The Macroeconomic Effects of Targeted Credit Funding Programs: Evidence from Hungary

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Abstract

In the aftermath of the sovereign debt crisis, the Central Bank of Hungary implemented a large-scale funding-for-lending scheme designed specifically to subsidize lending to Small and Medium Enterprises (SMEs). The unique design of this program allows me to identify its effects as SME-specific 'asymmetric credit supply shocks'. I find that, for a unit increase in lending, such shocks had larger and more persistent effects on aggregate output than general credit supply shocks, significantly improving lending conditions and supporting Hungary's post-crisis recovery. Moreover, rather than crowding out lending to large enterprises, the program also produced considerable positive spillover effects on this sector over time. 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 can relax borrowing constraints and have a meaningful positive impact on the broader economy. Moreover, targeting these programs toward SMEs enhances their effectiveness.

Keywords: SME Finance, Heterogeneous Firms, Structural Shocks, Funding for Lending Schemes

JEL codes: C11, E32, E44, E58

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1 Introduction

The quick succession of the 2008 financial crisis and the subsequent sovereign debt crisis prompted central banks across Europe to expand their unconventional monetary policy toolkit. The Bank of England introduced the Funding for Lending Scheme, which provided subsidized funding to banks conditional on net lending expansion. In a similar spirit, the European Central Bank implemented the Targeted Longer-Term Refinancing Operations (TLTRO), offering subsidized funds proportional to the volume of loans held on banks' balance sheets. These programs aimed to offset high funding costs identified as key impediments to the recovery of credit markets. Lower funding costs for banks were expected to ease credit constraints and stimulate investment, thereby accelerating the recovery of the broader economy. Although funding-for-lending schemes (FLS) have become a recurring element of the unconventional policy toolkit in a low-interest-rate environment, assessing their macroeconomic impact remains a significant challenge.

This paper estimates the macroeconomic effects of the *Növekedési Hitelprogram* (NHP), a large-scale FLS introduced by the Central Bank of Hungary (MNB). The NHP provided subsidized funds to banks to be directly channelled to small and medium-sized enterprises (SMEs) at a modest mark-up. This policy design provides a unique opportunity to isolate the effects of the program as *asymmetric credit supply shocks* originating from SME finance. Despite their widespread adoption, the effectiveness and optimal design of funding-for-lending schemes remains relatively underexplored. Therefore, beyond evaluating the specific case at hand, this paper also aims to contribute to the broader debate on how funding-for-lending programs should be designed to effectively support credit markets and the real economy.

I use monthly dataset from 2012 to 2019 that combines macroeconomic indicators from national accounts with administrative data on credit markets, collected by the Central Bank of Hungary. Moreover, I separate corporate lending into finance for SMEs and large-enterprises manually, which allows the identification of the NHP's effects in a Structural Vector Autoregression (SVAR) as asymmetric credit supply shocks that raise total corporate lending while leaving lending to large enterprises contemporaneously unaffected – indicating that the shock originates in SME lending. To clearly distinguish these from unrelated shocks, I identify general credit supply shocks as episodes with simultaneous increases in total corporate debt and declines in average lending rates. Additionally, I include aggregate demand (inflationary) and aggregate supply (deflationary) shocks in order to capture output fluctuations unrelated to credit market conditions.

To confirm the validity of this identification strategy, I compare the timing of major NHP disbursements with the occurrence of asymmetric credit supply shocks. The program's design ensured an immediate pass-through from banks to borrowers, making this comparison straightforward. These shocks align closely with the main phases of NHP lending, suggesting that the identification strategy captures the program's effects. However, several large shocks outside the NHP disbursement periods indicate that it may also pick up other, unrelated asymmetric credit shocks in the economy.

The NHP's focus on SMEs represents a key design feature that likely enhanced its effectiveness. Policy discussions often highlight SMEs as drivers of diversification and sustainable economic growth (Novy, Meissner, and Jacks, 2008; Yoon, Shin, and Lee, 2016). However, SMEs are also widely recognized as being more credit-constrained than large enterprises, as information asymmetries and related market failures are more pronounced in their case (OECD, 2006; Rao et al., 2022). The NHP was implemented in recognition that, during periods of financial stress, these market failures justify targeted and countercyclical support to SME lending.

The results of the SVAR model support the effectiveness of this approach. Asymmetric credit supply shocks linked to SME-targeted subsidies have a stronger effect on output than general credit supply shocks associated with broad-based subsidies. A one percent credit expansion due to asymmetric shocks increases output by 0.413%, with effects remaining significant through the 56th month, whereas general credit supply shocks of the same magnitude raise output by only 0.355%, significant until the 45th month. These results are robust to alternative identification schemes and to the use of different indicators of aggregate performance, confirming the stability of the estimated effects. I conclude that during periods of severe financial stress, funding-for-lending schemes are likely to be more effective when they prioritize SME financing rather than providing broad-based credit support across all firms.

Additionally, to the concern that subsidized SME lending under the NHP may have displaced credit to large enterprise, I study the spillover effects of asymmetric credit supply shocks on lending to large enterprises. The results indicate a strong positive response: a one percent expansion in total credit associated with asymmetric shocks increases LE lending by 0.679% after one year and by more than 0.75% in the long run. This suggests that subsidized SME credit did not crowd out lending to larger firms but instead supported a broader expansion of credit, possibly by improving banks' overall liquidity and profitability. Forecast error variance decompositions (FEVDs) show that asymmetric credit supply shocks play a substantial role in explaining fluctuations in SME lending and real economic activity. These shocks account for roughly 15% of output variation after one year and more than 30% after four years, highlighting their persistence and macroeconomic relevance. In contrast, their contribution to movements in LE debt remains more limited, suggesting that the primary transmission of the NHP operated through the SME sector and its real effects.

The paper is structured as follows: Section 2 reviews the related literature, Section 3 describes the introduction and design of the NHP in detail, and Section 4 introduces the dataset used for the estimation. Section 5 outlines the SVAR framework and identification strategy, Section 6 presents the results, and Section 7 reports the sensitivity analyses. Section 8 concludes.

2 Literature

Small and medium-sized enterprises play a central role in employment, innovation, and productivity growth, yet access to finance remains one of their most persistent constraints. This structural problem, often referred to as the SME financing gap, arises when economically viable firms cannot obtain credit on reasonable terms. This financing gap reflects market failures that justify public intervention in SME finance (OECD, 2006). Monitoring and maintaining borrower relationships involve fixed costs that are largely independent of firm size, implying proportionally higher costs for lending to small enterprises (Diamond,1996; Boot and Thakor, 2000; Chen and Elliehausen, 2020). Moreover, SMEs often face weaker accounting and transparency requirements, which further raise monitoring costs and deepen information asymmetries (Berger and Udell, 1998; Thorsten and Demirguc-Kunt, 2006). While collateral can help mitigate these frictions, it also places an additional burden on SMEs, as legal and administrative costs of pledging collateral are high, valuations uncertain, and collateral often scarce (Chatzouz et al., 2017).[1]

The SME financing gap is typically more severe in less developed credit markets, where limited monitoring capacity and scarce collateral exacerbate adverse selection and perceived credit risk (OECD, 2006; Rao et al., 2023). Economic downturns further reduce collateral values and heighten risk perceptions, prompting banks to curtail SME lending sharply. Consequently, banks tend to demand more collateral, charge higher interest rates, and restrict SME lending, particularly during periods of economic stress. For these reasons, policy interventions that support SME lending are often designed to act countercyclically.

To address these failures, many governments have introduced targeted policies, such as credit guarantee- and funding-for-lending schemes that share credit risk with public institutions or reduce the funding costs for SME lending. These programs aim to close the financing gap by supporting viable but asset-poor firms. This paper contributes to the literature that examines the effectiveness of these government programs by empirically estimating the effects of large-scale policy interventions that share SME lending risk with financial intermediaries, thereby alleviating the information and collateral frictions described above (Boocock and Shariff, 2005; Caselli et al., 2019).

