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Shock Propagation in the Banking System with Real Economy Feedback

(Sokkok terjedése a bankrendszerben reálgazdasági visszacsatolásokkal)

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Abstract

In this paper we develop a model of shock propagation in the banking system with feedback channels towards the real economy. Our framework incorporates the interactions between the network of banks (exhibiting contagion mechanisms among them) and the network of firms (transmitting shocks to each other along the supply chain) which systems are linked together via loan-contracts. Our hypothesis was, that the feedback mechanisms in these coupled networks could amplify the losses in the economy beyond the shortfalls expected when we consider the subsystems in isolation. As a test for this, we embedded the model into a liquidity stress testing framework of the Central Bank of Hungary, and our results proved the importance of the real economy feedback channel, which almost doubled the system-wide losses. To illustrate the versatility of our modeling framework, we presented two further applications for different policy purposes: (i) We elaborated a way to use the model for SIFI identification, (ii) and we showed an example of assessing the impact of shocks originated in the real economy.

JEL: G01, G21, G28, C63.

Keywords: systemic risk, financial network, production network, contagion.

Összefoglaló

A tanulmány egy, a magyar bankrendszerre fókuszáló, reálgazdasági visszacsatolásokat is tartalmazó sokkterjedési modellt mutat be. A modellkeret magában foglalja a bankok hálózatát (a köztük megjelenő fertőzési csatornákkal), a cégek termelési hálózatát (a beszállítói kapcsolatokon keresztüli sokkterjedéssel), illetve ennek a két rendszernek a hitelszerződésekkel történő összekapcsolását. Hipotézisünk szerint ebben a visszacsatolási mechanizmusokat is tartalmazó összetett rendszerben a gazdaságban várható veszteségek meghaladják a két hálózat izolált vizsgálata során felmerülő veszteségeket. Ennek tesztelésére beépítettük a modellt a Magyar Nemzeti Bank likviditási stressztesztjébe. Az eredmények szerint a reálgazdasági visszacsatolás majdnem megduplázta a rendszerszintű veszteségeket. A modellkeret sokoldalúságának illusztrálása érdekében két további alkalmazást is bemutatunk a tanulmányban: (i) Kidolgoztunk egy módszert, amelynek segítségével a modell alkalmas lehet a rendszerszinten jelentős pénzügyi intézmények azonosítására, (ii) valamint bemutatunk egy példát a reálgazdaságból érkező sokkok hatásainak felmérésére is.

1 Introduction

The 2008 economic crisis shed light on a distinctive feature of the financial intermediary system: banks and other financial institutions are constituents of a multi-layer network, in which their interactions and feedbacks create non-linear processes. As the recognition of this *complexity*[1] as an intrinsic and influential characteristic which requires special attention has become widely accepted, a vast amount of research was conducted on network-based contagious mechanisms in the financial system. However, while this newly explored justification for the unique regulation of the financial sector unfolded in various forms, another, more traditional consideration was often neglected in the models. Namely, a more conventional line of reasoning grants a special role to the financial intermediary sector based on its connectedness towards all the other economic sectors, which puts banks in a special position from the point of view of shock propagation in the economy. This consideration – among others[2] – led at the first place to the regulatory frameworks, which have been even before the crisis much stricter than one can experience in almost any other industry.

In this project we are attempting to take a step towards the synthesis of the two above described considerations about the distinguished role of the financial sector by creating a banking system contagion model with real economy interlacement. As we experienced also during the escalation of the crisis after 2008, shock events either in the financial sector or in the real economy can be easily transmitted to the other: since in most countries banks are the main sources of firms' financing, if the banking system is hit by a shock, it can lead to financial problems for firms dependent on bank loans[3] due to the lower lending activity. In turn, if the real economy is declining, banks can suffer losses e.g. on non-performing loans or through the lack of demand due to the setback of investments. Crucially, these shocks can even be augmented not only in the banking system, but also in the production network of firms. Hence, the environment, in which the underlying processes beyond the observed emergent phenomena in the financial system are taking place is not limited to the financial sector, but it interferes heavily with the realm of the real economy.

