



BARNABÁS SZÉKELY

FUNDING FOR LENDING SCHEMES SHOULD PRIORITIZE SME LENDING

MNB OCCASIONAL PAPERS | 138

2020

NOVEMBER



FUNDING FOR LENDING SCHEMES SHOULD PRIORITIZE SME LENDING

MNB OCCASIONAL PAPERS | 138

2020

NOVEMBER

The views expressed are those of the authors and do not necessarily reflect the official view of the Central Bank of Hungary, Hungarian Central Statistical Office and Ministry of Finance.

MNB Occasional Papers 138

Funding for lending schemes should prioritize SME lending*

(Aszimmetrikus hitelkínálati sokkok és a jegybanki hitelprogramok hatékonysága)

Written by Barnabás Székely

Budapest, November 2020

Published by the Magyar Nemzeti Bank

Publisher in charge: Eszter Hergár

H-1054 Budapest, Szabadság tér 9.

www.mnb.hu

ISSN 1585-5678 (online)

* We are grateful to Balázs Vonnák, Máté Bálint and Zsolt Oláh for their strong support.

Contents

Abstract	5
Összefoglaló	5
1 Introduction	7
1.1 Funding for lending schemes and the SME financing gap	7
2 The introduction and design of the NHP	9
3 Literature review	11
4 Data	14
5 Methodology and identification	15
5.1 Methodology	15
5.2 Identification of asymmetric shocks	16
6 Results	17
6.1 Time series of shocks	17
6.2 Asymmetric credit supply shocks – the benchmark model specification	18
7 Sensitivity analyses	23
7.1 Alternative differentiation of credit market and real shocks	23
7.2 Industrial production as a proxy of economic activity	23
8 Conclusion	27
9 Appendix	28
Appendix A: data	28
10 References	30

Abstract

In the aftermath of the sovereign debt crisis the Central Bank of Hungary implemented a great-scale funding for lending scheme designed specifically to subsidize SME finance. This creates a unique opportunity to identify this policy in the SVAR framework as *asymmetric credit supply shocks* specific to SME lending. I find that during the post-crisis recovery, such disturbances had a substantial effect on lending conditions and the real economy. Moreover, rather than supplanting lending to large enterprises, the program had considerable positive spillover effects to this sector. Finally, for a unit of lending, these shocks had larger and more persistent effect on output than general credit supply shocks. These results are robust to different proxies of economic performance and alternative identification strategies. I conclude that under tight lending conditions funding for lending schemes are more effective if concentrated to SMEs.

JEL: C11, E32, E44, E58

Keywords: Bayesian SVARs, Credit supply shocks, Funding for lending scheme, SME finance

Összefoglaló

A Magyar Nemzeti Bank által, 2013 júliusában bevezetett Növekedési Hitelprogram (NHP) támogatott forrásokat biztosított hazai bankok számára, amennyiben ezeket kis- és középvállalkozásoknak számára hitelezték tovább. Ez konstrukció egyedülálló lehetőséget kínál, hogy az NHP-t olyan *aszimmetrikus hitelkínálati sokként* azonosítsuk a SVAR keretrendszerben, amely egyidejűleg nincs hatással a nagyvállalati hitelezésre. Azt találom, hogy ezek a sokkok jelentős hatással voltak a válság utáni magyar hitelviszonyokra és reálgazdaságra, továbbá idővel a nagyvállalati hitelezésre is pozitív hatást fejtettek ki. Emellett, egységnyi hitelezésre vetítve, az aszimmetrikus hitelkínálati sokkok számottevően nagyobb pozitív hatással voltak a gazdaságra, mint az általános hitelkínálati sokkok. Ezek az eredmények a gazdasági aktivitás különböző mérőszámaira és alternatív identifikációs stratégiák alkalmazására is robusztusok maradnak. Ez arra enged következtetni, hogy pénzügyi stresszhelyzetben a hitelezést támogató programok hatékonyabbak, ha a kis- és középvállalkozásokat helyezik előtérbe.

1 Introduction

1.1 FUNDING FOR LENDING SCHEMES AND THE SME FINANCING GAP

The quick succession of the 2008 financial crisis and the sovereign debt crisis prompted Central Banks across Europe to expand their unconventional monetary policy toolkit. The Bank of England launched a Funding for Lending Scheme (FLS) which granted subsidized funding for banks given that new credit outflows represented an expansion to net lending. In a similar spirit, the European Central Bank has implemented Targeted Longer-term Refinancing Operations (TLTRO) which provided subsidized funds in proportion to the stock of loans banks held on their balance sheets. These programs were designed to counter high funding costs that were identified as major impediments to the swift recovery of credit markets. Cheaper funding to banks was expected to trickle down to borrowers through the relaxation of credit conditions and reduction of interest rates. These schemes were viewed as complements to QE programs: the former boosted the economy through reducing funding costs in the banking sector while the latter sought to circumvent financial intermediaries altogether (Churm et al., 2012).

The Növekedési Hitelprogram (NHP), a funding for lending scheme implemented by the Central Bank of Hungary (MNB) represented a more direct intervention to credit markets. It granted subsidized funds to the banking sector provided that these were channelled directly (and instantly) to small and medium enterprises (SMEs) at a modest mark-up. Recent policy discussions often refer to SMEs as engines of diversification and sustainable economic growth (Novy, Meissner and Jacks, 2008; Yoon, Shin and Lee, 2016). However, it is also widely acknowledged, that these enterprises are more credit constrained than large enterprises (LE) because market failures stemming from information asymmetries are more acute in their cases. The NHP was designed under the presumption that these market failures, exacerbated under periods of financial stress, necessitate a more direct and cyclical support to SME finance.

This study isolates the effects of the NHP in the SVAR framework as asymmetric shocks that increased total corporate lending volumes while leaving lending to large enterprises contemporaneously unaffected. Moreover, since the program offered subsidised funding to banks, it is also safe to assume it created downward pressure on interest rates. *Hence, the effects of NHP are characterized as asymmetric credit supply shocks specific to the SME sector.* These shocks overlap well with large issuances of NHP loans which implies that the proposed identification strategy captures the effects of the policy sufficiently well – although it is probable that it also picks up some of the asymmetric effects of other disturbances that are independent of central bank policy. Along with these shocks, traditional (i.e. general) credit supply shocks are identified by the expansion of total corporate debt and contemporaneous fall in average lending rates. Additionally, aggregate demand (inflationary) and aggregate supply (deflationary) shocks are identified to isolate output disturbances that are not attributable to credit market turbulences.

There is an extensive theoretical and empirical evidence suggesting banks tend to discriminate against SMEs. This phenomenon is often referred to as the SME financing gap and it is recognized to be wider in emerging economies and under periods of financial stress. Based on this literature, I hypothesise that a unit of subsidized lending allocated specifically to SMEs have a more substantial impact on the economy than the same subsidy allocated to the whole of the credit market. I find that asymmetric credit supply shocks (associated with SME-specific subsidies) have larger effect on output than general credit supply shocks (associated with universal subsidies). In the case of asymmetric credit supply shocks, a credit expansion of 1% is associated with a 0.443% higher level of output which remains significant until the 56th period. On the other hand, general credit supply shocks of the same size lift output by just 0.355% which is significant until the 45th month. This is interpreted as evidence that under periods of considerable financial stress, funding for lending schemes should prioritize financing SMEs.

Identifying the effects of NHP as asymmetric credit supply shocks also creates the opportunity to assess some of the effects of the program. One such highlighted issue is to establish whether subsidized lending to SMEs displaces some of the lending to large enterprises. It is found that asymmetric credit supply shocks have significant positive effect on LE lending over time. This implies that the program had no “crowding out” effect at the expense of large enterprises. On the contrary, cheap funding made available in the SME sector had a very considerable positive spillover effects on LE finance. This result is robust to different identification strategies and model setups. But the extent to which it is attributable to the direct spillover effects of the NHP is not straightforward to determine. It is possible that the significant positive response of LE lending captures the asymmetric effect of the economic upswing and the contemporaneous dissipation of the SME financing gap. Forecast error variance decompositions show that shocks related to the NHP had a very significant impact on the real activity: these drive more 14.9% of the error variation of output after one year and 30.8% after four. Such significance of asymmetric credit supply shocks might raise some concerns that the benchmark identification strategy is not conservative enough, but this result is robust to alternative identification strategies.

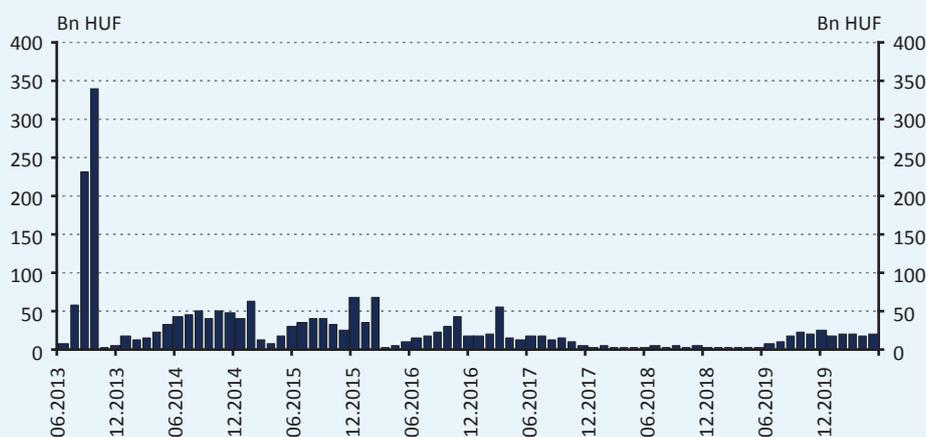
Section 2 of the paper describes NHP in detail, section 3 revises related literature, section 4 introduces the dataset. Section 5 expounds the SVAR framework and the identification strategy, section 6 describes results and section 7 presents sensitivity analyses. Finally, section 8 concludes.