The empirical strategy of this paper draws on SVAR methodologies developed to identify credit market shocks and unconventional monetary policy effects. The

[1] The SME financing gap is well documented in Hungary as well. Endresz, Harasztosi, and Lieli (2015) show that smaller firms were substantially more credit-constrained in the aftermath of the sovereign debt crisis. Endrész (2020) finds clear evidence of a credit tightening in Hungary following the collapse of Lehman Brothers in 2008, using firm-level balance sheet data from Hungarian non-financial corporations.

2008 financial crisis highlighted the role of financial intermediaries in amplifying economic fluctuations. It is now standard to identify credit market shocks alongside traditional aggregate demand, supply, and monetary policy shocks. Credit supply shocks are typically characterized by the opposite movement of credit volumes and interest rates. To distinguish them from real shocks, it is often assumed that they have no contemporaneous effect on real activity (Barnett and Thomas, 2013; Duchi and Elbourne, 2016).

Several studies also attempt to identify regulatory shocks or the effects of unconventional monetary policies, treating policy interventions as exogenous disturbances. The unique design of the NHP allows me to contribute to this literature by identifying the policy's effects as asymmetric credit supply shocks. While such shocks could also arise endogenously, their timing and characteristics align closely with the implementation of the NHP in Hungary. In addition, I examine the effectiveness, design efficiency, and potential unintended spillover effects of funding-for-lending policies.

Table 1. summarizes some of the most relevant contributions in this literature. For instance, Tamási and Világi (2011) decompose credit supply shocks into two structural components: shocks due to changes in risk appetite and those arising from regulatory changes. They find that regulatory shocks exert a greater and more persistent impact on GDP than credit multiplier shocks. Peersman (2011) provides one of the earliest analyses of non-conventional monetary policy shocks in Europe, assuming that these operate analogously to conventional policy shocks but without contemporaneous effects on the policy rate. Gambacorta and Hoffmann (2012) identify unconventional monetary policy shocks as changes in the size of central bank balance sheets. Both studies find that unconventional policies produce effects similar to conventional ones, though through distinct transmission channels. However, such identification strategies can capture only part of the impact of funding-for-lending schemes, and results may be confounded by other unconventional measures such as quantitative easing.

Study	Method and Data	Endogenous variables	Identified Shocks
Gambetti and Musso (2017)	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
Hristov, Hülsewig and Wollmershäuser (2012)	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
Bijsterbosch and Falagiarda (2015)	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
Mumtaz, Pinter and Theodoridis (2015)	Comparison of SVAR methods United Kingdom, 1973–2013 Quarterly frequency	GDP growth Consumer Price Index Loan Growth Spread Three-month T-Bill	Credit Supply
Barnett and Thomas (2013); **Duchi and Elbourne (2016)**	SVAR United Kingdom, 1967–2012; Quarterly frequency 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 Credit Demand Equity Price
Peersman (2011)	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 Interest Rate Innovation Unconventional Monetary Policy
Darracq-Paries and De Santis (2015)	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
Gambacorta and Hoffmann (2012)	Panel SVAR 8 advanced economies, 2008–2011 Monthly frequency	GDP proxy (from IP and retail sales) Consumer Price Index Central bank assets Stock market volatility	Unconventional Monetary Policy
Tamási and Világi (2011)	SVAR Hungary, 1995–2010 Quarterly frequency	Real GDP Consumer Price Index Corporate Loans Credit spread 3-month BUBOR Nominal effective exchange Default rate	Banks' Risk Assessment Regulatory Changes Risk Premium Monetary Policy

Note: Relevant studies: data, variables and identified shocks. This table summarizes SVAR-based studies on credit and monetary transmission, listing sample, frequency, endogenous variables, and the structural shocks identified in each paper.

Estimating the effects of funding-for-lending schemes using SVAR models has also been adopted in the literature. Darracq-Paries and De Santis (2013) equate the ECB's longer-term refinancing operations (LTROs) with positive credit supply shocks around their introduction, while Churm et al. (2015) do not separate the effects of the Bank of England's Funding for Lending Scheme, instead analyzing correlated loan shocks during the same period. In contrast, the asymmetric SVAR design used here allows for a more policy-specific identification by isolating shocks that originate exclusively in SME lending.

Finally, several empirical contributions exploit panel data to identify the impact of FLS programs by contrasting the responses of participating banks or firms with those outside the scheme. However, distinguishing between genuine additional lending and simple substitution of existing projects remains challenging. If subsidized funds finance investments that would have occurred anyway, their real impact is limited. Consequently, many papers use difference-in-differences estimators to identify causal effects. Havrylchyk (2016) uses bank-level data to evaluate the effects of an FLS update that provided extra incentives to finance SMEs, finding no significant impact. In contrast, Endresz et al. (2015) use Hungarian firm-level data to show that the Növekedési Hitelprogram (NHP) significantly increased investment among participants.[2]

[2]Their analysis requires augmenting the standard DiD approach with a correction term to account for potential violations of the parallel-trends assumption.

3 Introduction and design of the NHP

The NHP represented, a more direct intervention in credit markets than the European Central Bank's Targeted Longer-Term Refinancing Operations or the Bank of England's Funding for Lending Scheme. These programs aimed to alleviate high credit funding costs on the presumption that these subsidies would pass through to borrowers over time. Disbursing these funds was left to banks' discretion. The NHP differed in both its scale (relative to Hungary's credit market) and its immediacy. Banks received subsidized funds at 1% and could charge a maximum 2.5% margin, which was significantly lower than the prevailing market rate standing at 7.9% on average at the introduction of the program. Credit default risk was fully borne by banks. To ensure immediate pass-through of the program, additional funding was provided only when banks originated 'NHP loans' to SMEs.

The time series of NHP issuances, billion HUF

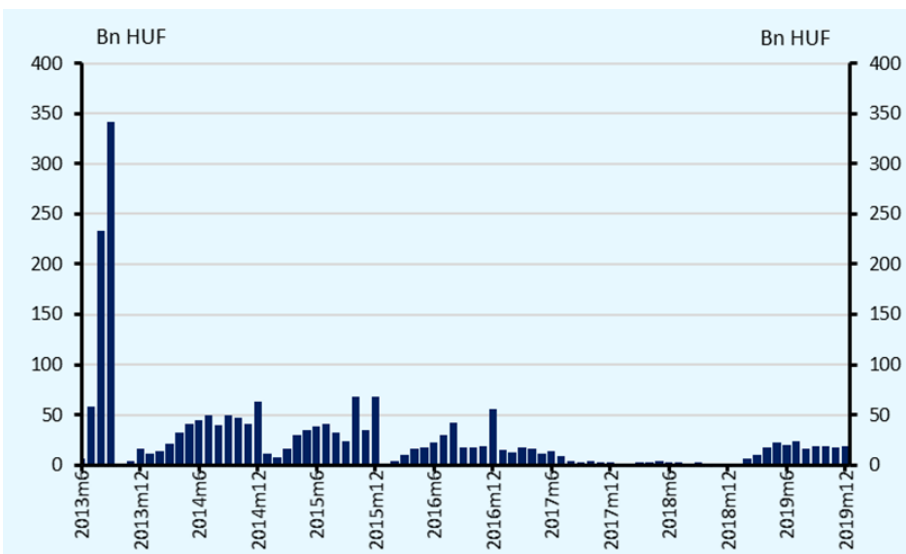

Figure 1: Time series of total NHP credit issuances (in billion HUF) across program phases between 2013 and 2019.

