shock. An unexpected widening of the 10-year government bond spread may result either from monetary policy actions or from country-specific factors related to the general level of financing in the economy (macroeconomic policies, reforms). Here we can see that this shock is transmitted to the real economy through the financial sector as lending margins widen and NFC lending is reduced. Meanwhile, inflation falls persistently and GDP growth slows. Unfavorable financial conditions dampen lending, GDP, and inflation.

Overall, we can conclude that the theory has helped us to inform the responses and that the structural shocks have an intended economic interpretation. Significant factors in the NFCs bank lending market are loan demand as well as credit supply shocks, which also have a limited effect on the real economy (inflation and GDP growth). On the other hand, real economy shocks such as AS and AD shocks drive the real economy with spillovers of the latter to the NFCs bank lending market. The NFCs bank lending market also contributes to the transmission of MP shocks to the real economy.

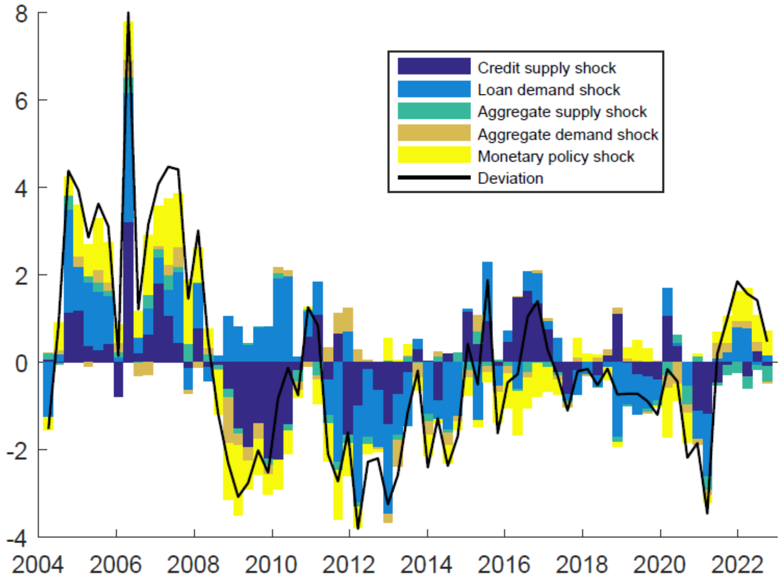
4.2. Macroeconomic importance of credit supply and loan demand shocks

Historical decomposition

In general, IRFs represent the responses of macroeconomic variables to typical (one standard deviation) structural shocks. However, they are not sufficient to describe the role of structural shocks historically, as the economy is usually hit by shocks of different magnitudes. Historical decomposition (HD) answers the question of what part of the deviation of observed macroeconomic variables from their baseline is due to the analyzed structural shocks.

Figure 4 decomposes the deviations of NFC loan growth from its baseline into the effects of the five identified structural shocks. Favorable credit supply shocks, positive loan de-

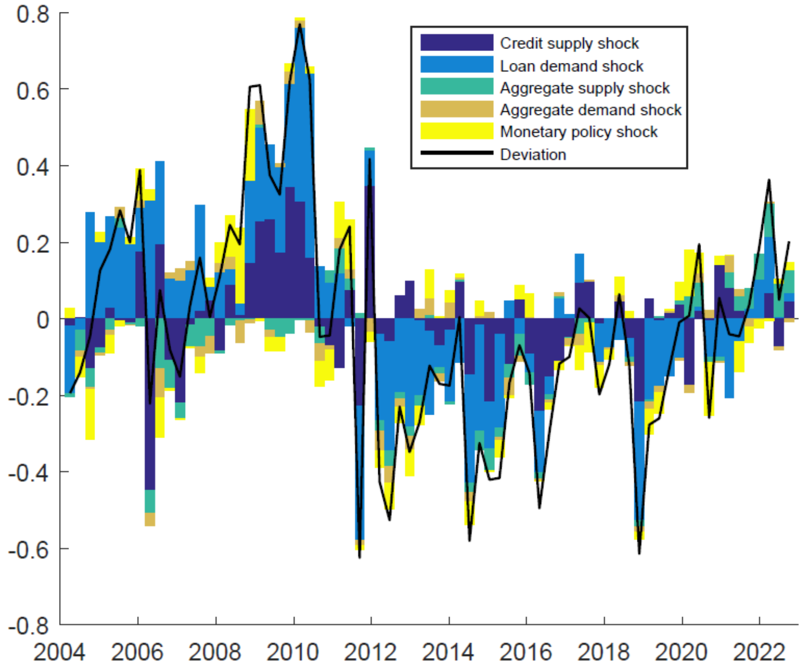
Figure 4: HD of NFC loans



Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables to not sum up exactly.
Source: Author's own computations.

mand shocks, and positive monetary policy shocks, consistent with the general pre-GFC narrative, explain the above-baseline growth of NFCs loans in the mid-to late-2000s. During and after the GFC, negative credit supply shocks (monetary policy was also less accommodative than would have been appropriate given the poor macroeconomic situation) depressed lending, an observation also found in Gambetti and Musso (2017). Diminishing negative shocks to credit supply and monetary policy (2011), with positive shocks to loan demand (in 1Q and 2Q 2010), contributed to a rebound in lending in mid-2011, just before the EDC. This development was probably related to the mild and short-lived recovery that began with the observation of the so-called green shoots after the GFC (Camacho (2010)). The EDC had a somewhat different impact. Lending was depressed not only because of tight credit supply but also because of contractionary loan demand shocks that lasted until 2015. The reluctance of firms to borrow more because of balance sheet factors or, more generally, a negative impact on agents' confidence in future economic prospects can explain these negative loan demand shocks. Corbisiero and Faccia (2020) came to a similar conclusion for other EA countries and found that both firm and bank characteristics were important determinants of NFCs lending. A series of positive supply shocks, possibly related to the introduction of QE by the ECB, started in 2015. However, firms were still reluctant to take out more loans, which kept NFC lending around baseline levels until 2018. Positive supply shocks faded in 2019, and unfavorable loan demand shocks (possibly due to the slowdown in Slovak and foreign economic growth) pulled lending below the baseline. The first quarters of the COVID-19-induced crisis were managed without significant adverse credit supply shocks (Q2 and Q3 of 2020 were even positive, due to government support measures). Later, NFCs lending growth returned from below baseline to above baseline in the second half of 2021 due to increased loan demand from firms which is currently waning.

Figure 5: HD of lending margins



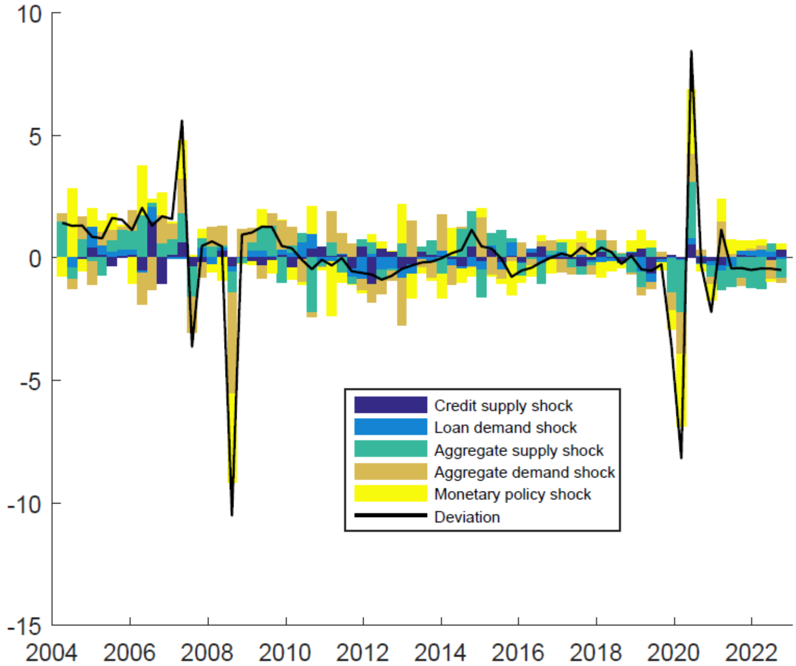
Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables to not sum up exactly.
Source: Author's own computations.

Figure 5 shows the HD for lending margins, which broadly mirror those for NFC loans. Prior to the GFC, positive shocks to credit supply reduced margins, while shocks to loan demand increased them. Overall, there was a slight tendency for margins to be above baseline in 2005/2006. During and after the GFC, margins rose above baseline, not only because of negative credit supply shocks and less accommodative monetary policy, but also because of higher demand from firms. In the aftermath of the GFC and EDC, lending margins were dominated by loan demand shocks. It may be that after these crises, central bank policy helped to mitigate the adverse effects of negative credit supply shocks and more cyclical loan demand shocks became dominant. One might expect that the monetary policy shock would have contributed more to the overall variability of lending spreads. However, as spreads are defined as the difference between lending and deposit rates, monetary policy tends to affect the general level of interest rates in the economy and also works through other channels.