2 The introduction and design of the NHP

The NHP represented a more direct intervention to credit markets than ECB's TLTRO program or BoE's FLS. These programs aimed alleviate the burden of high funding costs under the presumption that subsidies to banks will pass over to borrowers over time. The exact timing and course of the pass-through was left to banks' optimization. The NHP deviated from these programs in its' scale (relative to the Hungarian credit markets) and its' approach. Banks were allotted subsidized funds at the interest rate of 1% and were allowed to charge a maximum of 2.5% margin. Credit default risks had to be internalized by banks and to guarantee immediate pass-through, funding was made available to banks only as "NHP loans" were issued to SMEs.

First introduced in June of 2013, the NHP had a total of 5 phases until the end of 2019, with minor modification to its' design. The first and most intensive phase of the program, designed to kickstart SME lending was running from June to September 2013. During this period total of 641 billion HUF (2.17 billion Eur) was distributed amongst SMEs. It demonstrates the scale of the program well that in the closing months of this phase, NHP loans constituted 80% of the total new issuances of HUF denominated corporate loans. During the second phase of the program from October of 2013 to December of 2015, a total of 880 billion HUF (2.74 billion Eur) was distributed. Although less intensive than the first one, NHP loans still hovered around 40% of total the total new issuances of HUF denominated corporate loans. The intensity of the program has subsided at later phases: for a brief period between April 2017 and January 2019 no new NHP contracts were made available. In 2019 the Central Bank of Hungary re-launched the program under the name NHP fix that subsidized fixed interest rate loans to SMEs. The time series of NHP credit outflows are presented at chart 1.

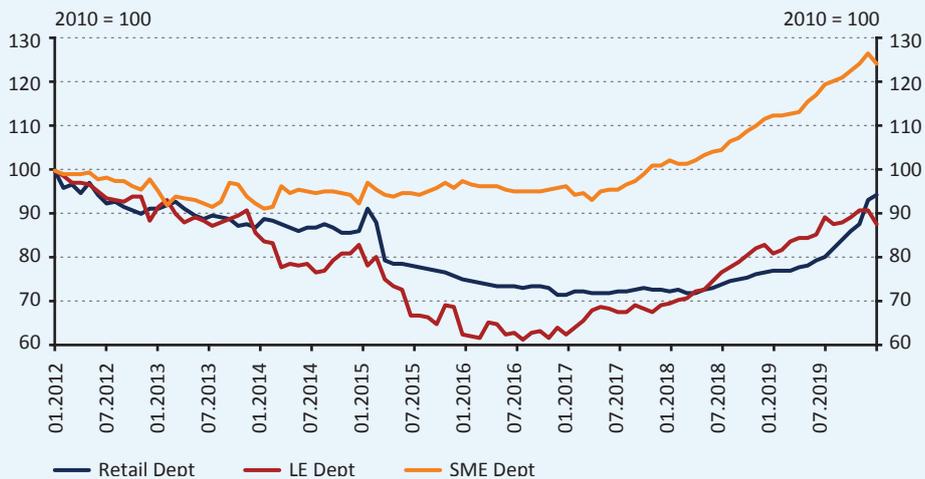
Chart 1
The time series of NHP issuances, billion HUF



Source: MNB database.

The dynamics of SME debt further stresses the significance of the NHP – chart 2. Until the introduction of the program, SME debt produced similar contraction to household debt and debt held by large enterprises. However, at around the second half of 2013 (the time of introduction of the NHP), SME debt started deviating from the rest. While these were mostly contracting until the general expansion of lending activity in 2017, SME debt remained stagnant slightly below of its’ 2012 levels. Although there is no rigorous exercise to determine how SME debt would have evolved in the absence of the NHP, the scale of the program makes it reasonable to assume that it had a significant impact on these dynamics.

Chart 2
Debt volumes: retail debt, LE debt and SME debt; 2010 = 100



Source: MNB database.

3 Literature review

Theoretical support for this paper rests in the description of the market failures that open the possibility of a constructive public intervention to SME finance. Jaffe and Russell (1976), and Stiglitz and Weiss (1981) demonstrate how information asymmetries on credit markets can elicit credit rationing behaviour. Unable to obtain sufficient information about their clients, banks may be reluctant to raise interest rates after a certain point because the level of interest rates affects the riskiness of borrowers. High interest rates could bring about the adverse selection of borrowers or it could incentivise them to take up excessive risks. Banks respond by keeping interest rates at a sub-optimal level meaning that demand for credit will exceed supply.

Monitoring and keeping up customer relationship with borrowers incurs fixed costs that are independent of the size of the enterprise. This implies that collecting information on small enterprises will be costlier in proportion to the credit distributed to them. Moreover, Chatzouz et al. (2014) argues that SMEs might not have to follow the same standard of accounting and transparency rules as larger enterprises do, which further raises the monitoring costs. Therefore, information asymmetries and the market failures stemming from these are more acute in the case of SMEs. A market-based solution to alleviate moral hazard and adverse selection is the use of collateral. Indeed, banks are often reluctant to extend credit to SMEs without a pledge of collateral. However, this too places a burden on SMEs (Chatzouz et al., 2017). Legal and administrative costs may be sizeable, differences in evaluation could mean that SMEs have to pledge more than it is internalized by banks and SMEs might not have sufficient collateral to begin with.

For the reasons listed above, it is rational for banks to demand more collateral, extract higher interest rates, and during crises, first start credit rationing in the SME sector. This phenomenon is extensively documented as the *SME financing gap* and it gave rise to credit guarantee schemes around the world that seek to alleviate these market failures by assuming some of the default risk for SMEs (Chatzouz et al., 2017). Such asymmetry between large enterprise and SME finance is well documented in the case of Hungary too: Endresz, Harasztosi and Lieli (2015) finds smaller enterprises were more credit-constrained in the aftermath of the sovereign debt crisis.

Furthermore, the SME financing gap can be more severe in emerging economies and during periods of economic turbulence. Emerging economies usually lack sufficient collateral relative to their developed counterparts and generally have a weaker infrastructure to monitor borrowers. This implies that banks have to rely more heavily on collateral-based lending despite the scarcity of good quality capital which further widens the gap between SMEs and large enterprises. Economic downturns, on the other hand, heighten banks' perceived uncertainty and exacerbate adverse selection of firms at the same time. This is compounded by the reduction in the value of collateral and rising default rates which could motivate banks to rapidly cut lending. Endrész (2020) finds that such credit rationing behaviour disproportionately damaged SME finance in Hungary after the collapse of Lehman brothers. For these reasons, subsidies to SME finance are often designed to be countercyclical.

Practical foundations of this paper rest on applications of the SVAR framework identifying the effects of credit supply shocks and unconventional monetary policies. The 2008 financial crisis highlighted the significance of financial intermediaries at exacerbating economic fluctuations. It is now common to identify credit market shocks along with traditional aggregate demand, supply and monetary policy shocks. Credit supply shocks are typically identified by the opposite motion of credit volumes and interest rates. Moreover, to clearly differentiate from real shocks, it is also often assumed that these do not have a contemporaneous effect on the economy (Barnett and Thomas, 2013; Duchi and Elbourne 2016). Table 1. summarizes some of the most relevant contributions for our purposes.