First introduced in June 2013, the NHP ran in five phases through end-2019, with only minor changes. Outflows of NHP loans over time are shown in 1. The first and most intensive phase (June-September 2013) disbursed 641 billion HUF (2.17 billion EUR). At the end of this phase, NHP loans accounted for about 80% of new HUF-denominated corporate lending. The second phase (October 2013-December 2015) disbursed 880 billion HUF (2.74 billion EUR); although this phase was less intense, NHP loans still hovered around 40% of new HUF-denominated corporate issuance. Program intensity declined thereafter; no new NHP contracts were available between April 2017 and January 2019. In 2019, the MNB relaunched the scheme as 'NHP Fix', subsidizing fixed-rate SME loans.

Debt Volumes

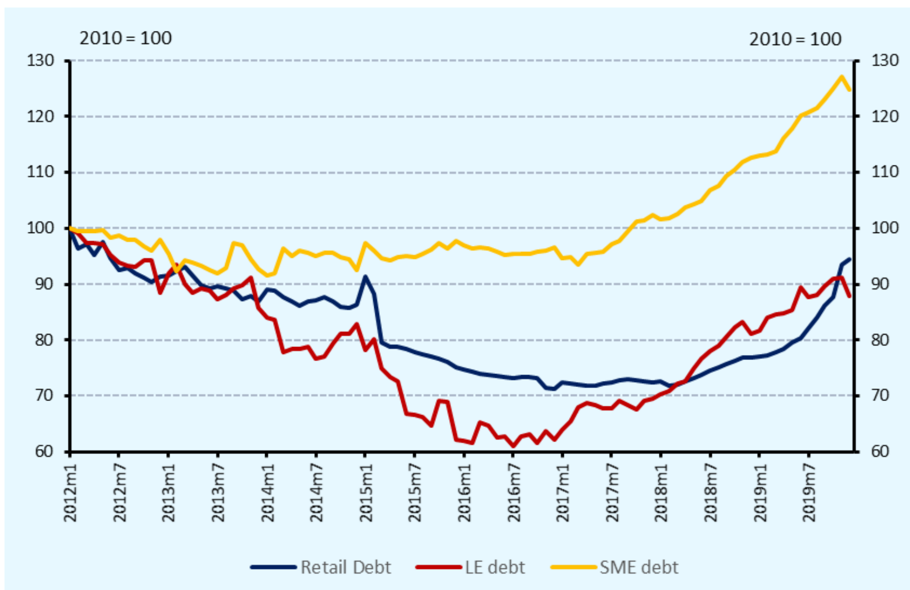

Figure 2: Debt volumes indexed to 2010 = 100, showing the evolution of retail, large enterprise (LE), and small and medium-sized enterprise (SME) debt.

The evolution of the total outstanding SME debt volume underscores the program's significance. Chart 2 shows that before the introduction of the NHP, SME debt followed a similar contractionary path as retail and large-enterprise debt, reflecting the broad deleveraging pressures of the post-crisis period. Starting in mid-2013, however, coinciding with the launch of the NHP, SME debt began to diverge markedly from these other segments. While retail and large-enterprise debt continued to decline until credit growth resumed more broadly around 2017, SME debt stabilized and remained broadly unchanged, hovering just below its 2012 level. This divergence suggests that the NHP mitigated what would likely have been a prolonged contraction in SME credit. Although no formal counterfactual can be estimated, the magnitude and timing of the intervention make it plausible that the program exerted a significant stabilizing influence on SME debt dynamics.

4 Data and Methodology

I utilize a monthly dataset spanning from 2012m1 to 2019m12 that contains time series characterizing real economic activity, price dynamics, and corporate credit market developments. For economic activity, I use two measures: seasonally adjusted industrial production, and a proxy for GDP constructed as a linear combination of retail sales, industrial production, and the number of guest nights (all publicly available from the Hungarian Central Statistical Office). With the inclusion of this GDP proxy, I aim to create a monthly indicator of economic activity that incorporates information from the service and retail sectors alongside seasonally adjusted industrial production. The weights of the variables in the GDP proxy are estimated through a linear regression model, which is then used to predict GDP on a monthly basis. The resulting proxy tracks GDP closely, with a correlation of 0.91 for year-on-year growth and 0.61 for quarter-on-quarter growth. Benchmark results are reported using this proxy, while estimates based solely on industrial production serve as a robustness check. Yearly inflation is calculated from the seasonally adjusted CPI.

Credit market variables are drawn from the Central Bank of Hungary's records. Total corporate debt is obtained directly, and large-enterprise debt is computed as the residual of total corporate and SME debt. Constructing a consistent SME debt series required harmonizing multiple confidential data sources, which limits the sample period since high-quality SME debt data are unavailable before 2012. Major shocks stemming from accounting changes have been smoothed, though minor distortions may remain. Finally, average monthly interest rates on new corporate loans are also obtained from Central Bank data. A more detailed description of the data sources and construction procedures is provided in Table A1 of the Appendix.

5 Methodology and Identification

5.1 Methodology

Consider the following model:

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

where Y_t is a 5×1 vector of endogenous variables describing the level of output, yearly inflation, total corporate debt, debt held by large enterprises, and average interest rates on corporate loans. B_j denotes the matrices of lagged coefficients, and c is a 5×1 vector of constants. Moreover, A_0 represents the contemporaneous impact matrix of uncorrelated structural disturbances, ε_t, such that:

$$E[uu'] = \Omega = A_0 E[\varepsilon_t \varepsilon_t'] A_0' = A_0 A_0',$$

where the structural shocks are normalized such that $E[\varepsilon_t \varepsilon_t'] = I$.

The model is estimated in log-levels with three lags. Although the deviance information criterion is not minimized for this specification, I use three lags to avoid the proliferation of parameters; this choice is also sufficient to mitigate autocorrelation in the residuals. Parameter values are assumed to be time invariant.[3]

In order to identify structural shocks, in the SVAR framework, one needs to impose restrictions on the contemporaneous impact matrix, A_0. This is often achieved via short-run zero restrictions (Sims, 1980). However, this approach can be overly restrictive and may not capture the full range of plausible economic dynamics. Sign-identified models (Canova and DeNicolo, 2002; Uhlig 2005), allow for a more flexible set of restrictions. In sign-identified SVAR models, each structural shock is charac-

[3]One could extend the model to a time-varying parameter SVAR model, but the relatively narrow sample and the absence of structural breaks do not justify introducing parameter variation.

terized by a unique pattern of positive or negative responses across selected variables over a chosen horizon. Only model draws that yield impulse responses consistent with the imposed sign restrictions are retained; all others are discarded. In these models, the covariance matrix of reduced-form residuals is expressed as:

$$\Omega = A_0 P P' A_0',$$

where P is obtained from the QR decomposition of a randomly drawn orthogonal matrix. If the impulse responses generated by a given draw satisfy the imposed sign restrictions, the draw is retained; otherwise, it is assigned a prior weight of zero. The identification strategy adopted in this paper follows the general methodology proposed by Arias, Rubio-Ramirez, and Waggoner (2014), which supports the use of a combination of zero and sign restrictions.

Sign-identified SVARs yield a set of admissible models rather than a single one. Each model satisfying the imposed restrictions differs only by its particular draw of the orthogonal matrix P, and thus all share identical likelihoods. In the absence of further identifying assumptions, none of these models can be regarded as uniquely preferable Kilian (2011). To address this issue, I use Bayesian inference to produce a smooth posterior distribution of impulse responses across all admissible models. For reduced-form parameters, I assume independent Normal-Wishart priors with a Minnesota structure. To reflect the persistence of the endogenous variables, the first autoregressive coefficient is shrunk toward 0.8, and all other coefficients are shrunk toward zero. Setting the first autoregressive term slightly below one allows the priors to capture persistence without imposing unit roots, as discussed by Koop and Korobilis (2010). Prior variances of the error terms are obtained from separate AR models. Following the literature, the hyperparameters are set as $\lambda_1 = 0.1$ (overall tightness), $\lambda_2 = 0.5$ (cross-variable weighting), and $\lambda_3 = 2$ (lag decay). Convergence is reached after 10,000 burn-in draws, and 5,000 retained draws used for inference.