In Figure 6 we can identify periods in which lending market shocks affected GDP[25]. Positive lending market shocks contributed to GDP growth before the GFC (2006-2007). In line with the empirical evidence on the transmission of credit supply shocks to the

[25]From a modeling point of view, GDP QoQ growth in Slovakia has an odd behavior during recessions and is significantly influenced by outliers. This is one of the reasons why we used an additional identification restriction for GDP.

Figure 6: HD of GDP

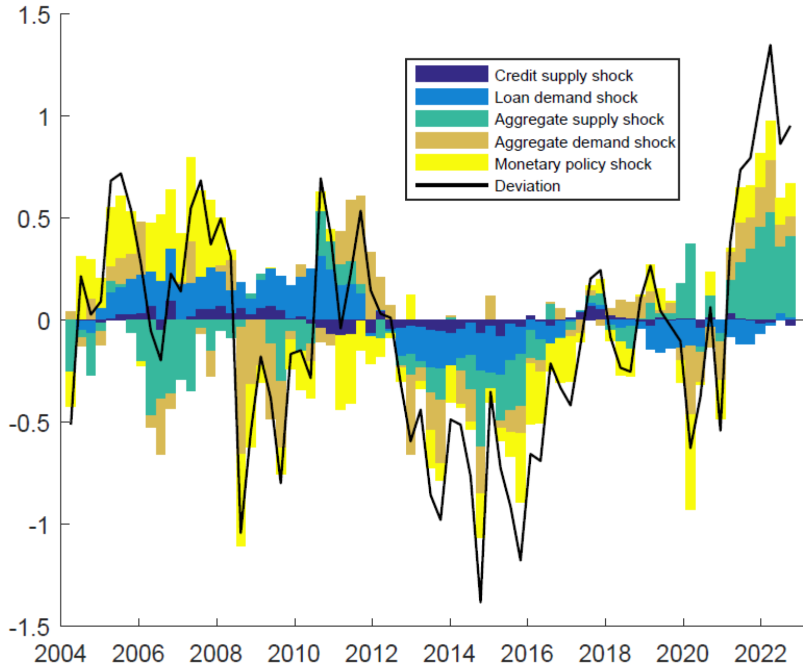


Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables to not sum up exactly.
Source: Author's own computations.

real economy (Gambetti and Musso (2017)), they contributed to the negative GDP growth during the GFC. The Slovak banking sector entered the GFC in good shape, so the limited impact of credit supply shocks on GDP is natural. Low demand for loans and tight credit conditions played an important role in the slowdown of GDP growth during the EDC, as was the case in the whole euro area (Corbisiero and Faccia (2020)). Later, these types of shocks were important but not as dominant as other shocks for GDP growth. From the analysis of the IRFs, it is clear that the most important shocks to GDP growth are real shocks. For example, in 2008Q1, 2009Q1, 2020Q1, and 2020Q2, GDP growth collapsed due to negative aggregate demand and supply shocks. On the other hand, a series of positive aggregate demand and supply shocks helped GDP recover after the GFC and EDC. More recently, after the COVID-19 crisis, negative aggregate supply shocks associated with the energy shocks kept GDP growth below the baseline.

Figure 7 shows the historical decomposition of the CPI. Interestingly, NFC bank lending shocks do not have a negligible impact on inflation. In particular, loan demand shocks appear to be significant, which is consistent with earlier findings in Calza et al. (2006) on the links between credit-related indicators and inflation in the EA. The authors find that deviations of credit from the equilibrium level can be used to predict future changes in inflation over the policy-relevant horizon. The economic intuition is very simple, as the credit overhang could lead to excessive credit accumulation, which in turn could reflect potential inflationary pressures. Indeed, this is what we observed prior to the EDC. A new piece of evidence, in addition to the Calza et al. (2006) findings, is that this observation has been structurally reversed after the EDC, probably due to the subdued

Figure 7: HD of CPI



Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables to not sum up exactly.
Source: Author's own computations.

demand for credit.

Once again, inflation is primarily driven by aggregate shocks. For example, the collapse in aggregate demand during the GFC and insufficiently accommodative monetary policy were the main drivers of the slowdown. Similarly, the decline in demand, the collapse in oil prices, and contractionary monetary policy due to the existence of a lower bound on interest rates slowed inflation in 2012-2018, which was also observed in the whole euro area (Conti et al. (2017)). During the most intense part of the COVID-19 crisis, aggregate demand and monetary policy shocks were the main factors. Energy shocks have been central to inflation dynamics in most recent periods. On the other hand, periods of loose monetary policy and higher demand in the mid-and late-00s could have explained higher inflation.

Forecast error variance decomposition

FEVD decomposes the variance of the forecast error into the contribution of specific structural shocks. It shows how important a structural shock is in explaining the variation of the endogenous variables in the model. It also shows how this importance changes over the forecast horizon, as some shocks may be more important in the short run than in the long run and vice versa.

In Table 2 we can see the FEVD for NFCs loans and lending margins. As expected, the variability of NFCs loans is largely explained by credit supply and loan demand shocks. In the short run, a credit supply shock accounts for 37% and a credit demand shock for 39% of the variability of NFCs loans. In later periods, both credit market shocks explain about 30% of the variability, while the remaining variability is explained by a monetary policy shock (18%) and aggregate shocks (together 11%). Thus, at a horizon of 1-2 years, changes in the financing of the economy, as well as the general economic situation, are important sources of variability for NFC loans. In the case of lending margins, the most important factors overall are loan demand shocks (45%) and credit supply shocks (30%), while other shocks explain about 20% of the variability. Since loan demand shocks are related to the decisions of firms, this implies that lending margins are more cyclical in nature.

Table 2: FEVD of NFCs loans and lending margins

	Credit supply shock	Loan demand shock	Aggregate supply shock	Aggregate demand shock	Monetary policy shock	Variability across models
			NFC	loans		
1Q	36.93%	39.24%	3.15%	4.81%	11.07%	4.80%
4Q	32.98%	32.74%	4.70%	5.35%	17.26%	6.97%
8Q	32.13%	30.96%	5.46%	5.72%	17.60%	8.11%
			Lending	margins		
1Q	36.68%	45.96%	3.51%	2.47%	7.09%	4.30%
4Q	31.74%	45.94%	5.77%	4.29%	8.37%	3.89%
8Q	29.66%	44.91%	6.51%	4.76%	9.03%	5.13%

Notes: The FEVD for the first (1Q), fourth (4Q), and eighth (8Q) quarters was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes FEVD to not add up to 100%.
Source: Author's own computations.

The situation is reversed when we look at other macroeconomic variables (Table 3 in Appendix D). GDP, CPI, and the 10-year government bond spread are driven by real shocks ($> 40\%$) as well as the monetary policy shock ($> 25\%$). Interestingly, the variability in the 10-year government bond spread is mainly explained by the monetary policy shock (40%), but the aggregate demand shock is also important (23%). There is also some variability in the macroeconomic variables explained by the NFC bank credit shocks. In the case of inflation, only 1.5% of inflation variability is explained one quarter ahead, but at a monetary policy horizon of two years, it is 11.5%. This is consistent with the results of Calza et al. (2006).

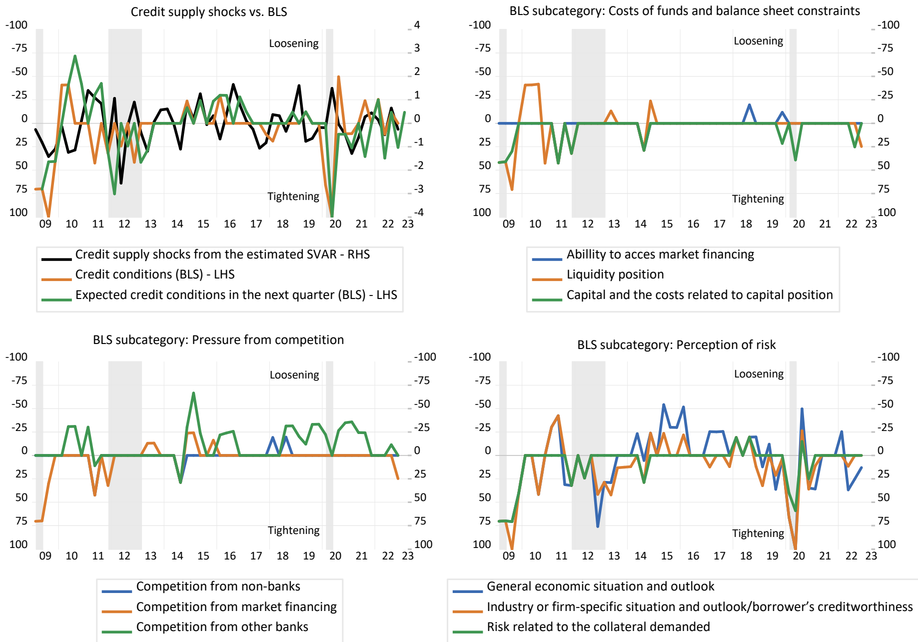
4.3. What could be driving the bank lending shocks?