Table 1			
Relevant studies: data, variables and sign restrictions			
Study	Data	Endogenous variables	Structural Shocks
<i>Gambetti and Musso (2017)</i> Time varying parameter SVAR - SV	Euro area 1980–2010 Quarterly frequency	Real GDP Consumer Price Index Loan Volume Lending rate Policy rate	Aggregate Supply: +,-,+,+, Aggregate demand: +,+,+,+, Credit Supply: +,?,+,-,?
<i>Hristov, Hülsewig and Wollmershäuser (2012)</i> Panel SVAR	Euro Area countries, 2003–2010 Quarterly frequency	Real GDP GDP deflator Loan Volume Lending rate Policy rate	Aggregate Supply: -,+,?,?,+ Aggregate demand: -, -, ?, -, - Credit Supply: -, ?, -, +, - Monetary Policy: -, -, ?, ?, +
<i>Bijsterbosch and Falagiarda (2015)</i> Time varying parameter SVAR	Euro area countries, 1980–2013 Quarterly frequency	Real GDP GDP deflator Loan Volume Lending rate Policy rate	Aggregate Supply: +,-,?,?,? Aggregate demand: +,+,?,+, Credit Supply: +,+,+,-, Monetary Policy: +,+,?,?,-
<i>Mumtaz, Pinter and Theodoridis (2015)</i> Comparison of SVAR methods	United Kingdom 1973–2013 Quarterly frequency	GDP growth Consumer Price Index Loan Growth Spread Three-month T-Bill	Credit Supply: +,+,+,-,+
<i>Barnett and Thomas (2013); Duchi and Elbourne (2016)</i> SVAR	United Kingdom 1967–2012; Netherlands 1998–2014 Quarterly frequency	GDP growth Consumer Price Index Loan Growth Spread Policy rate Equity prices growth	Aggregate Supply: -,+,?,?,?,? Aggregate demand: +,+,?,?,+? Monetary Policy: +,+,?,?,-, Credit Supply: 0,0,+,-,0,? Credit Demand: 0,0,+,-,0,? Equity Price: 0,0,0,0,1
Identification of Unconventional Policies			
<i>Peersman (2011)</i> SVAR	Euro area 1999–2010 Monthly frequency	Industrial production Consumer Price Index Loan Volume (c) Lending rate Policy rate Monetary base (b) c-b	Credit multiplier: 0,0,+,-,+,?,+ Interest rate innovation: 0,0,+,-,+,?, Unconventional monetary policy: 0,0,+,-,0,?,?
<i>Darracq-Paries, De Santis (2015)</i> SVAR	Eurozone 2003–2012 Quarterly frequency	Real GDP growth Inflation Loan growth Interest rates Cost of lending BLS supply factors BLS demand factors	Aggregate demand: -, -, ?, -, -, ?,- Monetary policy: -, -, ?, +, +, ?, ? Credit Supply: -, -, ?, -, +, +, ? (These are equated to LTROs at the time of introduction)
<i>Gambacorta, Hoffman (2012)</i> Panel SVAR	8 advanced economies 2008–2011 Monthly frequency	GDP proxy (from IP and retail sales) Consumer Price Index Central banks assets Stock market volatility	Unconventional monetary policy 0,0,+,-
<i>Tamási and Világi (2011)</i> SVAR	Hungary 1995–2010 Quarterly frequency	Real GDP Consumer Price Index Corporate Loans Credit spread 3-month BUBOR Nominal effective exchange rates Default rate	Banks' risk assessment +,?,+,?,0,?,+ Regulatory changes +,?,+,-,0,?,0 Risk premium: ?, -, ?, 0, -, -, ? Monetary policy: +,+,?,0,-,+0
<i>Note: The sign restriction in the n'th column corresponds to the endogenous variable in the n'th row denote positive sign restrictions, denote negative sign restrictions, denote negative sign restrictions</i>			

There have also been several attempts to identify the effects of regulatory shocks or the effects unconventional monetary policies. These contributions provide precedence at equating the effects of policy interventions to exogenous disturbances and present guidance on the identification of such shocks. For instance, Tamási and Világi (2011) decomposed credit supply shocks into two structural shocks: credit supply shocks due to changing risk-appetite and due to regulatory changes. They find that regulatory shocks have a greater and more persistent effect on GDP than credit multiplier shocks.

One of the earliest contributions identifying non-conventional monetary policy shocks in Europe is Peersman (2011): it assumes that these have an analogous effect to standard monetary policy shocks but without contemporaneously affecting the policy rate. Gambacorta and Hoffmann (2012) identify unconventional monetary policies as shocks to the size of central bank balance sheet. These studies find that unconventional monetary policy shocks have very similar effects to conventional ones, albeit through different transmission channels. However, these identification techniques can only partly pick up of the effects of funding for lending schemes. Moreover, these could be confounded with shocks to QE programs or other unconventional tools. Generally speaking, it is difficult to isolate the effects of funding for lending schemes in the SVAR framework. Darracq-Paries and De Santis (2013) simply equate the ECB's longer-term refinancing operations (LTROs) to the positive credit supply shocks at around the time of the introduction. Churm et al. (2015) on the other hand, do not attempt to separate the effects of BoE's FLS scheme: it analyses the unidentified (i.e. correlated) loan shocks at around the time of the introduction.

Finally, attempts have been made to assess the effects of funding for lending schemes with the use panel data. Detailed panel data allows researchers to track and compare the behaviour firms (or banks) who took part in the program and those who did not. However, the extent to which subsidized funds have generated additional credit outflows (or investments) is not trivial to determine. If market participants used subsidies to finance projects that were already planned, these funds merely represented money transfers to recipients – and thus had much less direct effect on economic activity. Hence, these studies use difference in differences to identify the effects of funding for lending schemes. Havrylchuk (2016) uses bank-level data to measure the effects of an update to the BoE's FLS that provided extra incentives to banks to finance SMEs. For Hungary's NHP, Endresz et al. (2015) use firm level data to contrast investment decision of participant and non-participant enterprises. Evidence presented by these studies is mixed. Havrylchuk (2016) does not identify a significant effect of the FLS update. Endresz et al. (2015) on the other hand, identifies significant impact on firms' investment decision – however, they have to augment standard diff-in-diff method with a correction term as the parallel trends assumption might not be reasonable.

4 Data

I utilize a monthly dataset spanning from 2012m1 to 2019m12 which contains time series characterizing real economic activity, price dynamics and corporate credit market dynamics. For economic activity, two measures are proposed: one is seasonally adjusted industrial production, the other is a proxy of GDP constructed as a linear combination of retail sales, industrial production, and the number of guest nights (these are publicly available data gathered by the national statistical office of Hungary). The construction of an output proxy is necessitated by the quarterly frequency of GDP data. The goal was to create a measure of economic activity that internalizes information from the service and retail sector along with seasonally adjusted industrial production. The weight of these variables in the proxy is established by a linear regression model, which is then used to “predict” GDP on a monthly basis. The estimate of economic activity follows GDP data sufficiently closely, with a 0.91 correlation if year-on-year growth is considered, and 0.61 correlation on a quarter-on-quarter basis. Benchmark results are reported with this proxy, but I re-estimate the model with industrial production as a robustness exercise. Yearly inflation rate is calculated from seasonally adjusted CPI.

As for credit market information, total corporate debt is extracted from the records of the Central Bank of Hungary. Debt held by large enterprises is calculated as a residual of total corporate debt and SME debt. Assembling the time series SME debt was challenging as several privileged data sources had to be harmonized to get a consistent time series. In fact, the enquiry is limited to this time span because there is no SME debt data of sufficient quality available before 2012. It should also be addressed that some of the most significant shocks due to accounting changes have been smoothed out, but the dataset is not completely free of these disturbances. Finally, average monthly interest rates of new corporate loans could also be extracted from data published by the Central Bank of Hungary.

A more detailed description of data sources and construction can be found in table A1 of the appendix.

5 Methodology and identification

5.1 METHODOLOGY

Consider the following model:

$$Y_t = c + \sum_{j=1}^p B_j Y_{t-p} + A_0 \varepsilon_t$$

Where Y is a 5×1 column matrix of endogenous variables describing level of output, yearly inflation, total corporate debt, debt held by large enterprises and average interest rates of corporate loans. B_j is a matrix of lagged coefficients, 5×1 is a matrix of constants. The model is estimated in log levels and with 3 lags. Although the deviance information criterion is not minimized by this model setup, I have confined to the use of 3 lags to avoid the proliferation of parameters – this many lags also sufficient to mitigate the autocorrelation of residuals. Parameter values are time invariant. One could extend the model into a time varying parameter SVAR, but the narrow time frame and the absence of structural breaks does not necessitate the introduction of parameter variance. is the contemporaneous impact matrix of uncorrelated structural disturbances, ε such that $E[uu'] = \Omega = A_0 E[\varepsilon\varepsilon'] A_0 = A_0 A_0$ – where the last step uses $E[\varepsilon\varepsilon'] = I$.

Recursively identified models typically solve $\Omega = A_0 A_0$ by Cholesky decomposition which produces a set of zero restrictions on the contemporaneous correlation matrix, A_0 . Sign identified models, established by Canova and DeNicolo (2002) and Uhlig (2005), allow a more flexible set of restrictions. In these models each structural shock is associated with a unique sign pattern. Then, the Cholesky decomposition of Ω is augmented with an additional orthogonalization step, such that $\Omega = A_0 P P' A_0$ where P is the product of the QR decomposition of a randomly drawn matrix. If the IRFs produced by the given draw satisfies restrictions established by the sign pattern, the draw is saved – if restrictions are not satisfied, the draw receives a prior weight of 0. The exact identification of structural shocks follows the general methodology proposed by Aries, Rubio-Ramirez and Waggoner (2014)¹ which supports the use of a combination of zero and sign restrictions.

This identification strategy implies that a set of models are admitted rather than a single one. These models are all consistent with the *a priori* restrictions and only differ by their respective draw of the orthogonal matrix – meaning their likelihood is identical. This implies that without additional assumptions there is no saying if a model produced by a random draw is superior to another (Kilian, 2011). Therefore, Bayesian methods of inference are used to produce a smooth posterior distribution of impulse responses from all admissible models. For reduced form parameters, Independent Normal-Wishart priors and Minnesota structure is assumed. To reflect that the endogenous variables in the model are fairly persistent, the first autoregressive coefficient shrinks to 0.8 and rest of the coefficients shrink to 0. Setting the first autoregressive term slightly below one, is preferred when we want our priors to reflect persistence of the variables, but we do not want to impose unit roots, see: Koop and Korobilis (2010). The prior variances of error terms are calculated from separate AR models. Furthermore, following the literature, hyperparameters are set to $\lambda_1=0.1$ (overall tightness of priors), $\lambda_2=0.5$ (cross-variable weighing), $\lambda_3=2$ (lag decay). To reach convergence a total of 5000 draw saved is used after 10000 burn-in draws. The model is estimated using the BEAR software.

¹ This is the general methodology employed by the Bayesian Estimation, Analysis and Regression toolbox (BEAR) software

5.2 IDENTIFICATION OF ASYMMETRIC SHOCKS

The identification of the quantitative effects of the NHP is described in table 2.