The identification of the NHP's quantitative effects is outlined in Table 1. While it might initially appear more straightforward to analyze shocks to SME and LE lending separately, this would make it impossible to identify general credit supply shocks, since requiring positive restrictions on both would exclude cases where one component declines but total corporate debt still expands. Hence, asymmetric shocks are better defined as episodes in which total corporate debt increases without a contemporaneous change in LE lending. Since total corporate debt is the sum of SME and LE lending, this implies that SME lending rises in these episodes.

	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	−	−

Table 1: Baseline identification strategy of conversion shocks model. Note: + denotes positive sign restrictions, − denotes negative sign restrictions, and 0 denotes zero restrictions.

As shown in Table 1, contemporaneous zero restrictions are often used to distinguish credit market shocks from real-economy disturbances. The standard assumption is that credit shocks do not affect output or inflation within the same period. Since the purpose here is precisely to estimate these effects, I adopt a more agnostic approach regarding their contemporaneous impact. Instead, to make sure a clear distinction of the identified structural shocks, I assume that real shocks do not influence credit markets within one month. Since this approach deviates from the conventional identification framework, Section 7 presents a robustness exercise using the standard restrictions.

6 Results

This section presents the main results. I find that the identified asymmetric credit supply shocks closely follow the timing and intensity of NHP disbursements, indicating that the identification strategy captures the program's effects well. These shocks have stronger and more persistent effects on output and lending conditions than general credit supply shocks, consistent with SMEs being more financially constrained. Moreover, LE lending responds positively, suggesting the presence of spillovers rather than substitution between firm segments. Finally, forecast error variance decompositions show that asymmetric credit supply shocks account for an increasing share of output fluctuations over time, underscoring their key role in transmitting the effects of the NHP to the real economy.

6.1 Time Series of the 'NHP Shocks'

The NHP was designed to ensure an immediate pass-through from banks to SMEs. Subsidized funding was made available to banks only as "NHP loans" were issued to SMEs. This feature provides a clear timeline for when the strongest effects of the program should appear. The sequence of asymmetric credit supply shocks can therefore be directly compared to NHP loan issuances to assess the precision of the identification strategy. This comparison is presented in Figure 3, which plots the estimated asymmetric credit supply shocks alongside the timeline of NHP disbursements.

The first major positive shock coincides with the initial disbursements in July and August 2013, indicating that the NHP indeed generated significant asymmetric credit supply shocks. At the same time, the data provide limited support for certain fluctuations, such as the large negative asymmetric credit supply shock observed at the beginning of 2017. Although the program was briefly suspended between 2017 and 2019, this interruption alone is unlikely to have generated a shock of that magnitude. Interestingly, all credit shocks show considerable volatility during this period, even though neither LE lending nor total corporate lending exhibit notable fluctuations. This raises some concern that the identification of asymmetric shocks, while capturing the effects of the NHP, may also reflect other, unrelated credit market disturbances.

Asymmetric Credit Supply Shocks and the NHP

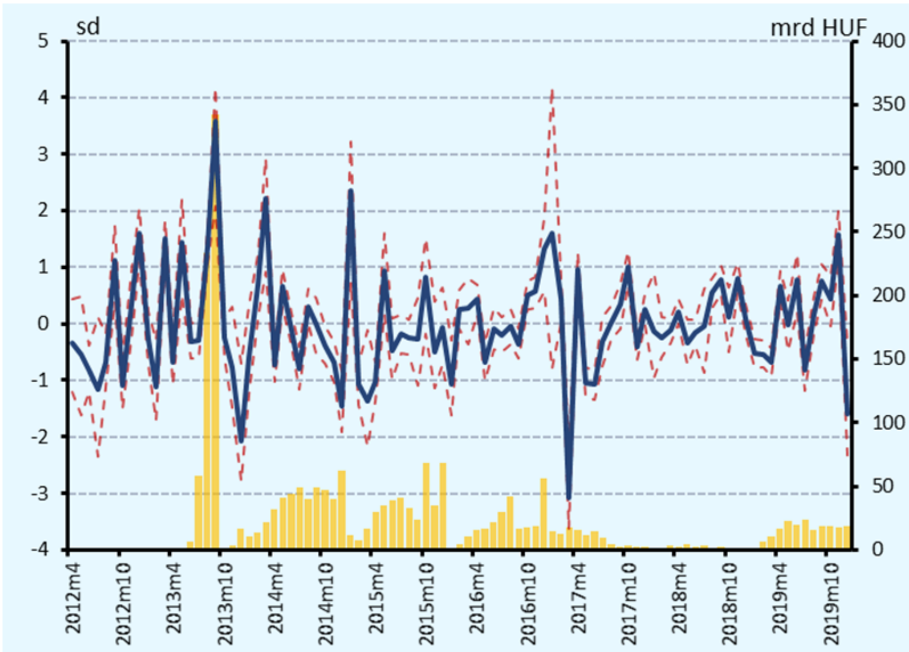

Figure 3: Time series of asymmetric and general credit supply shocks and NHP issuances (in billion HUF). The blue line represent monthly the estimated asymmetric credit supply shocks, while the orange bars show NHP loan issuances. The dashed red lines represent the 95% credibility intervals for the asymmetric credit supply shocks.

This finding is somewhat surprising, as few endogenous market mechanisms or exogenous policy interventions would be expected to benefit SMEs systematically without affecting large enterprises. One possible explanation is that the identification procedure picks up part of the asymmetric component of general shocks during this period. For instance, the post-2012 economic recovery may have disproportionately benefited SMEs, just as the 2012 crisis had affected them more severely. As financial intermediaries became less risk-averse during the upswing, discrimination against SMEs diminished, narrowing the SME financing gap. Such developments could appear as asymmetric shocks insofar as they favored SMEs more strongly, even if the overall improvement in credit conditions also benefited larger firms.

Despite some noise captured by the identification strategy, the estimated asymmetric credit supply shocks follow the intensity of the NHP reasonably well. Asymmetric credit supply shocks resemble white noise before the program's introduction (mid-2013), display heightened volatility during its first three phases, and stabilize once the program is paused after April 2017. Hence, while these shocks should not be exactly equated with the NHP, they appear to capture its main effects sufficiently well.

6.2 Asymmetric and General Credit Supply Shocks

The effects of asymmetric and general credit supply shocks in the benchmark specification are reported in Figure 4. The benchmark model specification confirms the central hypothesis of the study. Credit supply shocks that expand total corporate debt through SME lending have a stronger impact on the economy than general credit supply shocks. For a 1% credit expansion, the former increases output (approximated by the GDP proxy) by 0.413%, remaining significant up to the 56th period, whereas the latter raises output by 0.355%, significant until the 45th period. General funding-for-lending programs tend to generate broad credit supply shocks, whereas targeted interventions focused on SMEs create asymmetric shocks limited to the affected segment. The estimated responses confirm that these asymmetric shocks have larger and more persistent macroeconomic effects, reflecting the tighter financing constraints faced by smaller firms, suggesting that targeted programs may be more effective during periods of financial stress.