So far, we have examined the aggregate macroeconomic implications of credit supply and loan demand shocks. We have analyzed the average responses of variables to a typical structural shock through the IRFs, examined the importance of structural shocks in explaining the variability of endogenous variables, and also decomposed the historical evolution of variables into separate structural shocks.

To gain a deeper understanding of what may be driving CS and LD shocks, or how we can explain the shocks themselves, we compare them with the results of the ECB's Bank

Lending Survey (BLS). The BLS questionnaire is classified according to the two borrower categories that are the focus of the survey, i.e. NFCs and households. Concerning the supply of credit, the focus is on changes in the credit standards that banks apply in approving loans to NFCs (households) and changes in the credit terms of new loans. Banks are asked to assess how specific factors may have contributed to changes in credit standards and terms. For loan demand, the focus is on increases or decreases in loan demand. Banks are also asked to assess the impact of various factors on the financing needs of NFCs (households) and the impact of the use of alternative sources of finance on loan demand. Our focus is on the results for credit standards and loan demand in the category of NFCs (for further details see Köhler-Ulbrich et al. (2016)).

Figure 8: Credit supply shocks vs. BLS



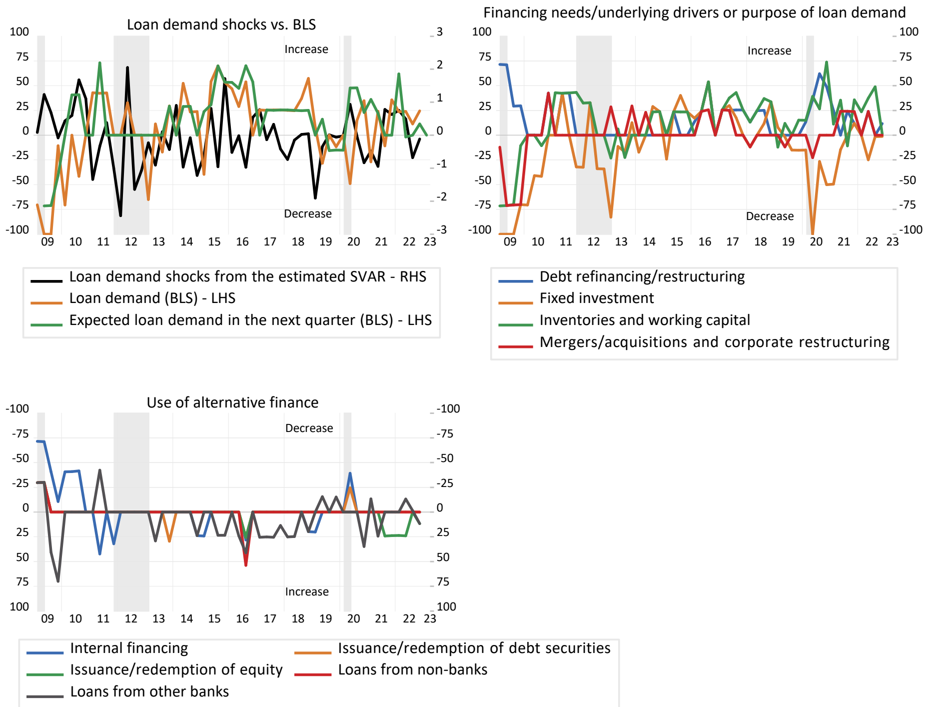
Notes: Positive (negative) values mean positive (negative) credit supply shocks because of their assumed positive (negative) effect on GDP growth. In the BLS survey, a positive value means that the percentage share of banks reporting a tightening of credit standards was bigger than the share of banks reporting an easing, so a net tightening is reported (inverted in the graph). Shaded areas represent EA recessions according to Euro Area Business Cycle Network.
Source: Author's own computations and BLS.

Credit supply shocks vs. BLS on credit standards

Figure 8 (top left panel) shows a time series of credit supply shocks and the BLS results for bank credit standards. In 2009, both measures point to a tightening of credit, as credit supply shocks are negative and credit standards (including expected standards) tighten, although credit standards point to a faster recovery. There was another round of credit tightening during the EDC. However, there were some discrepancies in 2011-2012, as expected credit standards tightened sharply, probably due to the intensification of the crisis in the first quarter of 2012. In 2013-2019, periods of loosening credit conditions (2013-2017) were followed by some periods of tightening credit conditions (2018-2019), both in the series of credit supply shocks and (expected) credit standards. In early 2016, there was an increase in the quarterly volatility of NFC loan growth, which was interpreted as a negative credit supply shock, but the trend of loosening credit standards and positive credit supply shocks remained intact. During the early stages of the COVID-19 crisis, we observe a notable deviation between the two. BLS credit standards tightened significantly, but the credit supply shock in this period was positive. We can explain this discrepancy by discretionary government guarantees. Banks expected the COVID-19 shock to lead to an economic recession and adjusted credit standards accordingly. However, the government stepped in with guarantees and helped stabilise the economy. On the other hand, as it became clear that the COVID-19 crisis would persist, further tightening followed in 2020-2021. After that, all series were similar.

Looking at the different BLS categories (Figure 8 top right, bottom left, and bottom right panels), we can see that the perception of risk is the most important. This category is related to the banks' perception of the risk arising from either general $(\rho = 0.31^{**})$[26] or firm-specific $(\rho = 0.38^{***})$ economic situations and the risk associated with the collateral demanded $(\rho = 0.31^{**})$. Other specific subcategories such as competition from market funding (2009, 2014-2016, $\rho = 0.22^{*}$), costs related to capital position (2011, $\rho = 0.08$) or bank liquidity (2009-2010, $\rho = 0.04$) seemed to play a role in different periods.

Figure 9: Loan demand shocks vs. BLS



Notes: Positive (negative) values mean positive (negative) loan demand shocks because of their assumed positive (negative) effect on GDP growth. In the BLS a positive value means that the percentage share of banks reporting an increase in demand was larger than the share of banks reporting a decrease in demand, so a net increase in loan demand is reported. Shaded areas represent EA recessions according to Euro Area Business Cycle Network.
Source: Author's own computations and BLS.

[26] We use the Spearman rank correlation coefficient (ρ) to measure the strength and direction (not causality) between the BLS results and the identified credit supply shocks in the whole sample.

Loan demand shocks vs. BLS on loan demand

Figure 9 (top left panel) shows the evolution of loan demand shocks and the BLS results for bank loan demand by NFCs. As the figure shows, the evidence is a bit more mixed, as different subcategories (top right and bottom left panels) can pull loan demand in opposite directions. We interpret the result with this in mind. In 2009, the BLS data on loan demand were negative, while the estimated shocks to loan demand were positive. We can explain this by noting that the estimated demand shocks may have captured subcategories such as debt refinancing/restructuring ($\rho = 0.25^{*}$) or a decline in the use of internal financing ($\rho = -0.49^{***}$) rather than other subcategories. The results are comparable after 2009. During the EDC, loan demand fell mainly due to the collapse in demand for fixed investment. BLS shows positive demand from 2015 to 2019 as a result of increased demand for inventories and working capital. In the opposite direction, demand was pulled down by issuance of debt securities ($\rho = -0.31^{**}$), loans from non-banks ($\rho = -0.25^{*}$), loans from other banks ($\rho = -0.14$) in the BLS subcategory use of alternative finance. The COVID-19 crisis was a relatively volatile period. Financing needs for inventories, working capital, and debt restructuring helped increase the demand for bank loans, but the (lack of) need for fixed investment significantly reduced demand, which may explain the up-and-down movement of the estimated loan demand shocks during and after the COVID-19 crisis.

Our estimated credit supply and loan demand shocks are broadly consistent with the BLS results, highlighting the economic validity of our model and identifying restrictions. In particular, the credit supply shocks are nearly identical to the BLS credit standards and are mostly related to banks' risk perceptions and competition among banks. There is some discrepancy between the estimated loan demand shocks and the BLS demand shocks as different demand subcategories (financing needs or use of alternative financing) moved in opposite directions in different periods.

5. Robustness Checks

The suitability of a given identification scheme, the choice of endogenous variables, or the lag length in the VAR model is often not obvious. In this section, we provide several robustness checks for our main results regarding the identification scheme, the choice of endogenous variables, or the choice of lag length.

Stricter vs. looser identification scheme, one lag vs. two lags

In the original Barnett and Thomas (2013) paper, the authors use an identification scheme that applies only to the quarter in which the shocks occur (looser identification restrictions). Duchi and Elbourne (2016) add an additional restriction to this original scheme. They add the (negative) sign restriction for the following quarter in the case of (negative) loan demand shocks. The economic intuition is that negative loan demand shocks will lead to a decrease in credit, and this decrease in credit will lead to lower economic activity and lower GDP growth. Based on this intuition, we add a similar (negative) sign restriction for (negative) credit supply shocks for the next quarter (tighter identification restrictions). Again, after a negative credit supply shock, there is less lending, less economic activity, and lower GDP growth. We were also motivated by the erratic behavior of Slovak GDP growth. In the baseline specification, we use one lag (1 lag) as the lag length criteria suggested, Barnett and Thomas (2013) and Duchi and Elbourne (2016) used two lags in their baseline specification. Since we are limited by the length of the time series, we only experiment with two lags (2 lags).