Table 2
Identification strategy of benchmark model

	Aggregate Demand	Aggregate Supply	Asymmetric Credit Supply	General Credit Supply
Output	+	+		
Inflation	+	-		
Total corporate debt	0	0	+	+
Total LE debt	0	0	0	
Interest rates	0	0	-	-

Note: denote positive sign restrictions, denote negative sign restrictions, denote zero restrictions

At a first glance, one might consider it a more straightforward to analyse shock to SME and LE lending separately, but this approach would not allow to identify general credit supply shocks (positive restrictions on both would exclude instances where one is falling but overall debt is still expanding). Therefore, asymmetric shocks are identified when there is an expansion in total corporate debt with no contemporaneous change in LE lending – since LE and SME debt add up to total corporate debt this identification immediately implies that under such circumstances SME debt is increasing.

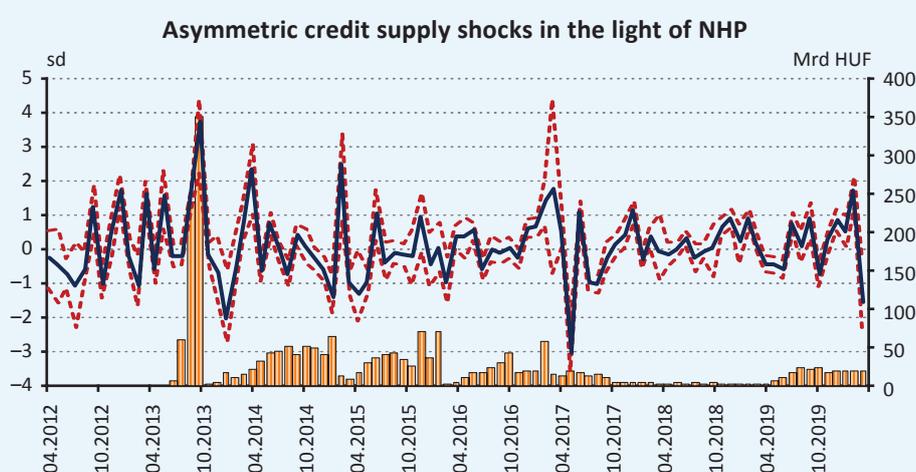
As it can be seen in table 1, it is conventional to use contemporaneous 0 restrictions to differentiate credit market disturbances from real economy shocks. The standard approach is to assume that credit market shocks do not affect output and inflation within a period. However, the focus of this study is to measure these very effects. Hence, I prefer to remain as agnostic about the contemporaneous real effects of credit supply shocks. Instead, I assume that real shocks do not affect credit markets within one month. Since this represents a deviation from the standard identification procedure, I conduct a robustness exercise in section 7 that uses the standard identification strategy. I find that although the difference of the two credit supply shocks is not as substantial as in the benchmark model, the main result persists.

6 Results

6.1 TIME SERIES OF SHOCKS

NHP was designed to immediately pass through from banks to SMEs: subsidized funding was only made available to banks as “NHP loans” were issued to SMEs. This design leaves no doubt about the timing of the most substantial effects of the program. The sequence of asymmetric credit supply shocks can thus be compared to the issuances of NHP loans to check the precision of the identification strategy.

Chart 3
Time series of asymmetric and general credit supply shocks and NHP issuances



Note: dashed red lines represent the 95% credibility interval

Source: own calculation

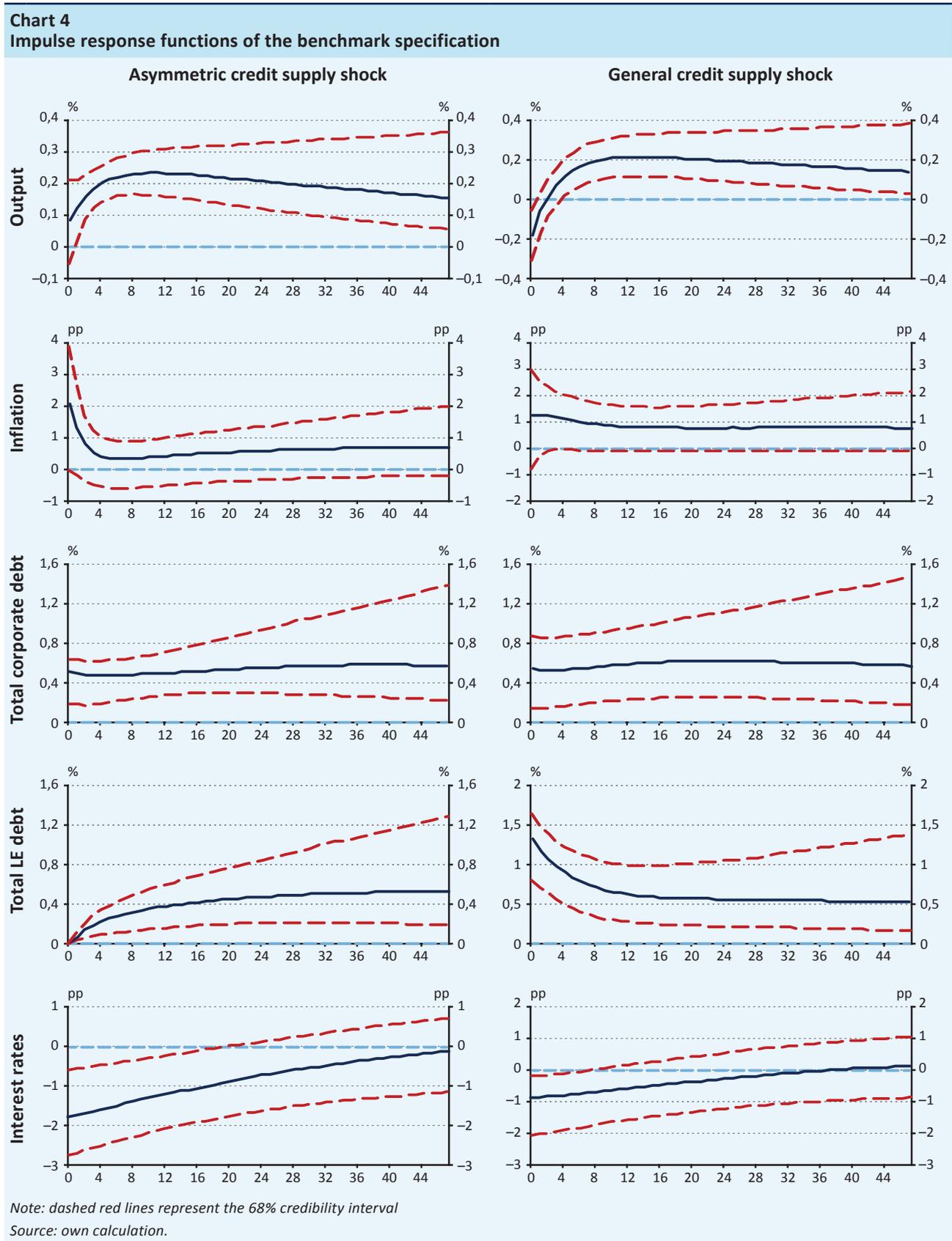
Immediately apparent, that this identification strategy picks up the most significant issuances of NHP loans in July and August of 2013. However, there is little support in the data for some fluctuations, such as the negative asymmetric credit supply shock at the beginning of 2017. Although the program was briefly halted between 2017 and 2019 this should not incur a negative shock of this magnitude. Interestingly, all credit shocks display a very significant turbulence at this time despite that neither LE lending nor total corporate lending experienced any significant fluctuation around this period. This raises some worries that although the identification of asymmetric shocks picks up the effects of NHP, it might also subsume some shocks independent to the program.

This result might come as a surprise since few endogenous market forces or other exogenous policy interventions come to mind that would consistently benefit the SME sector without having an effect on large enterprises. One potential explanation is that this identification scheme gathers some of the asymmetric effects of the general shocks during this period. For instance, the general economic expansion after 2012 might have disproportionately benefitted SMEs (or to put it differently, the 2012 crises had a disproportionate negative effect on SME finance). As financial intermediaries became less risk averse during the upswing, discrimination towards SMEs eased up (i.e. the SME financing gap has narrowed). This development could be identified as an asymmetric shock to the extent it has benefitted SMEs more than their larger counterparts, even if general the shift in the prevailing mood of financial intermediaries benefitted large enterprises as well.

Overall, however, asymmetric credit supply shocks follow the intensity of the program well: they resemble a white noise before introduction (mid-2013), their volatility is higher during the first- to third phase and it subsides as the program is briefly halted after the April of 2017. Therefore, it can be argued that even if asymmetric credit supply shocks cannot be exactly equated to NHP, these gather the effects of the program sufficiently well.

6.2 ASYMMETRIC CREDIT SUPPLY SHOCKS – THE BENCHMARK MODEL SPECIFICATION

The effects of asymmetric and general credit supply shocks in the benchmark specification are reported in Chart 4.



The benchmark model specification confirms the central hypothesis of the study. Credit supply shocks that affect the total corporate debt through the expansion of SME debts have a more substantial effect on the economy than general credit supply shocks. For a credit expansion of 1%, the former raises output (approximated by the GDP proxy) by 0.443% which remains significant until the 56th period, while the latter raises GDP by 0.355% and remains significant until the 45th period. This is interpreted as evidence that funding for lending schemes that subsidize SME lending (thus creating asymmetric shocks) have a more substantial effect on the economy than universal programs because SMEs are more credit-constrained than their larger counterparts.