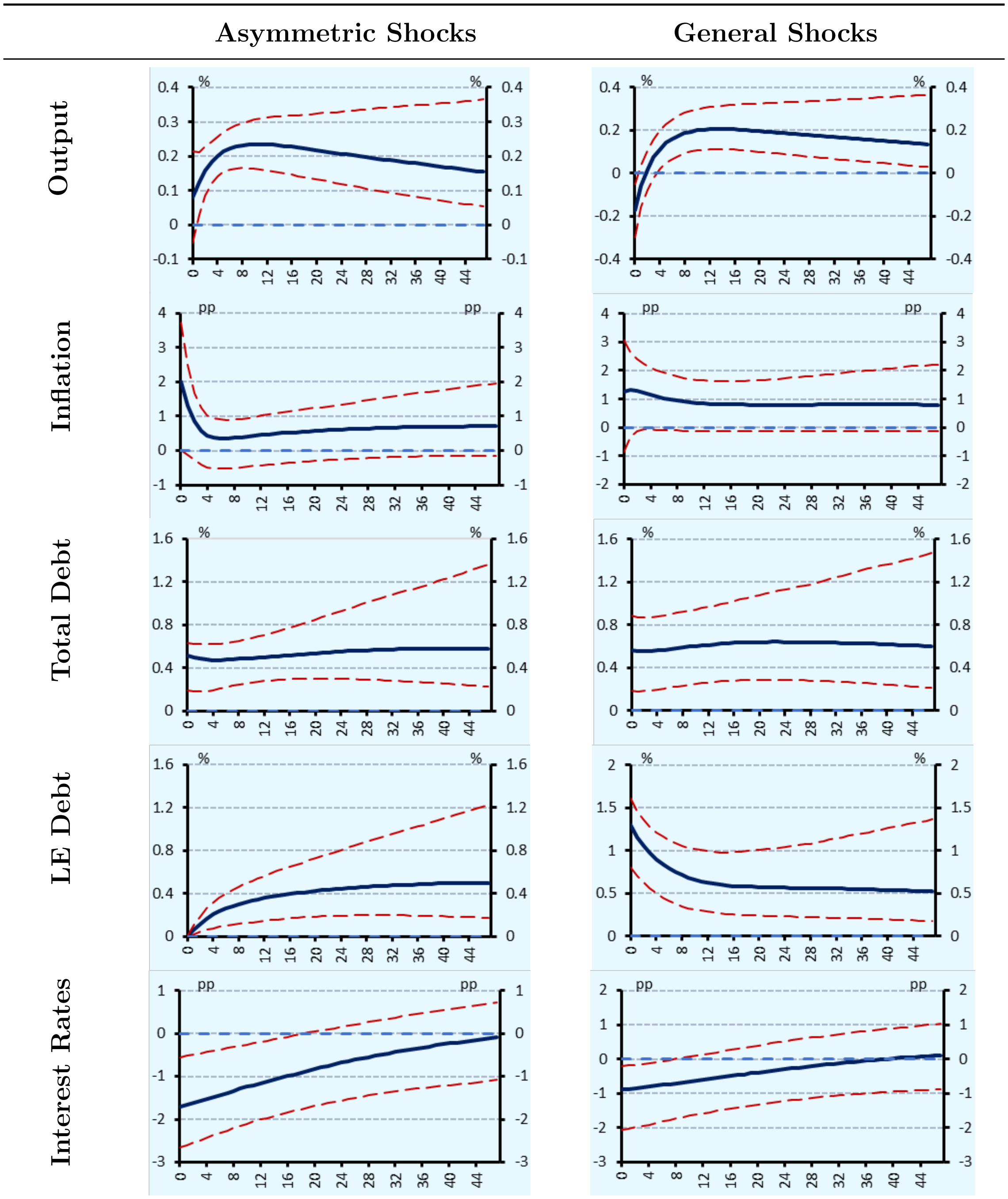

Figure 4: Impulse responses to asymmetric and general credit supply shocks.

Average interest rates respond more strongly to asymmetric credit supply shocks. For a 1% expansion in total debt, the average interest rate on new issuances declines by 1.68 percentage points in response to asymmetric shocks, compared with 0.96 percentage points for general credit supply shocks. This difference likely reflects the NHP's substantial intervention in credit markets. When the program was introduced, the average interest rate on corporate loans stood at 7.9%, while NHP loans were capped at 2.5%. Although this gap later narrowed, it remained considerable. In contrast, credit expansions arising from standard market mechanisms are unlikely to generate such pronounced rate reductions, as financial intermediaries would typically attract borrowers through gradual interest rate cuts, producing much smaller fluctuations in lending rates.

Somewhat puzzlingly, the immediate effect of credit supply shocks is negative, turning positive only after two periods. Moreover, the first-period output response to asymmetric shocks is statistically insignificant. One plausible explanation for these results is that accounting adjustments (such as loan write-downs) that could not be fully eliminated from the corporate debt series bias the estimated immediate effects downward. However, these accounting artifacts leave real quantities unchanged and thus exert no persistent influence on long-run dynamics. Hence, any short-term bias that might affect the estimated impact of these structural shocks is likely to fade quickly.

A key concern at the introduction of the NHP was that subsidized SME lending might crowd out credit to large enterprises as banks would redirect their efforts away from large firms toward the more profitable, subsidized SME lending. The results suggest the opposite effect. LE lending rises following an asymmetric credit supply shock. For a 1% expansion in total credit, lending to large enterprises increases by 0.679% after one year and by more than 0.75% in the long run. The finding suggests that targeted SME credit growth can reinforce credit expansion across the broader corporate sector.

The extent to which this spillover effect can be attributed directly to the NHP, however, is less clear. One possible explanation is that the observed increase in LE debt reflects the broader economic upswing that followed the 2012 financial downturn.

Between 2012 and 2019, Hungary transitioned from recession to strong expansion, marked by high output growth, rising asset prices, and improving credit conditions. As banks' risk tolerance increased, lending standards eased, narrowing the SME financing gap. If part of the SME debt expansion reflects this general improvement in market sentiment, then the concurrent rise in LE debt likely reflects the same macroeconomic recovery rather than direct spillovers from SME lending.[4]

The effects of aggregate demand and supply shock in the benchmark specification are reported in Chart A3 of the appendix. On the short run, aggregate demand and supply shocks a 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. In comparison, 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. This suggests that leaving the zero restrictions on credit market variables does not materially affect the estimated effects of real-economy shocks.

6.3 Forecast error variance decompositions

Forecast error variance decompositions (FEVDs) break down forecast errors by the structural shocks that cause them. This exercise helps to assess the relative influence of different shocks on the endogenous variables. In the short run, demand and supply shocks dominate the evolution of the GDP proxy, but as the forecast horizon expands, more persistent credit shocks account for an increasing share of the variance. Asymmetric credit supply shocks prove to be particularly important. Their contribution rises from near zero for one-period forecasts to 14.9% after one year and 30.8% after four years. As shown in Figure 5, these shocks also have a strong immediate impact on average lending rates, which then moderates over longer horizons.

[4] One possible explanation is a statistical reclassification: as firms grow and exceed the SME threshold, their obligations are reclassified as LE debt. However firm level data show that this is rare: between 2017 and 2018, only 64 of 21,500 SMEs changed status, making this explanation unlikely.