In Figure 18 in Appendix D we have results for the effect of a credit supply shock on GDP growth for the two types of identifying restrictions and for one and two lags. As can be seen, all versions point to a slowdown in GDP growth following a negative CS shock[27]. There is some uncertainty with the one lag and looser restrictions response in the first quarter (Figure 18 in Appendix D, top left panel). We attribute this uncertainty to noise in GDP growth. The results are robust when we analyze the effect of credit demand shocks (Figure 19 in Appendix D), and this is also true for all other IRFs (not reported in this paper).

Full identification vs. partial identification

In Table 1 we identify five structural shocks, so our system is fully identified. This is not always possible (sometimes we have quite a lot of variables in the VAR model, but economically we can identify only a few structural shocks), or not always desirable (Uhlig (2005) deliberately identifies only one monetary policy shock). Therefore, we compare our main results from the full identification scheme with the results based on partial identification, where we separately identify only one credit supply shock and one loan demand shock. Regarding the IRFs, the results from the full identification are very similar to those from the partial identification. Regarding the FEVD and HD, a notable difference is that in our baseline model with the full identification scheme, the variability across the generated models is significantly reduced. This implies that the generated set of models is more homogeneous and better suited for subsequent structural analysis.

Credit flow vs. credit impulse

Biggs et al. (2010) in their paper argue that when analyzing the relationship between credit and economic activity, one should be careful with the distinction between stock and flow definitions of variables. More specifically, what matters more for GDP growth (change in the flow of economic activity) is the credit impulse (change in the flow of credit) rather than the flow of credit (change in the stock of credit). They find that credit growth (flow of credit) is relevant to GDP growth in normal periods while credit impulse, in addition to that, is particularly relevant in recovery and non-recovery periods.

In this robustness check, we replace NFCs loan growth (credit flow) with the quarterly change in NFC loan growth (credit impulse). With respect to HD, the effect of loan demand shocks on lending margins and CPI inflation is reduced relative to the baseline model (see Figure 5 for lending margins and Figure 7 for CPI). In particular, the effect

[27] The results are robust to an even stricter identification scheme - a negative response of NFCs loans to both a negative aggregate demand shock and a negative monetary policy shock (- instead of ? in Table 1).

of loan demand shocks is reduced during the GFC and EDC, while the effect of credit supply and other shocks is amplified (see figure 20 in Appendix E). It seems that the credit impulse model down-weights the importance of credit demand shocks, but only during the crises and following recovery, which is consistent with the empirical evidence in Biggs et al. (2010). IRFs on loans to NFCs are, of course, short-lived.

Sample with and without COVID-19 period

As the COVID-19 pandemic has hit the global economy, the variation in some macroeconomic time series has been extreme. Therefore, it is reasonable to compare the baseline results with results stemming from the shorter sample up to 2019Q4. In this case, the IRFs, HD, and FEVD are broadly similar in both samples. A minor difference is the magnitude of the GDP responses to some structural shocks (see Figure 21 in Appendix E and baseline results).

The problem with the COVID-19 period in macroeconomic data and VAR models is how many COVID-19 observations are added to the estimation sample. Specifically, Bobeica and Hartwig (2021) find that the VAR model becomes explosive when the observations of 2020Q1, 2020Q2, and 2020Q3 are gradually added to the estimation sample. We observe similar issues in the earlier version of this paper. However, as more and less extreme data are added to the estimation sample, the problem of VAR explosiveness gradually disappears (as in our baseline specification). Nevertheless, the problem of the large variability in macroeconomic time series due to the COVID-19 crisis and related macroeconomic modeling problems is still an open research question.

Alternative monetary policy measures

As a measure of monetary policy, we use quarterly changes in the spread between Slovak and German 10-year government bond yields. We have argued why this is our preferred measure of monetary policy stance, but there are still other measures. In normal times, Walsh (2017) recommends using policy rates or interbank rates (BRIBOR, EURIBOR), at the ZLB the authors use shadow policy rates such as Wu and Xia (2016)'s shadow rate, Vacca et al. (2021) use the spread between the retail deposit rate at NFCs and EONIA as an approximation of bank funding costs, or just 10-year government bond yields as in Barnett and Thomas (2013) or Duchi and Elbourne (2016) (for comparison, see Figure 22 in Appendix D).

In general, the results were robust to the alternative monetary policy measures (not shown here), underscoring the consistency of our model. One expected difference was the response of monetary policy to the negative credit supply shock (Figure 23 in Appendix D). The IRF of funding costs was muted due to the low volatility of funding costs themselves. Next, the response of the shadow policy rate and the 3M interbank rate shows a tightening of monetary policy, which is insignificant in the latter case. On the other hand, the 10-year government bond and the 10-year government bond spread point to an easing. These results are expected because the shadow rate (interbank rate) is set for the whole euro area, while the 10-year bond is more country-specific and better reflects the economic situation. Finally, the transmission of monetary policy shocks to the financial sector (lending margins and credit growth of NFCs) is insignificant in the case of funding costs, the shadow policy rate, and the short-term interest rate (not shown here).

Different economic activity indicators

In this paper, we analyze the drivers and effects of the NFCs bank lending market. In the baseline specification, we use GDP growth as a proxy for general economic activity. Since we are interested in the bank lending market of firms, we re-examine the results when we approximate economic activity in Slovakia with the growth of investment and industrial production. Figure 24 in Appendix D shows the corresponding results. Again, the results are consistent with our baseline specification, but there is a significant amount of volatility that we control for with tighter restrictions.

External sector in the structural analysis

So far, we have only implicitly modeled the external sector as a part of the monetary policy shock, the aggregate supply shock, and the aggregate demand shock. Since Slovakia is a typical small open economy, we need to check the robustness of the main results regarding the external sector. To do this, we use an identification scheme of Bobeica et al. (2019) (Table 4 in Appendix E) that includes the external sector. In this model, additional endogenous variables are world GDP (qoq, %), oil price (Brent, qoq, %), and nominal effective exchange rate (NEER Broad, BIS, qoq, %), while two additional structural shocks are identified. First, an oil supply shock that increases the price of oil has a negative impact on economic activity in Slovakia and at the same time raises inflation. Second, a global demand shock that reduces world GDP, the price of oil, economic activity in Slovakia, and inflation. We have left the responses of the NEER unrestricted, as the analysis of the structural drivers of exchange rates is beyond the scope of this paper.

An expected difference is that in the model with the external sector, credit supply and loan demand shocks explain less (but still substantial) variation in NFC loan growth and lending margins in terms of FEVD and HD (see Figure 25 and Figure 26 in Appendix E). On the other hand, in the model with the external sector, the variability between the generated models has increased. Concerning the IRFs for the model with the external sector and our baseline specification, we found that the results were consistent (one minor difference was an insignificant response of lending margins to the monetary policy shock in the model with the external sector, but the median responses were similar (not shown here)).

6. Conclusion

After the Global Financial Crisis, the European Debt Crisis, and to some extent during the COVID-19 Crisis, it has become clear that the importance of credit supply shocks as a source of business cycle fluctuations is not negligible. But the credit supply shocks are only one part of the story. This paper analyzed the implications of credit supply and loan demand shocks in the NFCs bank lending market and their broader macroeconomic significance. We used structural VAR analysis with zero and sign restrictions to disentangle these shocks from other macroeconomic shocks. In addition, we have modified the modeling framework to make it suitable for other EA countries.

The results show that both the credit supply shock and the loan demand shock are important drivers of the NFCs bank lending market with spillovers to the broader economy. The importance of these shocks changes over the business cycle. Credit supply shocks are more important in times of economic distress, while loan demand shocks are more relevant in normal times. Moreover, there is evidence that these lending shocks affect the real economy and vice versa. The added value of the paper is that we examined the macroeconomic importance of NFCs loan demand in parallel with bank credit supply and developed a new country-specific adaptation of the VAR methodology to a euro area country - Slovakia - to capture its modeling specificities.

These findings have important policy implications, as these shocks may require different policy responses. More specifically, credit supply shocks were more important for the lending market in the stressed periods, while loan demand shocks were more important in the calmer periods. This result has implications for the conduct of monetary and macroprudential policies, as adverse (positive) credit supply shocks require a different policy response than negative (positive) loan demand shocks. Another implication of our study is that credit supply and demand shocks had a limited, but not negligible, impact on the real economy. However, this limited impact was not unexpected and is likely to be country-specific. The Slovak banking sector was relatively healthy and strong during the recent crises. The limited impact of lending shocks, especially in adverse scenarios, was to be expected. The other argument is that real economy shocks, as opposed to lending market shocks, are very broad categories of structural shocks, and one could expect their dominant role. We also find empirical evidence that the ECB's monetary policy is transmitted through the banking sector, which further underscores the importance of bank lending shocks in our model, variable selection and identification scheme.