Average interest rates respond much more intensively to asymmetric credit supply shocks. For a one percent total debt expansion, average interest rates of new issuances fell 2.8 percentage points for asymmetric credit supply shocks and 1.5 percentage points in the case of general credit supply shocks. This difference could reflect the NHP's drastic intervention to credit markets. At the time of the introduction of the program, average interest rates of corporate loans averaged at 7.9%. In this environment, the NHP maximized interest rates of "NHP loans" at 2.5% (later, this gap has considerably narrowed, but remained substantial). General credit supply shocks that are due to "natural" market mechanisms, are unlikely to induce such a radical interest rate reduction. For instance, a financial intermediary extending its' credit supply would attempt to draw in new borrowers by incremental interest rate cuts. This leads to significantly smaller interest rate fluctuations in the proportion of the credit allocated to market participants.

One puzzling result is that the immediate effect of credit supply shocks starts out negative, but this passes after just 2 periods – similarly, the first period output expansion due to asymmetric credit supply shocks is not significant. A potential explanation is that accounting changes, that could not be fully rooted out of the time series of corporate debt, bias results. If significant loan write-downs coincide with output expansions, the short-term effects of credit supply shocks might be biased downwards. However, such accounting shocks would have no long-term effects on real variables since they represent no changes actual real quantities at the time of occurrence. Therefore, it is safe to assume that such biases are mitigated after a short interval.

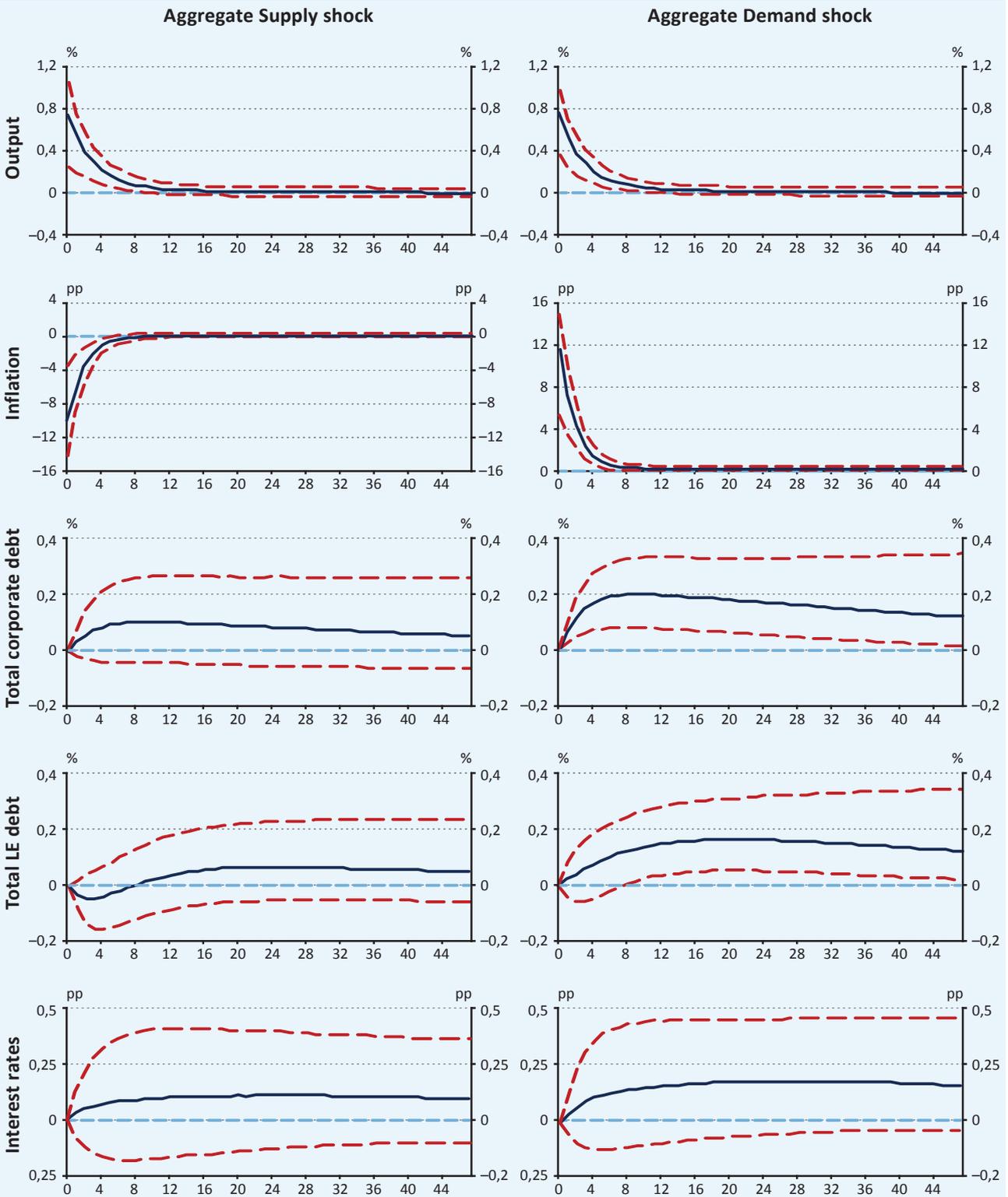
Another highlighted issue is answered by the response of LE debt to asymmetric credit supply shocks. It was not obvious whether access to subsidized funding in the SME sector would incentivise banks to substitute away from financing large enterprises – or on the contrary, higher profitability in one sector would allow them to extend more credit to the other one. The positive response of LE debt lets us conclude that the latter effect dominates by a large margin: for a credit expansion of 1% lending to large enterprises expands by 0.679% after just one year and more than 0.75% on the long run. This implies that expansion in one segment of the credit market induces a similar expansion of the other segment on the long run. This result is robust to alternative model setups and identification strategies.

However, the extent to which such spillover effects are attributable to the NHP is not obvious. One potential explanation could be that this result reflects an accounting artefact: as enterprises outgrow their SME status obligations of these firms towards financial intermediaries are reclassified as LE debt. However, firm-level databases indicate that Hungarian enterprises very rarely switch status: between 2017 and 2018 only 64 out of 21500 SME have upgraded their classification.² Hence, it is highly unlikely that such accounting routines substantially bias results.

It is also possible that the positive response of LE debt reflects the effects of a general economic expansion. Interpreting these results, one should take into consideration that the Hungarian economy has moved from a deep financial slump at the beginning of 2012 to an expansionary period characterized by rapid output growth, high asset prices and lender optimism by the end 2019. This upswing has allowed financial intermediaries to relax credit conditions and ease up discrimination towards the SME sector. To the extent to which SME debt expansion reflects the dissipation of the SME financing gap due to the shift in market sentiments, the positive response of LE debt could reflect this general upswing rather than direct spillover from the SME sector.

² This is probably attributable to the preferential treatment of SMEs by regulatory authorities and policy interventions

Chart 5
Impulse response functions of the benchmark specification



Note: dashed red lines represent the 68% credibility interval
Source: own calculation.

There is no rigorous way to determine the extent to which the positive response of LE lending reflects direct spillover effects from the SME sector, or the economy-wide upswing and the ensuing lender optimism. However, given the scale and the widespread communication of the NHP, it is possible that the program itself had a considerable role to play in the shift of market sentiments. Moreover, it should also be mentioned, that although this effect is statistically significant, forecast variance error variance decomposition (FEVD) indicates that it had modest impact on the evolution of LE debt. Asymmetric credit supply shocks only explain around the 15% of LE debts error variation, as opposed to the 43% explained by credit supply shocks and almost 39% of the variation is not identified by the model. In every other aspect, such as the response of inflation, interest rates and corporate debt the effects of asymmetric and general credit supply shocks are strikingly similar.