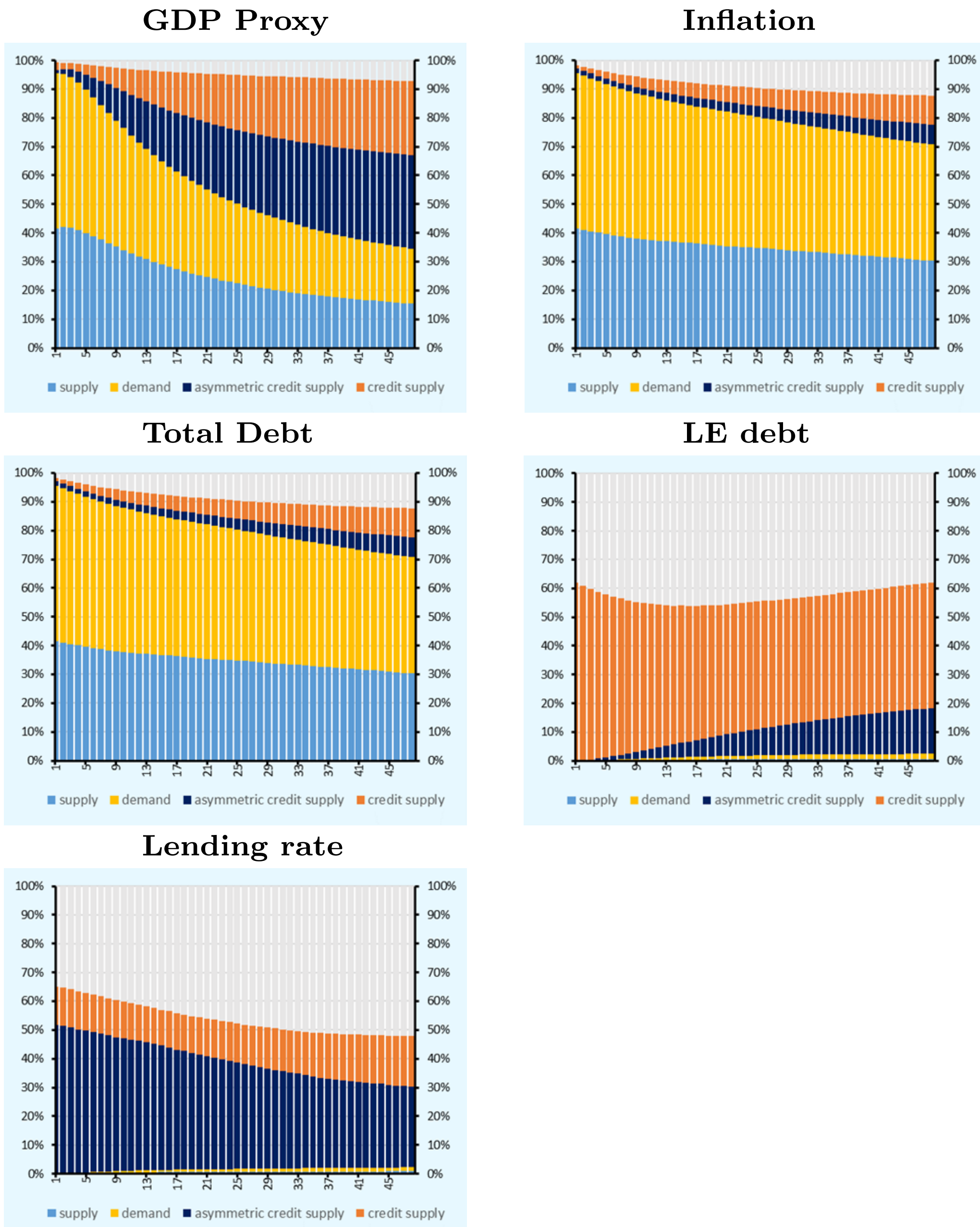

Figure 5: Forecast error variance decompositions (FEVDs) for output, inflation, and total corporate debt, debt to large enterprises and lending rates. The dark blue bars represent asymmetric credit supply shocks, orange bars general credit supply shocks, yellow and light blue bars represent aggregate demand and supply shocks respectively, and light grey bars the unidentified portion of the forecast error variance.

The forecast error variance decompositions indicate that total corporate debt is shaped in roughly equal parts by aggregate demand, asymmetric credit supply, and general credit supply shocks, while a notable share of variation remains unexplained. Inflation dynamics are mostly driven by real-side factors such as demand and supply shocks, with credit market disturbances playing only a minor role. Large-enterprise debt is primarily influenced by general credit supply shocks, with asymmetric shocks contributing little, reflecting the limited direct impact of SME-specific interventions. Lending rates are driven mainly by asymmetric credit supply shocks and, to a lesser extent, by general credit supply shocks, which likely reflects the scale and intensity of the NHP. Overall, asymmetric credit supply shocks are key to explaining debt dynamics, whereas real-side shocks initially account for most of the variation in prices and interest rates and lose their importance to credit supply factors over longer prediction horizons.

The strong explanatory power of asymmetric credit supply shocks for output raises the question that the identification strategy may be too permissive. Because it does not constrain the contemporaneous effect of credit shocks on real variables to zero, it is possible that it subsumes some of the effects of real-economy shocks as well. To address this concern, the following section presents a sensitivity analysis that reverses these zero restrictions, preventing credit shocks from immediately affecting the real economy.

7 Robustness Checks

This section tests the robustness of the baseline identification strategy in two ways. First, it reverses the contemporaneous zero restrictions between credit market and real-economy shocks. Second, it replaces GDP with industrial production as the measure of economic activity. The main results remain unchanged: asymmetric credit supply shocks continue to exhibit larger and more persistent effects on output than general credit shocks, suggesting that the benchmark findings are not driven by misidentification or proxy choice.

7.1 Reversed Zero Restrictions

The benchmark specification remains agnostic about the real-economy effects of credit supply shocks, as these are precisely the effects it seeks to measure. However, this is not the standard approach to distinguish between credit market and real economy shocks. This sensitivity analysis reverses the zero restrictions so that credit market shocks are prevented from having contemporaneous effects on the real economy. In all other respects, the model is identical to the benchmark specification, and the new set of restrictions is shown in 2.

	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			−	−

Table 2: Baseline identification strategy of conversion shocks model. Note: + denotes positive sign restrictions, − denotes negative sign restrictions, and 0 denotes zero restrictions.

The exercise serves two purposes. First, it replicates a restriction scheme that has become more common in recent literature (see Peersman, 2011; Barnett and Thomas, 2013; Duchi and Elbourne 2016). Second, it addresses a potential concern that the benchmark specification might attribute part of the real-economy shocks' effects to credit market shocks.[5] If this source of misidentification was important, the estimated impact of asymmetric credit supply shocks should decline substantially under this alternative identification scheme. The resulting impulse responses are presented in 6.

[5] This point is discussed in detail in Section 5.