To model the consequences of these intricacies on the financial stability of an economy we built a microsimulation based framework which is suitable to capture contagious mechanisms in an interconnected system of economic networks. More specifically, we are focusing on the interactions between the network of banks (exhibiting contagious mechanisms among them) and the network of firms (transmitting shocks to each other along the supply chain) which systems are linked together primarily via loan-contracts. Results obtained in theoretical models suggest, that the interconnected nature of networks causes qualitatively different behavior and alters the robustness of a complex system compared to the mere aggregation of its subsystems (Buldyrev et al. (2010), Leicht and D'Souza (2009)). Consequently, one can assume that to accurately assess financial systemic risks we need to consider the feedback channels between the interacting economic subsystems as well. Our hypothesis is, that these feedback mechanisms could amplify the losses in the economy beyond the shortfalls expected when we consider the interacting systems in isolation. According to our knowledge, this is the first model which integrates all the above mentioned mechanisms by using microsimulation jointly on empirical firm network data and the banking system.

Our framework consists of four modeling blocks: (i) contagions in the banking sector, (ii) modeling credit supply shocks for firms, (iii) assessing the amplification of these shocks in the production network and (iv) estimating banks' losses on their corporate loan portfolios. In the first block we built a banking system contagion model with channels for interbank losses, liquidity hoarding and fire sales effects, however, it also incorporates several balance sheet adjustment mechanisms to take into account the realistic behavior of banks in a stress scenario. This feature makes it possible to expand the propagation of distress towards the real sectors by acknowledging the procyclicality of the banking sector. Furthermore, additionally to the capital adequacy ratio (CAR) default condition, the liquidity coverage ratio (LCR) is also included to account for defaults

[1] In this sense a complex system is not merely a synonym for a complicated, large, sophisticated structure. Complexity is a scientific theory which asserts that some systems display emergent phenomena that are completely inexplicable by any conventional analysis of the systems' constituent parts. The source of complexity is usually assumed to be the non-linear, feedback-based interaction of many heterogeneous components.

[2] There are other characteristics of the financial sector which can justify its unique regulation as it operates in a highly leveraged way compared to other sectors and information asymmetries are present on multiple levels.

[3] Most importantly SMEs are vulnerable to these shocks as they cannot raise capital or issue bonds so easily as listed companies.

due to liquidity insufficiency. The other three blocks of the model are treated together in a spatial econometric model which gives estimates for the probability of default on corporate loan contracts. To carry out this estimation we borrowed tools from another stream of economic literature, which deals with shock propagation along the supply chain in production networks. As this research project does not aim to build a general economic model, we elaborated only those channels between the banking system and the real economy, which seem to be the most influential from the point of view of financial stability[4].

In order to build an implementation of the microsimulation environment we obtained access to several detailed datasets at the National Bank of Hungary and at the National Tax and Customs Administration, including balance sheet data of the Hungarian banks and firms, bilateral exposures at the interbank market, information about the investment portfolios of banks, details of loan contracts between banks and firms, and most notably, transaction level data about the supply chain connections among firms.

As a first application we embedded our model in the Hungarian Central Bank's liquidity stress test (which is calibrated to the 2008 crisis). The results of the simulation indicate that in the Hungarian banking system the magnitude of feedback-based losses on the non-performing loan portfolio coming from the firm network are similar in magnitude or in some cases even more severe than the losses caused by the usual firesales and interbank contagion channels. Additionally, the introduction of real economy feedbacks changed fundamentally the distribution of the losses among banks. The new contagion channels also made the interaction between solvency and liquidity problems more emphasized: some banks became unable to comply with the solvency criterion even in the case when only liquidity shocks were present in the stress scenario. As we are using firm-level granularity, it is also possible to assess some real economy consequences as well. In this particular application 0.5% of the firms in the model became non-performing on their loans.