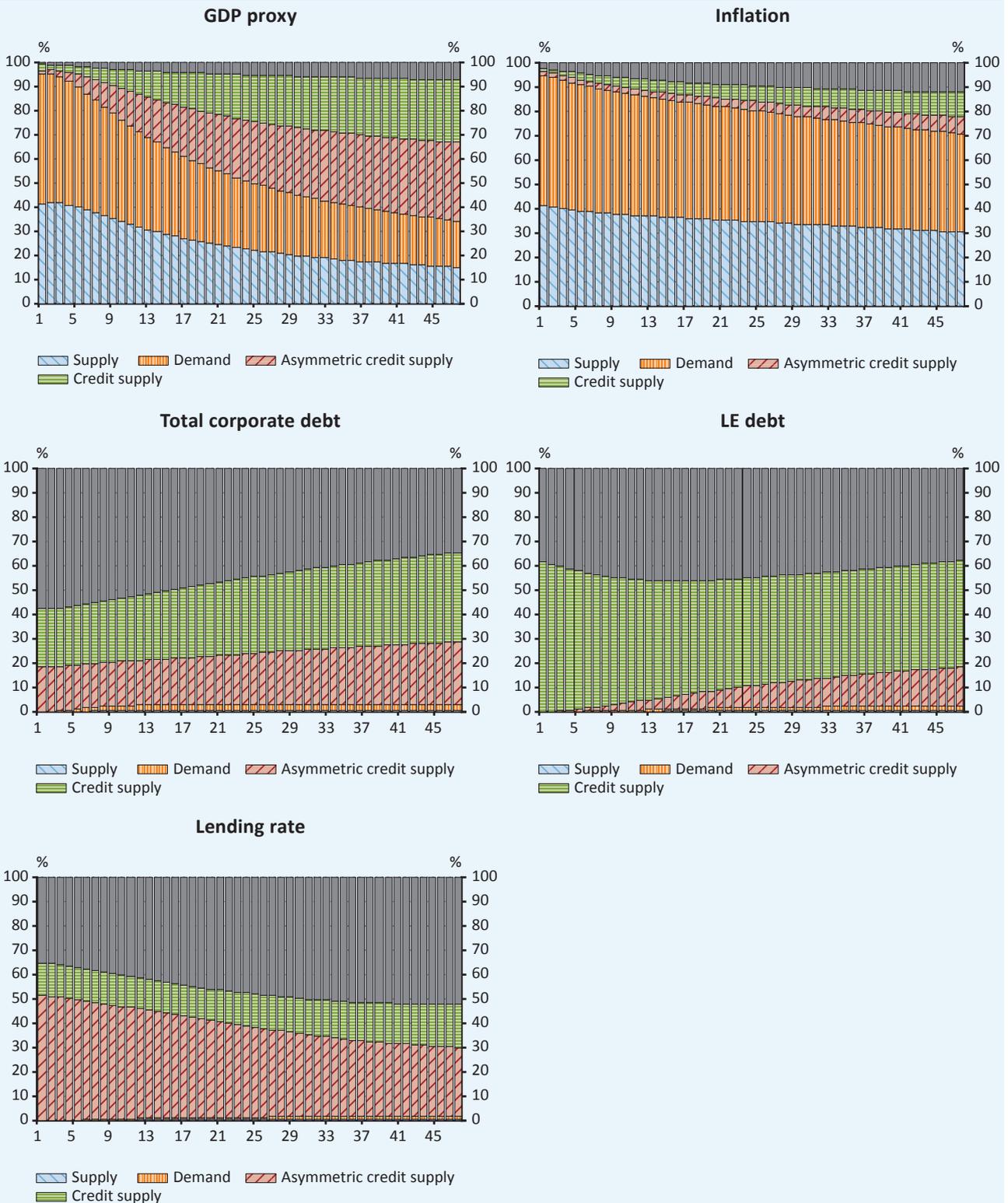
The effects of aggregate demand and supply shock in the benchmark specification are reported in Chart 4.

On the short run, aggregate demand and supply shocks have a more sizeable effect on output than credit market shocks. However, the impact of these disturbances subsides quickly. After just 12 periods both shocks have a minimal and non-significant effect on output – credit market shocks, on the other hand, are significant for at least 45 periods. Aggregate demand and supply shocks have almost analogous effects on the credit market, these impacts are mostly non-significant (an exception to this is the positive effect aggregate demand shocks exert on total corporate debt).

Forecast error variance decompositions (FEVDs) allow us to partition error variance by the structural shocks that induced them. This exercise is often used to establish the influence certain shocks have on endogenous variables. It indicates that on the short run real shocks dominate the evolution of GDP proxy, but as the forecast window is expanded, more persistent credit shocks take over a significant portion of the variance. Asymmetric credit supply shocks are particularly consequential: from almost non-existent impact for forecast of one period, these assume more 14.9% of the error variation after one year and 30.8% after four. As it can be seen at chart 6, asymmetric credit shocks also have a large immediate impact on average lending rates that moderates for a wider forecasting window. This is not very surprising since the NHP represented an immediate and drastic intervention to credit markets. The evolution of total corporate debt is driven by aggregate demand, asymmetric credit supply and general credit supply shocks to a near equal extent, but in this case, a very substantial part of the variation remains unidentified. The rest of the decompositions are less important for the purpose of this enquiry – inflation remains mostly unaltered by credit market disturbances; the identified part of LE debt remain weakly affected by asymmetric credit supply shocks and a significant part of credit market variation cannot be identified.

The vast influence of asymmetric credit supply shocks on output could raise some suspicion that the identification strategy is not conservative enough. Since this identification strategy does not restrict the immediate effect of credit market shocks to the real economy to zero, it is possible that these pick up some effects of real economy shocks that do reflect credit market disturbances. To better explore this issue, the sensitivity analysis in section 7 switches zero restrictions so that credit supply shock could not contemporaneously affect the real economy. If there was any misidentification of this sort, this approach would yield different results. However, I find that this identification scheme does not reduce the prominence of asymmetric credit supply shocks: asymmetric credit supply shocks still explain more than 25% of output error variation on the long run and have a maximum real economy effects (as evidenced by IRFs) that are roughly the same size as in the benchmark specification.

Chart 6
Forecast error variance decompositions of the benchmark specification



Note: the unidentified part of the error variation is represented by light grey
 Source: own calculation.

7 Sensitivity analyses

7.1 ALTERNATIVE DIFFERENTIATION OF CREDIT MARKET AND REAL SHOCKS

As it was mentioned before, the benchmark specification remains agnostic of the real economy effects of credit supply shocks since these are the very effects it aims to quantify. However, this is not the standard approach to differentiate credit market and real economy shocks. This sensitivity analysis switches zero restrictions so that it is credit market shocks that cannot have a contemporaneous effect on the real economy. In every other aspect, the model is analogous to the benchmark model, the new set of restriction are described in table 4.

Table 3
Identification strategy of conversion shocks model

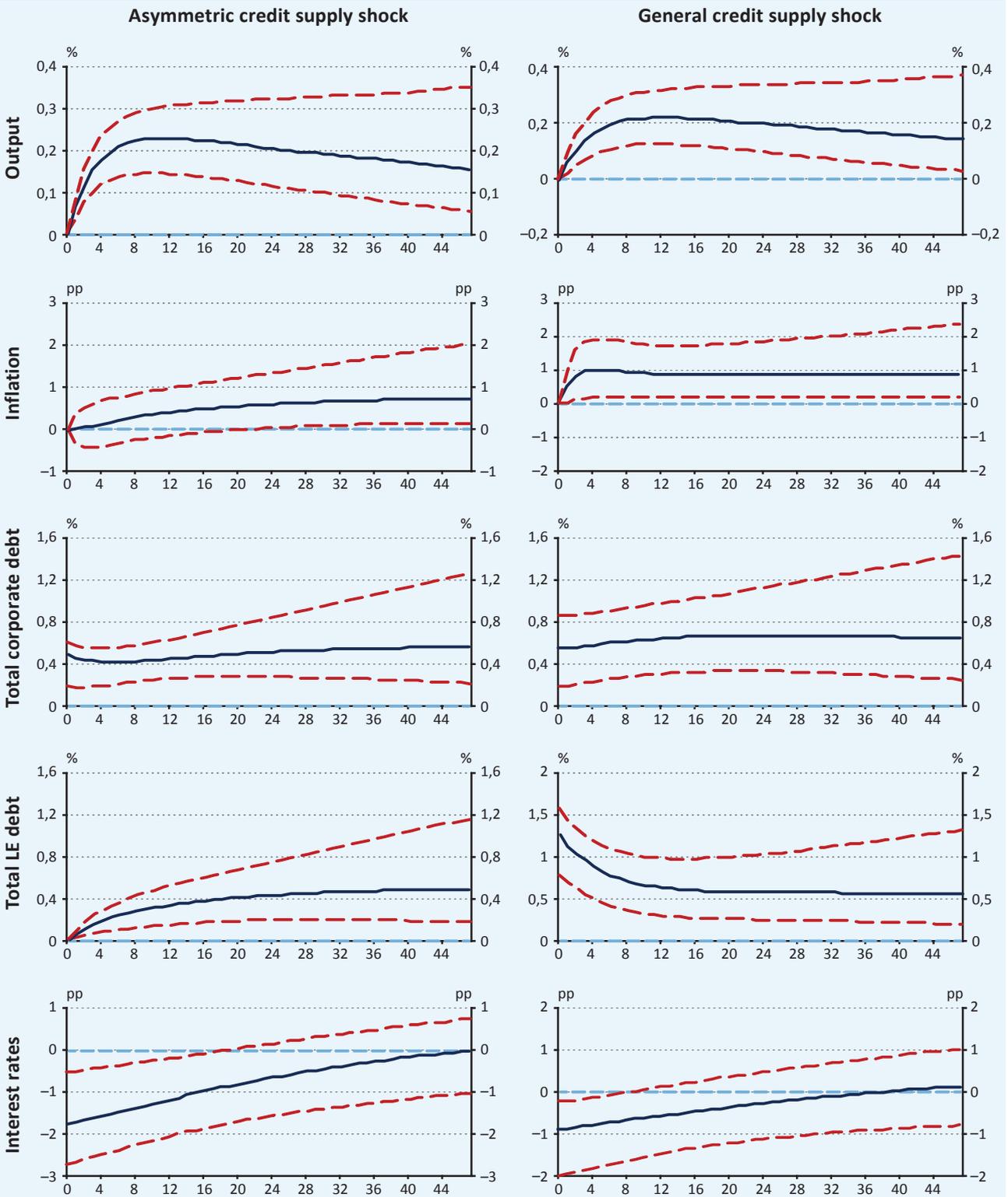
	Aggregate Demand	Aggregate Supply	Asymmetric Credit Supply	General Credit Supply
Output	+	+	0	0
Inflation	+	-	0	0
Total corporate debt			+	+
Total LE debt			0	
Interest rates			-	-

Note: denote positive sign restrictions, denote negative sign restrictions, denote zero restrictions

The purpose of this exercise is twofold. My primary goal is to recreate the set of restrictions that has become more common in recent literature. Moreover, the benchmark specification might attribute some effects of real economy shocks to credit market shocks (this issue was already discussed already in section 5 at the interpretation of forecast error variance decompositions). This exercise is well-fitted to explore this concern. If such misidentification played a significant role, the impact of asymmetric credit supply shocks should be considerably reduced by this identification scheme (as indicated by the FEVD and impulse response functions). The impact of credit market shocks is presented at chart 7.