	Asymmetric Shocks	General Shocks

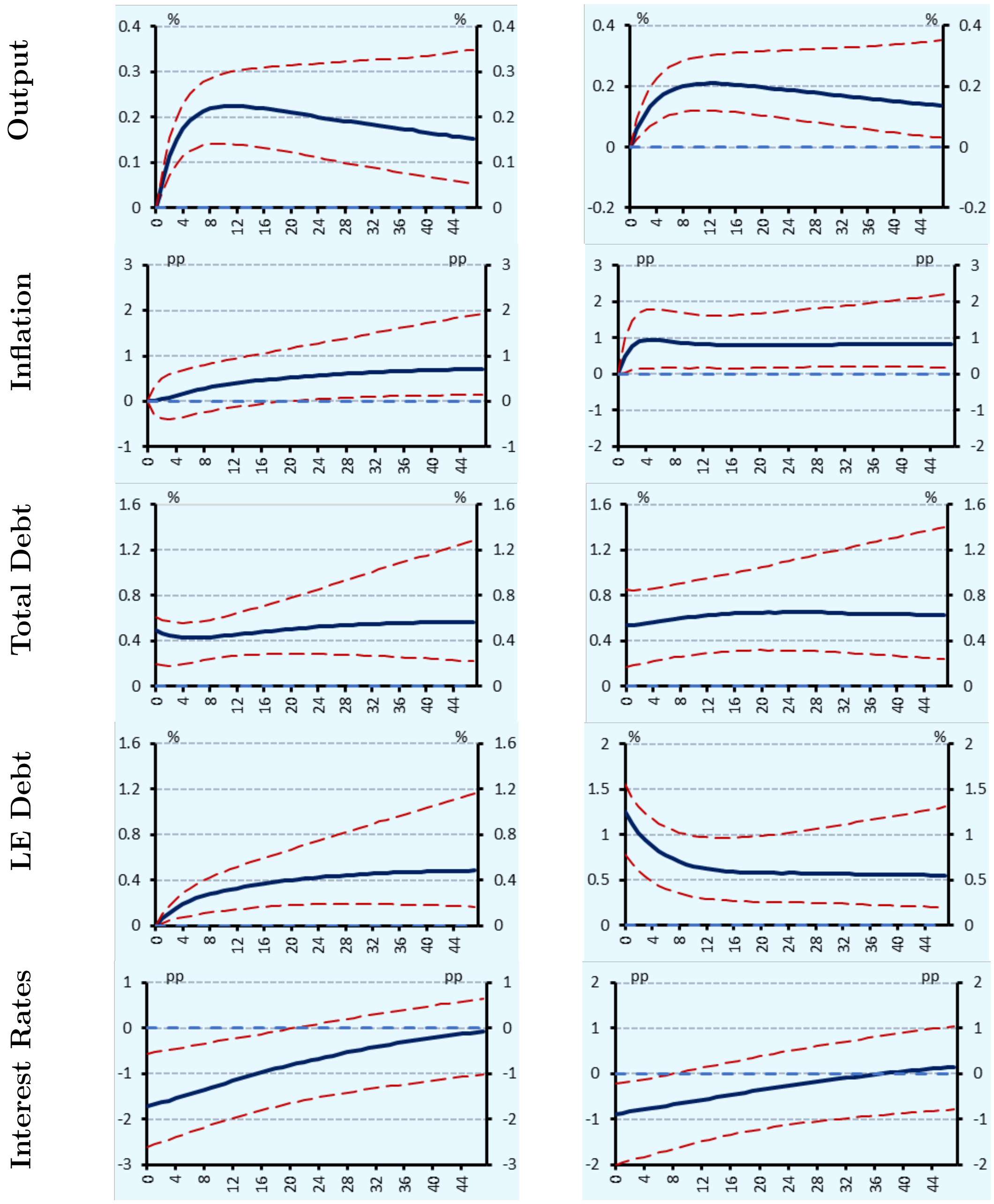

Figure 6: Impulse responses to asymmetric and general credit supply shocks.

The time series of shocks generated by this model are very similar to those from the baseline identification (see Chart 1 in the Appendix), though the shocks associated with the program's introduction are somewhat less pronounced. Under the alternative restrictions, the gap between asymmetric and general credit supply shocks narrows: a 1% loan expansion from an asymmetric shock raises output by 0.451% after 10 periods (remaining significant until period 59), while an equivalent general credit expansion raises output by 0.385% (remaining significant until period 48). Although this difference is smaller, the main conclusions of the paper remain unchanged. Furthermore, the FEVD indicates that asymmetric credit supply shocks continue to account for a sizable share of output forecast error variance, suggesting that the strong effects of credit supply shocks in the benchmark model are not due to misidentifying real-economy shocks as credit shocks.

7.2 Industrial production as a proxy of economic activity

Although the quarterly GDP proxy tracks the evolution of GDP closely and consolidates information from the production and the services sectors as well, it remains a composite measure rather than a real indicator of economic activity. To address this issue, I re-estimate the model using industrial production as the proxy for economic activity. The resulting impulse responses for credit supply shocks are shown in Figure 7.

This modification leaves the main results largely unchanged, though the difference between general and asymmetric credit supply shocks becomes more pronounced, and the peak effects of both shocks are smaller. A one percent credit expansion driven by an asymmetric shock increases industrial production by 0.368%, while the same expansion from a general credit shock raises it by 0.237%. This suggests that asymmetric credit supply shocks primarily stimulate industrial output rather than activity in retail or services. Credibility intervals also widen: general shocks remain significant until period 29, and asymmetric shocks until period 46. Other impulse responses are broadly unaffected. These results confirm that the main findings are robust to the choice of economic activity proxy.

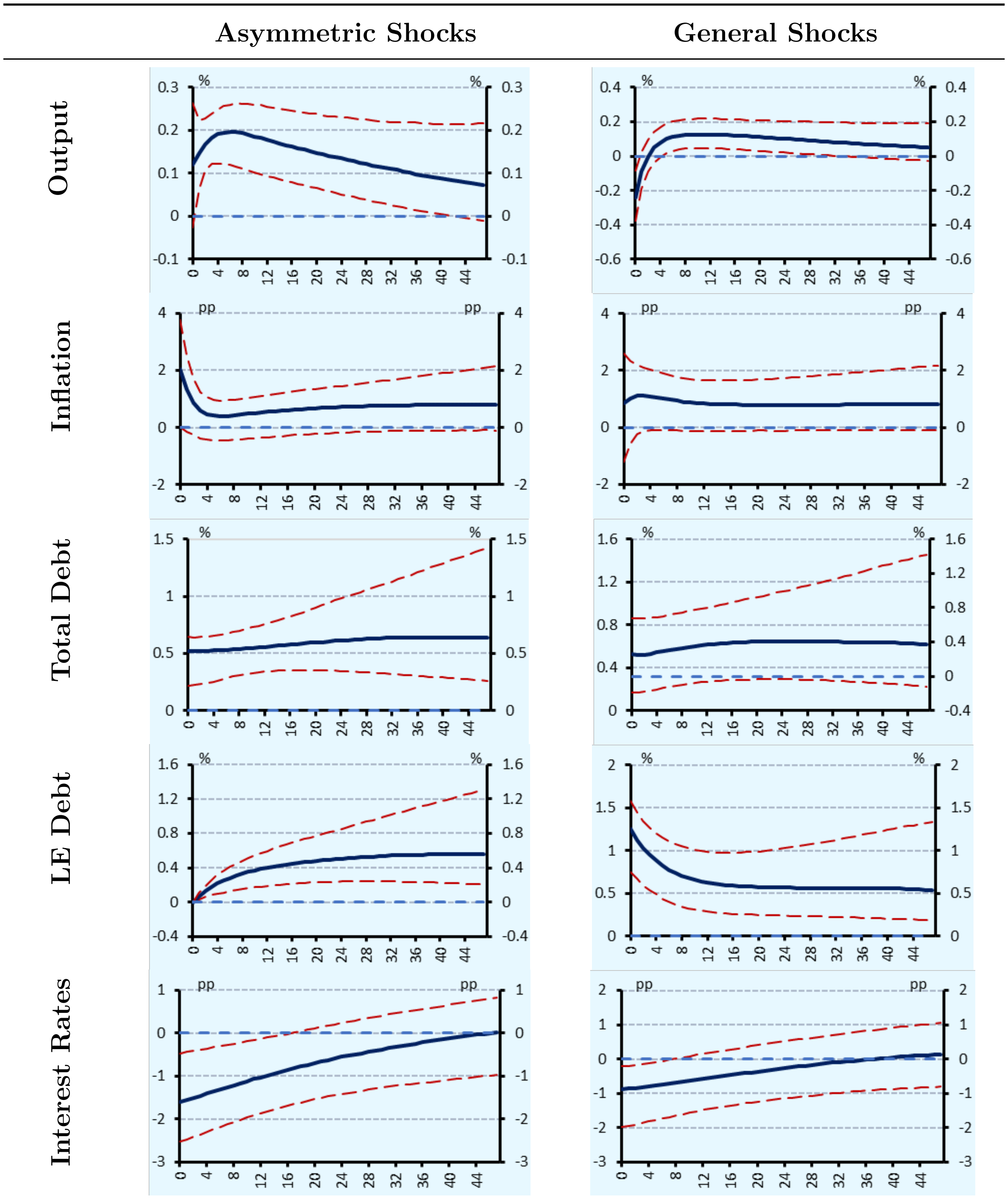

Figure 7: Impulse responses to asymmetric and general credit supply shocks.

8 Conclusion

I estimate the macroeconomic effects of the MNB's *Növekedési Hitelprogram* using a sign-identified SVAR on monthly data from 2012–2019. The program's SME-specific design enables the identification of asymmetric credit supply shocks that expand SME lending while leaving large-enterprise credit initially unchanged. These shocks have stronger and more persistent effects on output than general credit supply shocks. A one percent expansion in total lending due to asymmetric shocks increases output by roughly 0.441%, compared with 0.355% for general shocks, confirming that targeted SME credit interventions generate larger macroeconomic responses.

In addition, large-enterprise lending rises in response to asymmetric shocks, showing that SME-focused credit expansion produces positive spillovers rather than displacing other lending. The results suggest that strengthening SME credit conditions can stimulate broader credit growth, improve overall financial intermediation, and enhance the transmission of policy to the real economy.