Our results suggest some areas for future research. The focus of this paper was on the NFC bank lending market in Slovakia, but the methodology could easily be applied to other countries. It could be interesting to study how credit supply and demand shocks behave in financially stressed vs. non-stressed countries; how important bank lending and real shocks are in small open economies vs. in large economies; how monetary policy is transmitted to different EA countries, to name a few extensions. Another avenue for further research could be in terms of methodology. The assumption of a constant-parameter VAR model could be relaxed and one could use a time-varying parameter VAR model. However, this approach may only be suitable for countries with larger data samples than we use in this paper for Slovakia. One could also consider using a different, possibly larger, set of variables in the VAR model and/or different identification schemes.

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A. Estimation Algorithm

1. Estimate the reduced form VAR to obtain $\hat{c}, \hat{A}_1, \hat{A}_2, \ldots, \hat{A}_p$ and $\hat{\Sigma}_{\mathbf{u}}$. This can be done either by OLS or a Bayesian approach. In the latter, estimation algorithm follows Uhlig (1994) and Uhlig (2005) and estimates the reduced form coefficients with an uninformative Normal-Inverse-Wishart prior and obtains the posterior distribution, while using the $\hat{c}, \hat{A}_1, \hat{A}_2, \ldots, \hat{A}_p$ and $\hat{\Sigma}_{\mathbf{u}}$ as location parameters.

2. Construct a candidate structural impulse response:

   (a) compute an initial guess P' as $P' = chol(\hat{\Sigma}_{\mathbf{u}})$,

   (b) draw a random orthonormal matrix Q' (such that $Q'Q = \mathbf{I}$), if needed ensure that satisfies zero restrictions as in Arias et al. (2018),

   (c) compute candidate C as $C = P'Q'$.

3. Check weather the candidate orthogonal impulse responses C fulfil sign restrictions

   (a) yes, store the impulse response (structural model),

   (b) no, discard the proposed impulse response.

4. Perform steps 2 and 3 until the desired number of suitable structural models is obtained. Summarise the set of structural models and report desired results.

B. Unit Root Tests and Cointegration

Figure 10: Unit Root Tests

	CPI LEVEL			GDP LEVEL			GOV BOND SPREAD LEVEL			LENDING MARGINS LEVEL			NFC LOANS LEVEL		
Test	ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS
H0	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary
t-Statistic	1.2265	0.7177	1.1373	-2.3399	-2.6111	1.1280	-2.3331	-2.2667	0.1933	-3.3834	-5.2932	0.2874	-2.5243	-1.6955	0.9969
Prob.	0.9981	0.9918		0.1624	0.0952		0.1645	0.1854		0.0147	0.0000		0.1140	0.4294	
	ns	ns	***	ns	*	***	ns	ns	ns	**	***	ns	ns	ns	***
Constant	ns	*	***	**	**	***	*	ns	***	***	***	***	**	**	***
t-Statistic	-0.9823	-0.7967	0.1451	-2.7095	-2.7095	0.1787	-2.3207	-2.2406	0.1541	-3.3327	-5.2316	0.1298	-3.5971	-1.8775	0.1648
Prob.	0.9398	0.9610		0.2360	0.2360		0.4176	0.4604		0.0690	0.0003		0.0370	0.6563	
	ns	ns	*	ns	ns	**	ns	ns	**	*	***	*	**	ns	**
Constant	ns	**	***	***	***	***	ns	ns	***	***	***	***	***	*	***
Trend	ns	ns	***	***	**	***	ns	ns	ns	ns	ns	**	***	ns	***
t-Statistic	1.4150	3.6935		2.9849	3.1626		-1.3471	-1.3458		-0.1972	-0.7381		1.7807	2.7876	
Prob.	0.9598	0.9999		0.9992	0.9995		0.1635	0.1639		0.6118	0.3935		0.9812	0.9986	
	ns	ns		ns	ns		ns	ns		ns	ns		ns	ns	

	d(CPI LEVEL)			d(GDP LEVEL)			d(GOV BOND SPREAD LEVEL)			d(LENDING MARGINS LEVEL)			d(NFC LOANS LEVEL)		
Test	ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS
H0	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary	Has a unit root	Has a unit root	Is stationary
t-Statistic	-1.4467	-1.5630	0.2379	-9.5031	-9.5434	0.3177	-7.1206	-7.1206	0.0618	-9.3956	-15.5732	0.1345	-4.0476	-4.0754	0.1973
Prob.	0.5548	0.4963		0.0000	0.0000		0.0000	0.0000		0.0000	0.0001		0.0021	0.0019	
	ns	ns	ns	***	***	ns	***	***	ns	***	***	ns	***	***	ns
Constant	ns	ns	***	***	***	***	ns	ns	ns	ns	ns	ns	**	**	***
t-Statistic	-1.6993	-1.7281	0.1931	-9.8439	-9.8439	0.0610	-7.0744	-7.0744	0.0637	-9.3250	-15.8909	0.0546	-4.1856	-4.1958	0.1269
Prob.	0.7419	0.7288		0.0000	0.0000		0.0000	0.0000		0.0000	0.0001		0.0075	0.0073	
	ns	ns	**	***	***	ns	***	***	ns	***	***	ns	***	***	*
Constant	ns	ns	*	***	***	***	ns	ns	ns	ns	ns	ns	**	**	***
Trend	ns	ns	*	**	*	ns	ns	ns	ns	ns	ns	ns	ns	ns	*
t-Statistic	-0.7179	-0.6440		-8.4436	-8.5275		-7.1690	-7.1690		-9.4650	-16.0669		-2.0239	-3.0761	
Prob.	0.4024	0.4350		0.0000	0.0000		0.0000	0.0000		0.0000	0.0000		0.0419	0.0025	
	ns	ns		***	***		***	***		***	***		**	***	

	d(CPI LEVEL)
Test	ADF Break Test
H0	Has a unit root
t-Statistic	-4.8116
Prob.	0.0172
	**
Constant	***
Constant Break	***
Break Dummy (2021Q1)	***

Notes: Unit root tests: ADF (Augmented Dickey-Fuller test), PP (Phillips-Perron test), KPSS (Kwiatkowski, Phillips, Schmidt, and Shin test). ***/**/* indicates rejection of H0 at 1%/5%/10% significance level, ns means not significant. The yellow background suggests the statistical validity of the test equation specification, the orange background point to the presence of a unit root, while the green background suggests otherwise.
Source: Author's own computations.

Figure 11: Johansen Cointegration Tests

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.294837	46.77735	47.21	54.46
At most 1	0.166991	23.72181	29.68	35.65
At most 2	0.097944	11.66286	15.41	20.04
At most 3 *	0.070986	4.859665	3.76	6.65

Trace test indicates no cointegration at both 5% and 1% levels
*(**) denotes rejection of the hypothesis at the 5%(1%) level

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.294837	23.05554	27.07	32.24
At most 1	0.166991	12.05894	20.97	25.52
At most 2	0.097944	6.803198	14.07	18.63
At most 3 *	0.070986	4.859665	3.76	6.65

Max-eigenvalue test indicates no cointegration at both 5% and 1% levels
*(**) denotes rejection of the hypothesis at the 5%(1%) level

Notes: In the Johansen cointegration test equation, we assume an intercept in both the cointegrating vector(s) and the test VAR and use one lag.
Source: Author's own computations.

C. Reduced Form VAR Diagnostics

Figure 12: Reduced form VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-389.2642	NA	0.045806	11.10603	11.26538	11.16940
1	-317.7794	130.8877*	0.012391*	9.796604*	10.75267*	10.17680*
2	-297.4017	34.44118	0.014264	9.926809	11.67959	10.62383
3	-284.6056	19.82495	0.020662	10.27058	12.82008	11.28444
4	-264.0362	28.97105	0.024651	10.39539	13.74160	11.72607

Notes: * indicates lag order selected by the criterion. LR: sequential modified LR test statistics each test at 5% level, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quin information criterion.
Source: Author's own computations.