The time series of shocks produced by this model is almost analogous to those produced by the baseline identification (see: chart 1 in appendix), although the shock produced by the introduction of the program are slightly less significant. Under these restrictions, the gap between asymmetric and general credit supply shocks is narrowed: for a 1% loan expansion, asymmetric shocks lift output by 0.451% (after 10 periods), which remains significant until the 59th period while a same sized general credit expansion lifts output by 0.385% (after 10 periods) which remains significant until the 48th period. Although this gap is somewhat reduced, the general finding of the paper still holds. Moreover, FEVD shows that asymmetric credit supply shocks still explain a substantial part of output forecast error variance. This is interpreted as evidence that the sizeable impact credit supply shocks have on GDP in the benchmark specification is not attributable to the confusion of real economy shocks to credit market shocks.

Chart 7
Impulse response functions of the sensitivity analysis with alternative identification strategy

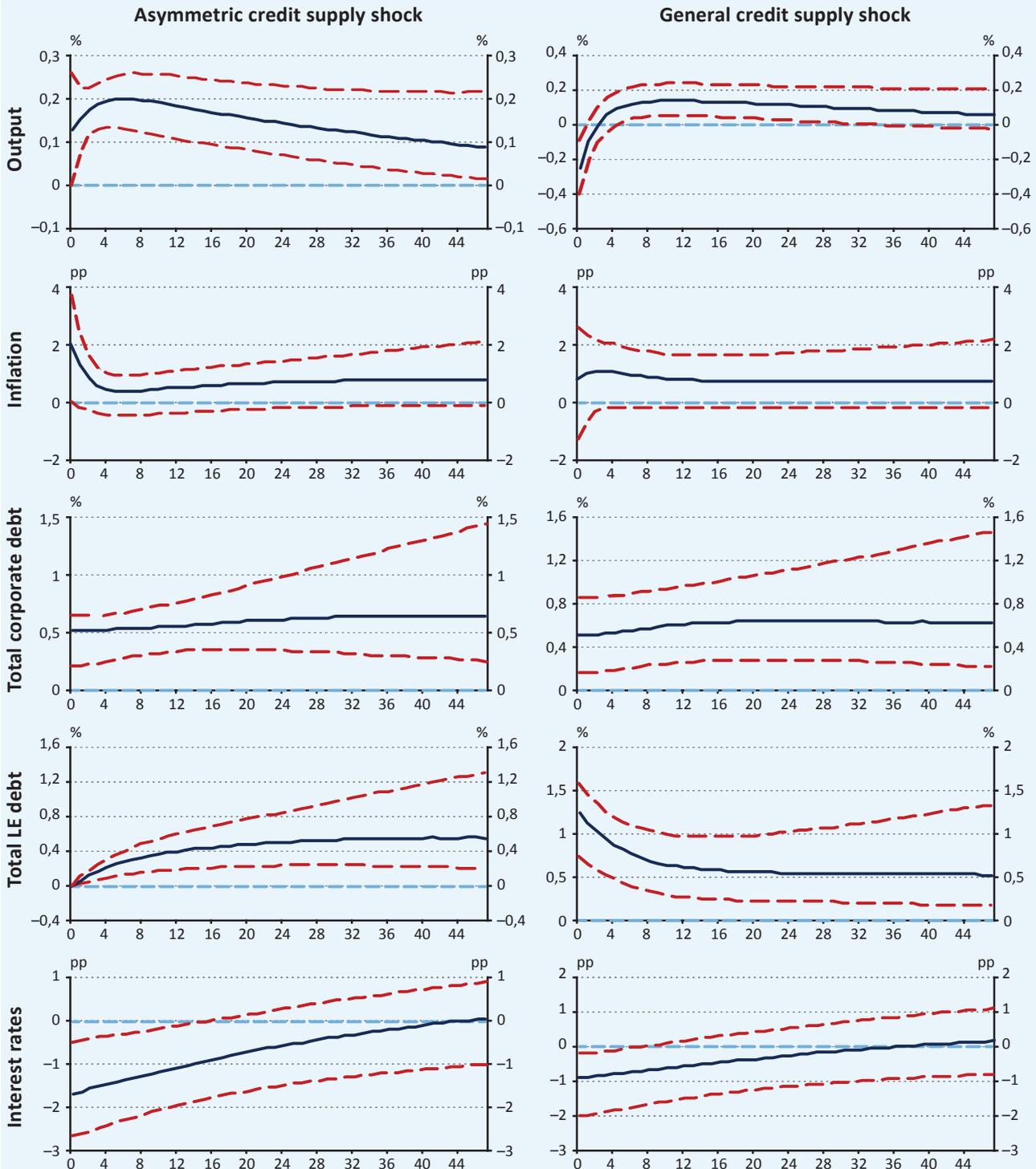


Note: dashed red lines represent the 68% credibility interval
 Source: own calculation.

7.2 INDUSTRIAL PRODUCTION AS A PROXY OF ECONOMIC ACTIVITY

Although the quarterly version of GDP proxy follows the evolution of GDP sufficiently closely one might consider it a shortcoming that it does not reflect a single time series. Therefore, the model is re-estimated with industrial production used as a proxy for economic activity. Results concerning credit supply shocks are presented in chart 9.

Chart 8
Impulse response functions of the sensitivity analysis with alternative proxy of economic performance



Note: dashed red lines represent the 68% credibility interval
Source: own calculation.

This iteration does not alter core results considerably, although the difference of general and asymmetric credit supply shocks becomes more extreme and the peak effects of credit supply shocks is considerably smaller. Asymmetric credit supply shocks inducing a 1% credit expansion are now associated with an IP growth of 0.368% while the effects of general credit supply shocks remain at 0.237%. This result implies that asymmetric credit supply shocks lift industrial production more than retail and services sector. Moreover, credibility intervals widen, meaning that general shocks only remain significant until 29th period and asymmetric supply shocks until the 46th period. The rest of the impulse responses are not altered considerably.

8 Conclusion

The Növekedési Hitelprogram (NHP) implemented by the Central Bank of Hungary (MNB) has some unique features making it easy to be identified in the SVAR framework. First, its' specificity to SMEs creates peculiar market dynamics that could be identified as asymmetric credit supply shocks: these boost SME lending while leaving lending to large enterprises contemporaneously unaffected. Second, its' direct pass-through to borrowers (i.e. SMEs) leaves no doubt about the timing of the program's most substantial real effects. Third, due to its' vast size, it represents a discernible intervention to Hungarian credit markets. This study aims to exploit these traits of the NHP to explore how funding for lending schemes influence credit markets and the real economy.

Using time series of the real economic activity, price and credit market dynamics, a total of four structural shocks are identified. Aggregate demand and supply shocks describe real economic fluctuations, general credit supply disturbances represent shocks to financial intermediaries while asymmetric credit supply shocks are in part attributed to the effects of NHP. This study places emphasis on the comparison of SME-specific (i.e. asymmetric) and general credit supply shocks.

It is widely held that SMEs are the engines of sustainable and diversified economic expansion. However, it is also acknowledged that access to finance for these companies is more limited compared to large enterprises. Information asymmetries and moral hazard are the main sources of distortions in credit markets. Gathering information is even more costly in the case of SMEs, therefore banks tend to discriminate against these enterprises by requiring more collateral, charging higher interest rates and in times of financial crises, start credit rationing in this sector. This phenomenon is often referred to as the SME financing gap.

Given that SMEs tend to be more credit constrained, I hypothesise that one unit of subsidized credit allocated to these enterprises have a more substantial long-run effect on the economy than the same loan extended to large enterprises. This further implies that, for one unit of subsidized credit, general funding for lending schemes (associated with general credit supply shocks) have less significant effect on the real economy than those prioritizing SME finance (associated with asymmetric credit supply shocks). The central result of the model confirms this hypothesis. Credit supply shocks that affect the total corporate debt through the expansion of SME debts have a more substantial effect on the economy than general credit supply shocks. For a credit expansion of 1%, the former raises output (approximated by the GDP proxy) by 0.443%, while the latter raises GDP by 0.355%. Naturally, this approach requires some caution, since there is a reasonable doubt that these asymmetric disturbances gather fluctuations independent of central bank policy. One such worry is that these results reflect the dissipation of the SME financing gap. However, core findings are robust to alternative identification schemes and the use of IP as a proxy of economic activity.

Identifying the NHP as asymmetric credit supply shocks also creates an opportunity to give some assessment of the program. One of such result is that rather than supplanting lending to large enterprises, subsidized funds and higher bank profitability in the SME sector had considerable positive spillover effect to larger corporations. Moreover, forecast error variance decompositions, show that shocks related to NHP had a very significant impact on the GDP proxy. These assume more 14.9% of the error variation of output after one year and 30.8% after four. These results let me to conclude that the NHP had a substantial effect on lending conditions and the real economy during the post-crisis recovery.