Taken together, the findings demonstrate that funding-for-lending schemes can play a significant role in supporting economic activity, particularly when conventional monetary policy is constrained or financial conditions are tight. Their impact is strongest when the design targets financially constrained sectors, such as SMEs, and ensures direct, rapid pass-through to borrowers. Well-designed, targeted credit programs can thus help stabilize lending, sustain output, and accelerate recovery during periods of economic stress.

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Appendix

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: hd14; 2016–2017: h7; 2017–2019: m03)	Consolidated from all Hungarian financial intermediaries. Quarterly data between 2016m6–2016m12 interpolated. Accounting shocks in 2016m1 and 2016m3 adjusted. Exchange rate adjusted. Constant prices at 2010 base.
Large enterprise debt	MNB privileged data	Calculated as the residual of total corporate debt and SME debt. Exchange rate adjusted. Constant prices at 2010 base.
Average lending rate	MNB public lending conditions reports	Average nominal interest rate of new corporate credit issuances.

Asymmetric Credit Supply Shocks and the NHP

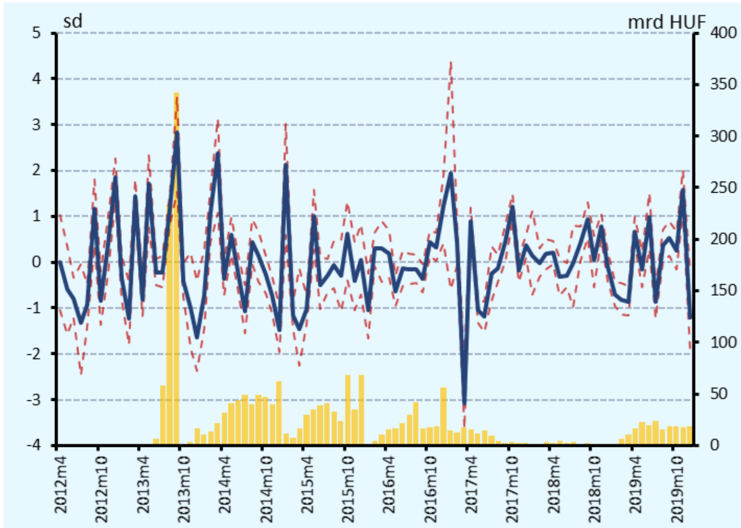

Figure A1: Time series of asymmetric credit supply shocks from the reversed zero restrictions specification.

Asymmetric Credit Supply Shocks and the NHP

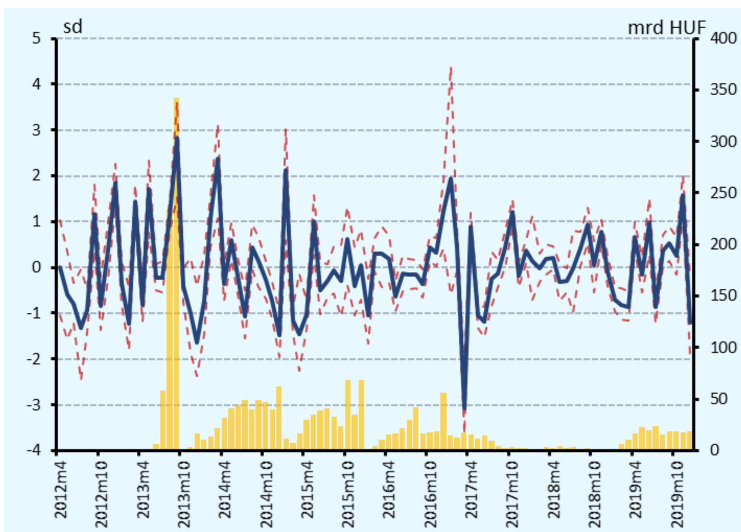

Figure A2: Time series of asymmetric credit supply shocks where industrial production is used as the activity proxy.

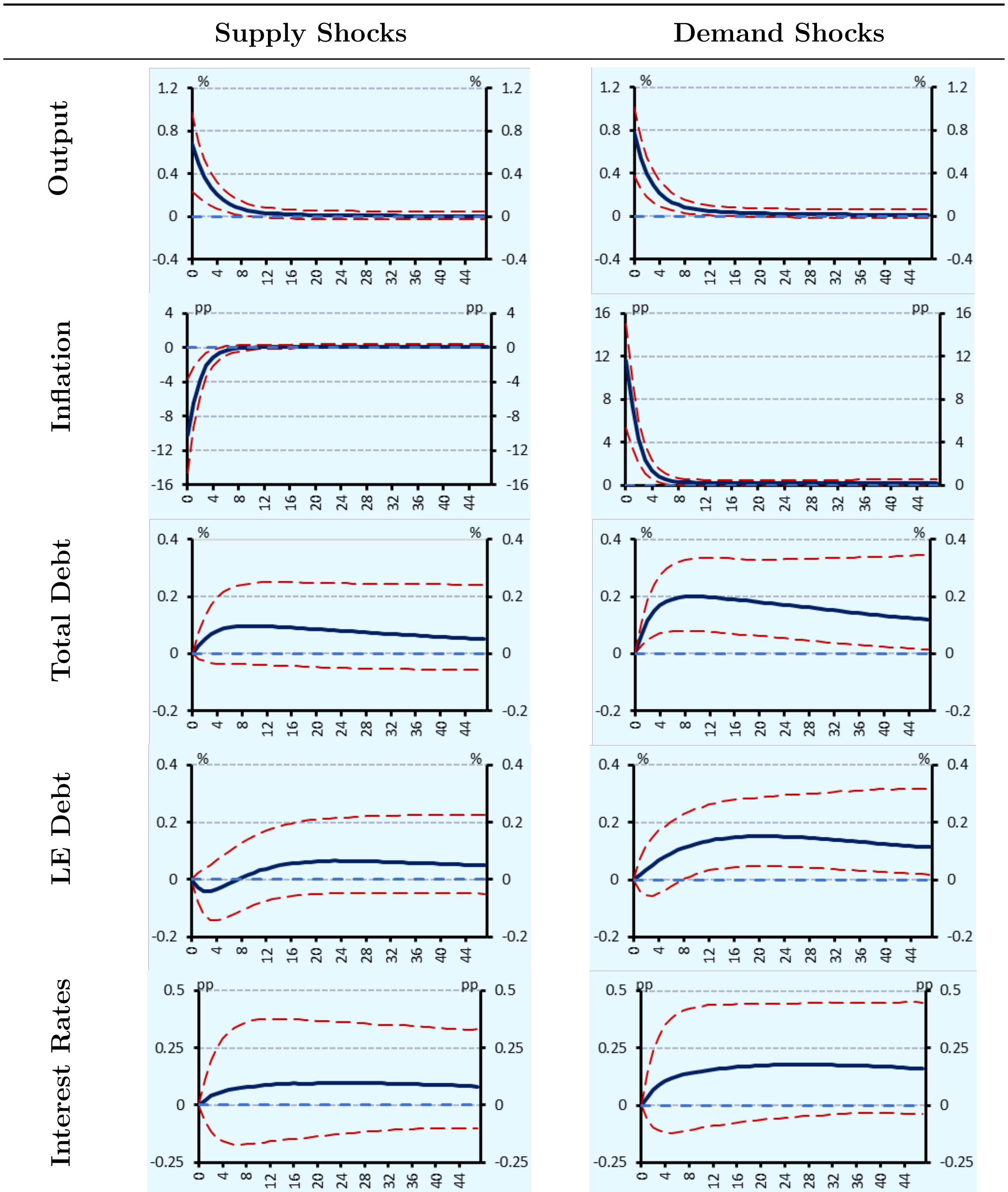

Figure A3: Impulse responses to demand and supply shocks.