Figure 13: Reduced form VAR residual serial correlation LM tests

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	29.91310	25	0.2276	1.213770	(25, 220.7)	0.2287
2	22.37818	25	0.6138	0.893142	(25, 220.7)	0.6150
3	32.01038	25	0.1577	1.304881	(25, 220.7)	0.1587
4	17.68492	25	0.8555	0.698628	(25, 220.7)	0.8560

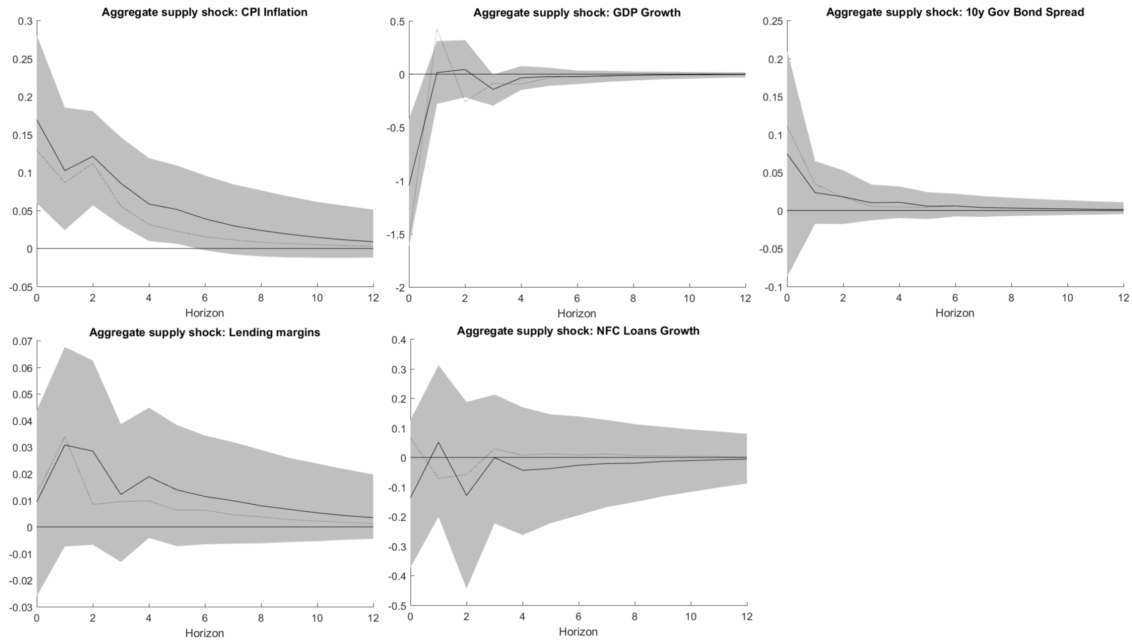
Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	29.91310	25	0.2276	1.213770	(25, 220.7)	0.2287
2	45.92307	50	0.6376	0.912320	(50, 249.6)	0.6424
3	84.40247	75	0.2143	1.142336	(75, 238.9)	0.2265
4	112.8986	100	0.1782	1.147307	(100, 219.3)	0.2027

Source: Author's own computations.

D. ADDITIONAL RESULTS

Figure 14: Transmission of a negative AS shock



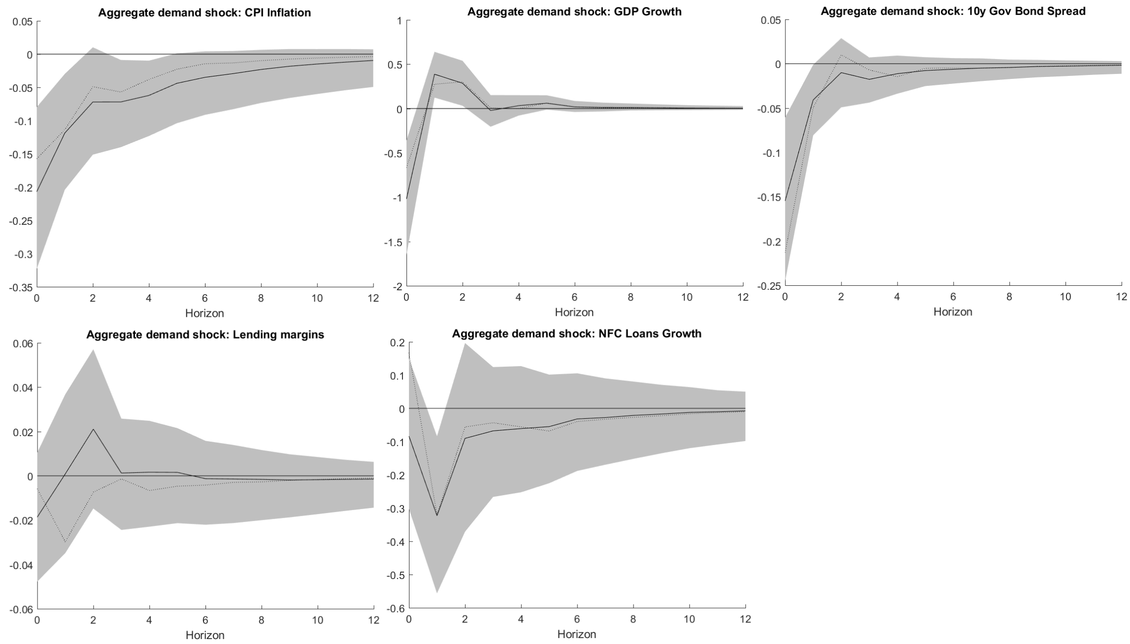
Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

Table 3: FEVD of GDP, CPI, and 10y Gov Bond

	Credit supply shock	Loan demand shock	Aggregate supply shock	Aggregate demand shock	Monetary policy shock	Variability across models
			GDP	Growth		
1Q	2.71%	2.30%	22.87%	24.63%	30.70%	16.79%
4Q	4.61%	3.82%	22.46%	24.98%	29.35%	14.78%
8Q	4.85%	4.07%	22.49%	24.89%	29.26%	14.43%
			CPI	Inflation		
1Q	0.52%	1.01%	19.75%	28.59%	30.05%	20.08%
4Q	2.19%	5.55%	22.09%	23.99%	25.81%	20.37%
8Q	3.37%	8.15%	20.29%	21.62%	25.33%	21.24%
		10y	Government	Bond Spread		
1Q	1.96%	0.80%	14.94%	24.28%	41.82%	16.20%
4Q	3.91%	5.31%	15.08%	23.07%	38.75%	13.88%
8Q	4.60%	6.48%	15.10%	22.60%	37.96%	13.26%

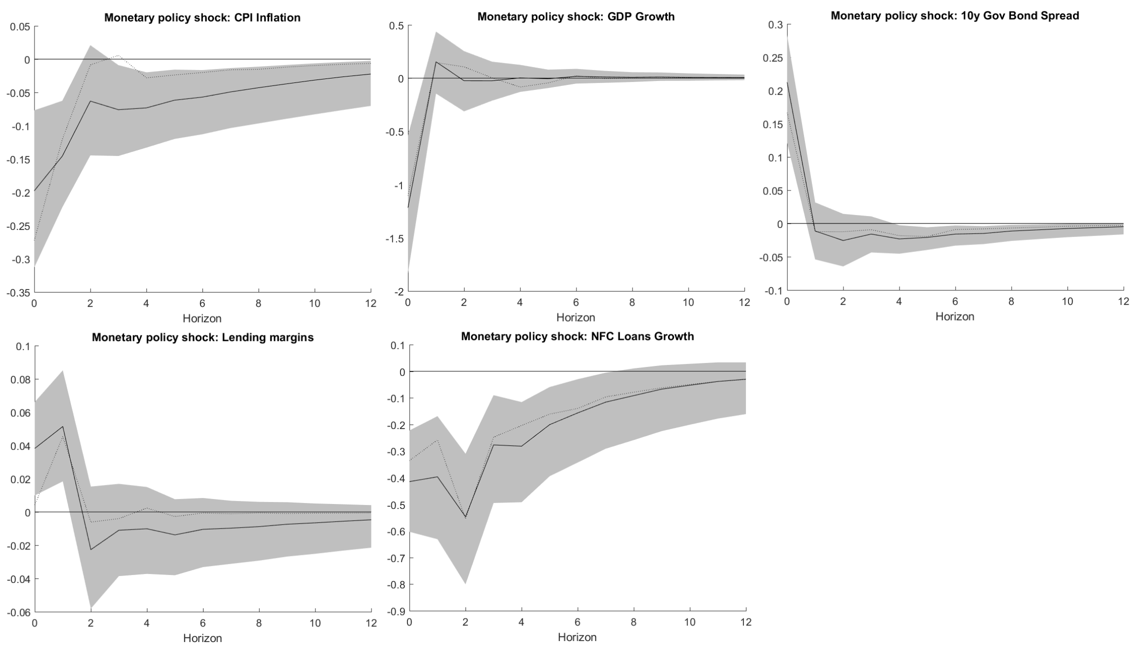
Notes: The FEVD for the first (1Q), fourth (4Q), and eighth (8Q) quarters was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes FEVD to not add up to 100%.
Source: Author's own computations.