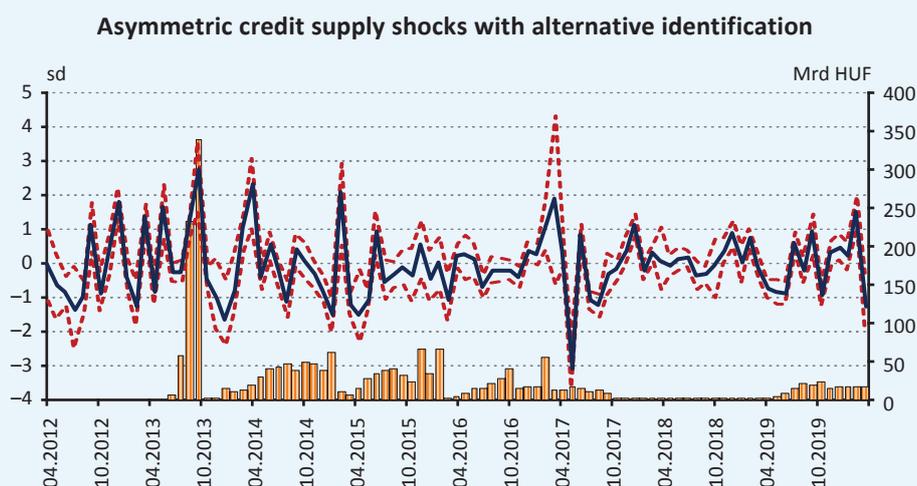
The difference between general and asymmetric credit supply shocks hold a policy recommendation: one unit of subsidized funding is more effective if allocated specifically to the SME sector rather than boosting the whole credit market. Therefore, credit funding schemes should prioritize SME lending. Naturally, some caveats should be kept in mind. First, there are worries that this identification mechanism subsumes some effects unrelated credit market shocks. Second, these results were produced under tight lending conditions and in an underdeveloped financial system (compared to most Eurozone countries). Under these circumstances the SME gap is wider, hence it would be reasonable to expect that this gap was narrower in more developed economies. On the other hand, the economic fallout due to the COVID-19 crisis could disproportionately hurt traditionally SME-heavy sectors. This could create further demand for funding for lending schemes that are more specific to the SME sector.

9 Appendix

APPENDIX A: DATA

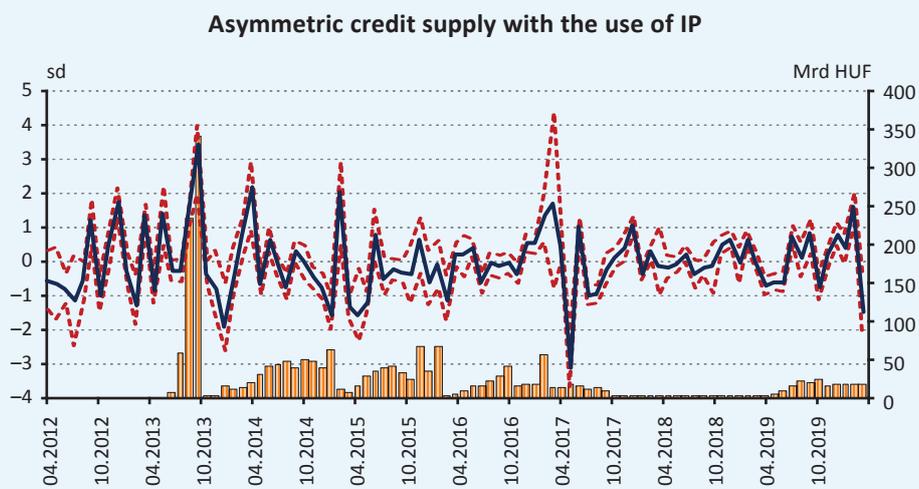
Table A1 Core variable sources		
Variable	Data Source(s)	Comments
GDP proxy	Own construction	Linear combination of industrial production, number of guest nights and retail sales. Constant prices at 2010 base
Industrial production	Hungarian Central Statistical Office	Seasonally adjusted Excluding water and waste management Constant prices at 2010 base
Inflation	Hungarian Central Statistical Office	Quarter-on-quarter percentage change of CPI Seasonally adjusted, core CPI
Total corporate debt	MNB, BAF database	Balance sheet information Consolidated from all Hungarian financial intermediaries Exchange rate adjusted; Constant prices at 2010 base
SME debt	MNB privileged data 2012 – 2016: <i>hd14</i> 2016 – 2017: <i>h7</i> 2017 – 2019: <i>m03</i>	Consolidated from all Hungarian financial intermediaries Between 2016m6-2016m12, quarterly data was interpolated The accounting shocks of 2016m1 and 2016m3 are adjusted Exchange rate adjusted; Constant prices at 2010 base
Large enterprise Debt	MNB privileged data	Calculated as a residual of total corporate debt and SME debt Exchange rate adjusted; Constant prices at 2010 base
Average lending rate	MNB public lending conditions reports	Calculated as an average of nominal interest rates of new corporate credit issuances

Chart A1
Time series of asymmetric and general credit supply shocks and NHP issuances



Note: dashed red lines represent the 95% credibility interval
Source: own calculation.

Chart A2
Time series of asymmetric and general credit supply shocks and NHP issuances



Note: dashed red lines represent the 95% credibility interval

Source: own calculation.

10 References

Arias, J.E., Rubio-Ramirez, J.F. and Waggoner, D.F., Jan. 2014. Inference based on SVARs identified with sign and zero restrictions: Theory and applications. *Dynare Working Papers* 30, CEPREMAP.

Barnett, A. and Thomas, R., 2013. Has weak lending and activity in the United Kingdom been driven by credit supply shocks?.

Bijsterbosch, M. and Falagiarda, M., 2015. The macroeconomic impact of financial fragmentation in the euro area: Which role for credit supply?. *Journal of International Money and Finance*, 54, pp.93-115.

Canova, F. and De Nicolo, G., 2002. Monetary disturbances matter for business fluctuations in the G-7. *Journal of Monetary Economics*, 49(6), pp.1131-1159.

Chatzouz, M., Gereben, Á., Lang, F. and Torfs, W., 2017. Credit guarantee schemes for SME lending in Western Europe(No. 2017/42). EIF Working Paper.

Churm, R., Joyce, M., Kapetanios, G. and Theodoridis, K., 2015. Unconventional monetary policies and the macroeconomy: the impact of the United Kingdom's QE2 and Funding for Lending Scheme.

Churm, R., Radia, A., Leake, J., Srinivasan, S. and Whisker, R., 2012. The funding for lending scheme. *Bank of England Quarterly Bulletin*, p.Q4.

Dalal, H.M., Taylor, R.S., Jolly, K., Davis, R.C., Doherty, P., Miles, J., Van Lingen, R., Warren, F.C., Green, C., Wingham, J. and Greaves, C., 2019. The effects and costs of home-based rehabilitation for heart failure with reduced ejection fraction: The REACH-HF multicentre randomized controlled trial. *European journal of preventive cardiology*, 26(3), pp.262-272.

Darracq Paries, M. and De Santis, R.A., 2013. A non-standard monetary policy shock: the ECB's 3-year LTROs and the shift in credit supply.

Endrész, M. 2020. The bank lending channel during financial turmoil. *Central Bank of Hungary, MNB Working Papers*, (5).

Endresz, M., Harasztosi, P. and Lieli, R.P., 2015. The impact of the Magyar Nemzeti Bank's funding for growth scheme on firm level investment (No. 2015/2). *MNB Working Papers*.

Gambetti, L. and Musso, A., 2017. Loan supply shocks and the business cycle. *Journal of Applied Econometrics*, 32(4), pp.764-782.

Havrylchyk, O., 2016. Incentivising Lending to SMEs with the Funding for Lending Scheme: Some Evidence from Bank-level Data in the United Kingdom.

Hristov, N., Hülsewig, O. and Wollmershäuser, T., 2012. Loan supply shocks during the financial crisis: Evidence for the Euro area. *Journal of International Money and Finance*, 31(3), pp.569-592.

Jaffee, D.M. and Russell, T., 1976. Imperfect information, uncertainty, and credit rationing. *The Quarterly Journal of Economics*, 90(4), pp.651-666.

Kilian, L., 2013. Structural vector autoregressions. In *Handbook of research methods and applications in empirical macroeconomics*. Edward Elgar Publishing.

-
- Mumtaz, H., Pinter, G. and Theodoridis, K., 2018. What do VARs tell US about the impact of a credit supply shock?. *International Economic Review*, 59(2), pp.625-646.
- Novy, D., Meissner, C. and Jacks, D., Globalisation and the costs of international trade from 1870 to the present.
- Peersman, G., 2011. Macroeconomic effects of unconventional monetary policy in the euro area.
- Schemes, G., 2014. Credit Guarantee Schemes for SME lending in Central, Eastern and South-Eastern Europe.
- Stiglitz, J.E. and Weiss, A., 1981. Credit rationing in markets with imperfect information. *The American economic review*, 71(3), pp.393-410.
- Tamási, B. and Világi, B., 2011. Identification of credit supply shocks in a Bayesian SVAR model of the Hungarian Economy. Central Bank of Hungary, MNB Working Papers, (7).
- Uhlig, H., 2005. What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2), pp.381-419.
- Yoon, B., Shin, J. and Lee, S., 2016. Open innovation projects in SMEs as an engine for sustainable growth. *Sustainability*, 8(2), p.146.

MNB OCCASIONAL PAPER 137

November 2020

Print: Prospektus Kft.

8200 Veszprém, Tartu u. 6.

mnb.hu

©MAGYAR NEMZETI BANK

1054 BUDAPEST, SZABADSÁG TÉR 9.