Figure 15: Transmission of a negative AD shock



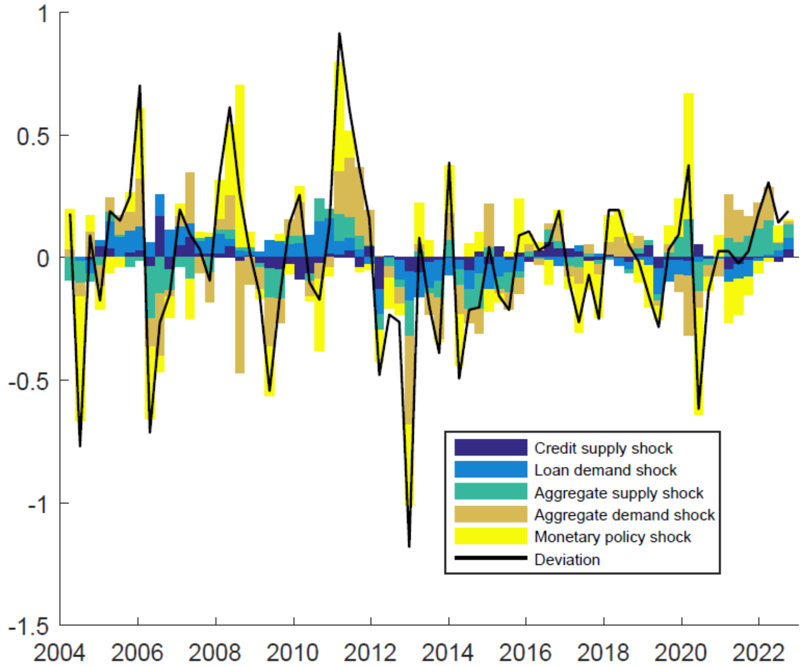
Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

Figure 16: Transmission of a negative MP shock



Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

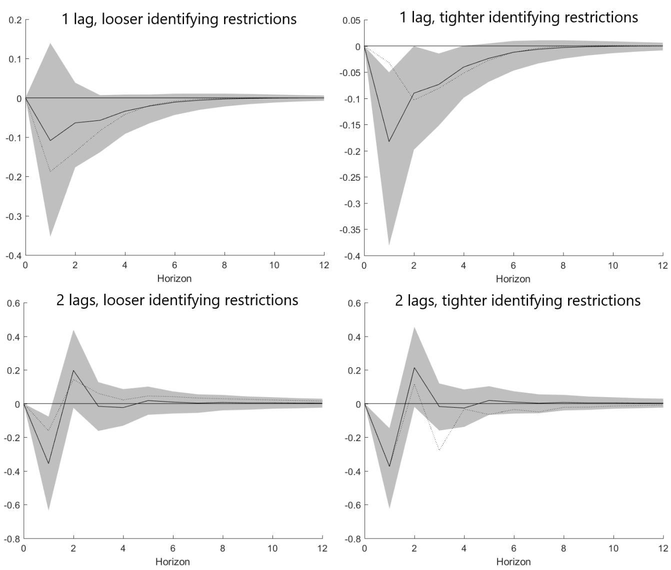
Figure 17: HD of 10y Gov Bond



Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables to not sum up exactly.
Source: Author's own computations.

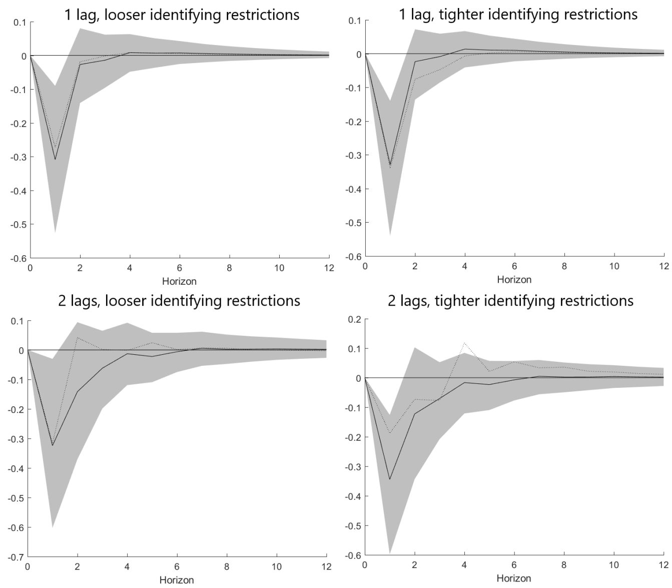
E. Robustness Checks Results

Figure 18: Effect of a credit supply shock on GDP



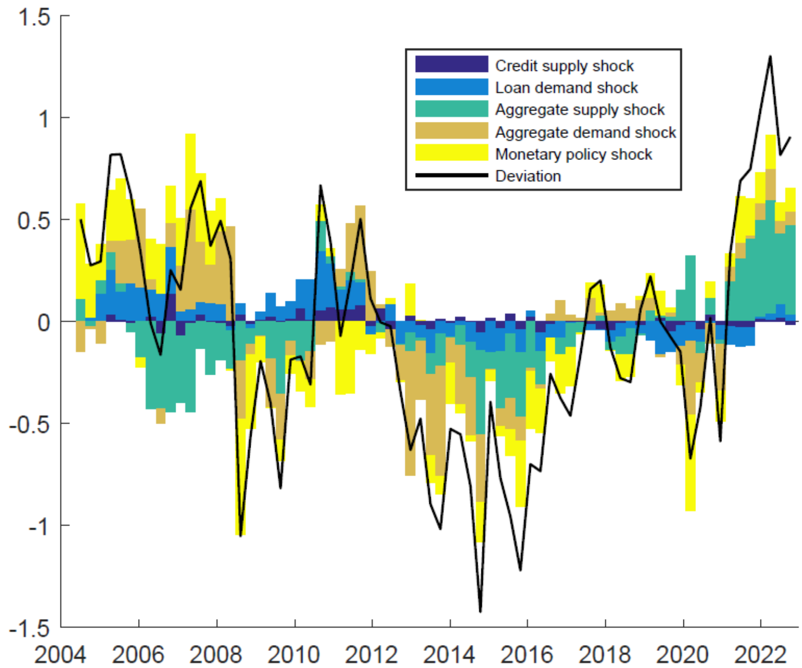
Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

Figure 19: Effect of a loan demand shock on GDP



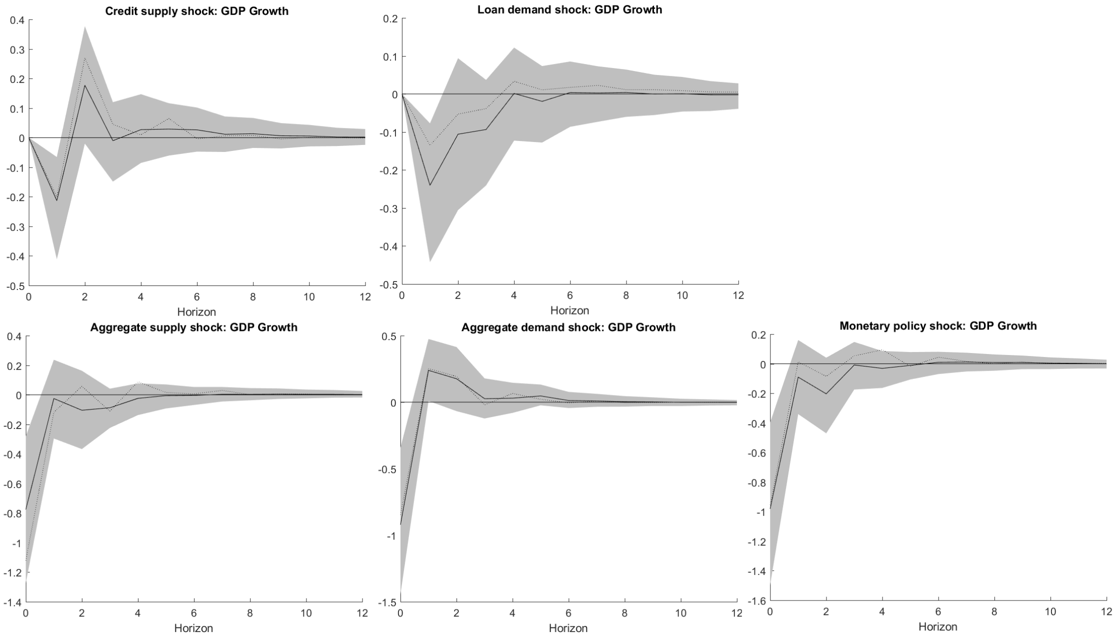
Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

Figure 20: HD of CPI - credit impulse



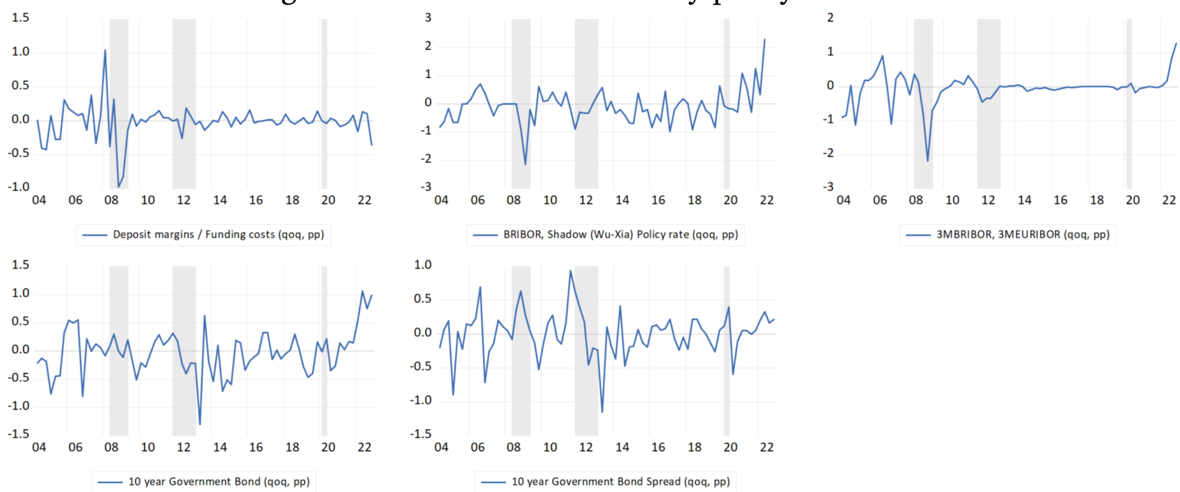
Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables not to sum up exactly.
Source: Author's own computations.

Figure 21: IRFs of GDP growth - sample until 2019Q4



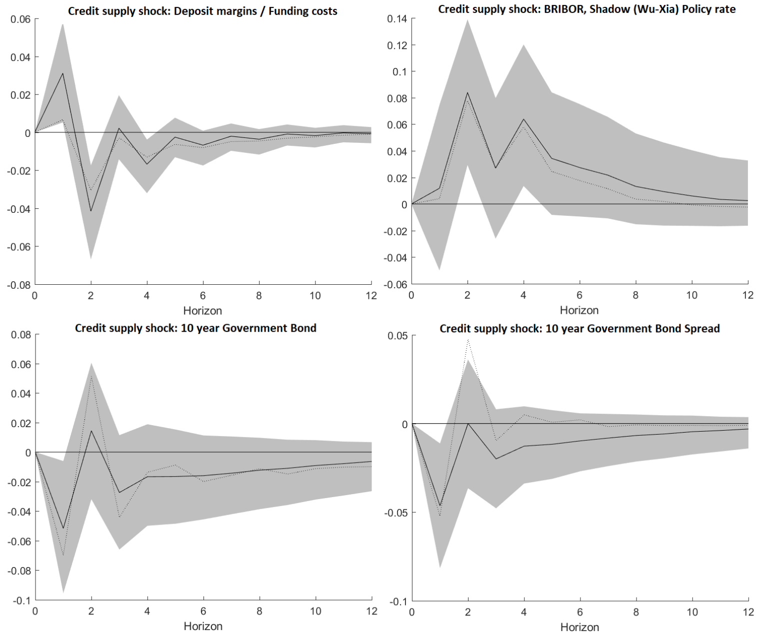
Notes: The black line depicts the median response at each horizon across all accepted models, the shaded grey area shows the middle 68% of models, and the dotted line represents the model which is closest to the median (CTM). All responses are in percentage points (pp).
Source: Author's own computations.

Figure 22: Alternative monetary policy measures



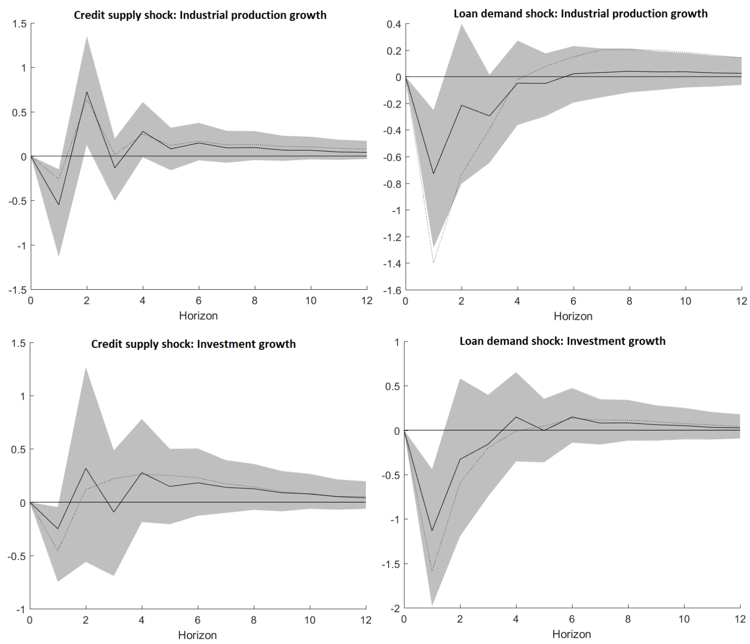
Notes: Shaded areas represent EA recessions according to Euro Area Business Cycle Network.
Source: NBS, ECB, Eurostat, Wu and Xia (2016).

Figure 23: IRFs of alternative monetary policy measures to a negative CS shock



Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

Figure 24: IRFs of investment and industrial production growth to structural shocks



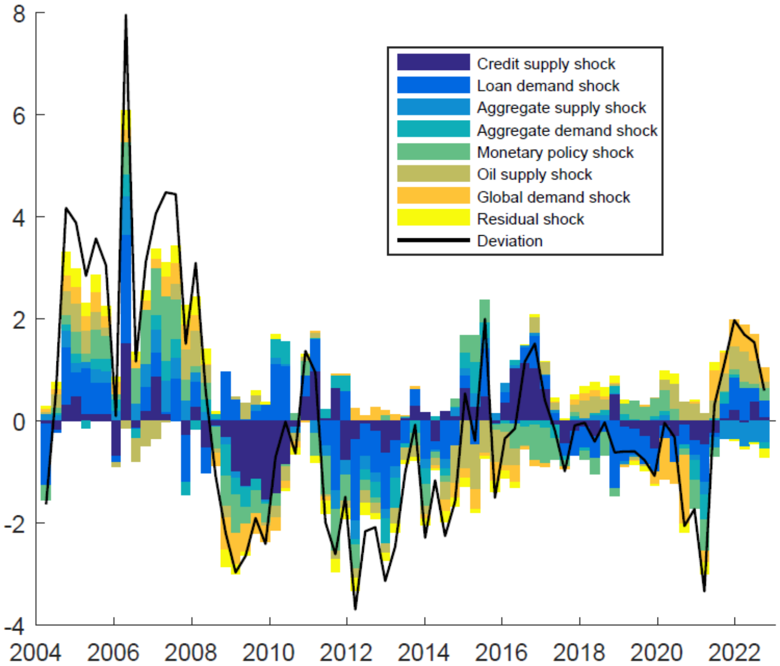
Notes: The black line shows the median response at each horizon across all accepted models, the shaded gray area shows the middle 68% of models, and the dotted line shows the model closest to the median (CTM). All responses are in percentage points (pp), and the horizon is in quarters.
Source: Author's own computations.

Table 4: Identification scheme

Struct. shocks → Endo. Variables ↓	Credit Supp (CS)	Loan Dem. (LD)	Agg. Supp. (AS)	Agg. Dem. (AD)	Mon. Policy (MP)	Oil Supp. (Oil)	Global Dem. (GD)	Residual
CPI Inflation	0	0	+	-	-	+	-	0
GDP Growth	0/-	0/+	-	-	-	-	-	0
10y Bond Spread	0	0	?	-	+	?	?	0
Lending Margins	+	-	?	?	?	?	?	0
NFCs Loans	-	-	?	?	?	?	?	0
World GDP	0	0	0	0	0	?	-	0
Oil Price Growth	0	0	0	0	0	+	-	0
NEER	?	?	?	?	?	?	?	+

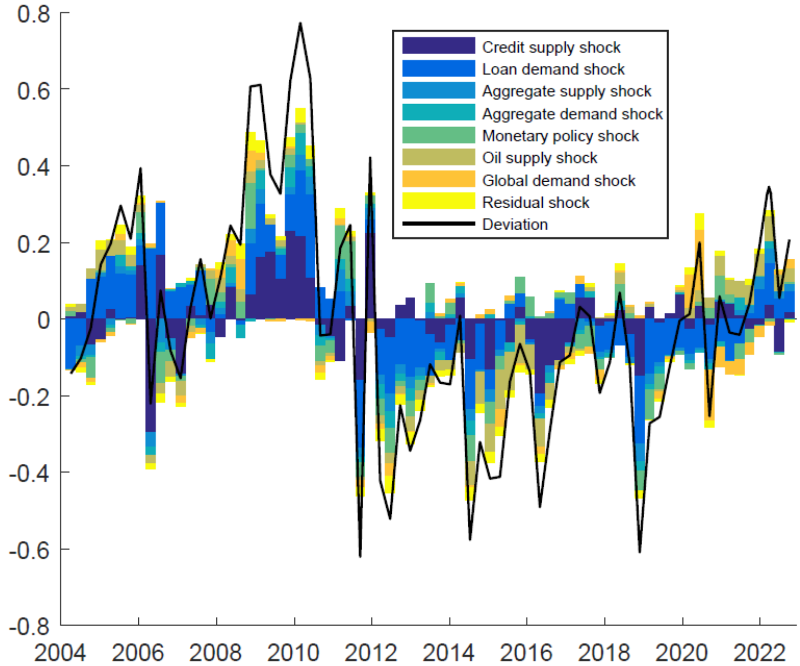
Notes: (+/-) sign restrictions, (0) zero restrictions, (?) parameters are not restricted, (0/-) or (0/+) mean a zero restriction in the impact period and a sign restriction in the next period.
Source: Duchi and Elbourne (2016) and Bobeica et al. (2019).

Figure 25: HD of NFC loans with the external sector



Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables not to sum up exactly.
Source: Author's own computations.

Figure 26: HD of lending margins with the external sector



Notes: The HD was calculated from the median model. The median model is calculated from the set of admissible models and is not related to any specific model, which causes HD of variables not to sum up exactly.
Source: Author's own computations.