A further important application of the model is to use it as a tool for identifying systemically important institutions (SIFIs). To construct a SIFI measure we embedded our model into a modified version of the Shapley value concept. Our indicator can be decomposed into three elements: i) system-wide losses caused by the default of a given bank, ii) losses suffered by the given bank due to external shocks, and iii) the part of other banks' losses which were caused by the shock amplifier effect of the given bank. The importance of these three factors can greatly vary among banks. In some cases the systemic importance is rooted mainly in the vulnerability of a bank, while others can be resilient from this perspective, but their default can represent more serious systemic risk. The third factor is usually less pronounced, which indicates that the complexity of the Hungarian banking system might not be as high as that of some larger countries. However, in some cases the ability to amplify shocks can also have significant influence on the systemic importance of Hungarian banks.

The modeling framework makes it also possible to simulate the effects of shocks originated not necessarily in the banking system, but also those coming from the real economy. By assuming firms in a given industry becoming non-performing on their loans, we could assess the significance of different economic sectors for financial stability. Following this logic we were able to apply the model for a preliminary assessment of the economic impacts of the COVID-19 pandemic. Although we do not have yet the necessary statistics to make confident assumptions about some crucial parameters, our results can still indicate a plausible range for the expected consequences.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 provides intuitive description and justification of our model. Section 4 specifies the detailed formulation of the simulations, while Section 5 deals with the calibration of the key parameters. Section 6 describes some applications, and Section 7 concludes and offers further research plans.

[4] Broer, Antony, et al. (2010) offers a comprehensive summary of several other potential interactions.

2 Literature review

The unexpected cascading spillovers in the global economy after the 2008 crisis fostered the emergence of network-based simulations as a popular modeling framework in economics (Elliott et al. (2014), Acemoglu et al. (2015)), but this recognition so far resulted mainly in numerous analyses about contagion channels only in the financial system. The topic of interconnected economic networks, although it was even listed as an objectives of the FuturICT project (Farmer et al. (2012)), remained so far largely unexplored in the economic literature. This way our project is most closely related to papers which connect the banking system and firms using loan contracts but do not consider the production network. One of the first attempts for this was done by Lux (2016), which study considered shock propagation via firms with multiple bank connections (similarly to the concept of contagion through overlapping portfolios). If a bank defaulted, the resulting credit crunch could force firms dependant on the banks' loan into bankruptcy. These firms then caused losses to their other bank connections. In their simulations they found that the joint exposures to counterparty risk in corporate lending is actually more important in the contagious spread of defaults than the interbank lending channel. A model in similar spirit was done by Silva et al. (2018), but in this case the simulations were run using empirical data as well. This paper extended a variant of the DebtRank model (Bardoscia et al. (2015)) to incorporate lending connections between banks and firms to create additional channels of shock propagation (but without including links among in the firm network). They showed that without taking into consideration the links between the financial and the real sectors one can severely underestimate systemic risks. Recent developments in the European Central Bank also include real economy feedbacks within their stress testing framework (Budnik et al. (2019)). In their work, they used a DSGE model to investigate how deleveraging the banking system affects the real economy, which effect feeds back into the aggregated macroeconomic variables. Additionally, they also consider cross-sectoral spillovers due to losses on claims of distressed banks, and then due to the equity holdings between sectors in the real economy (Dees and Henry (2017)). However, the DSGE approach entails some disadvantages: it produces only macro-level outcomes without revealing the heterogeneity of the economic actors and the role of the distinct components in the contagion along production chains. Gross and Siklos (2020) considers spillovers of financial shocks in the real economy without articulating a feedback component. They are using network-based econometric tools to estimate the transmission of bank and sovereign risks to the non-financial corporate sector based on CDS spreads. Furthermore, some papers depict connections between the financial and the real sector in the form of indirect interconnectedness among banks via exposures to common asset holdings (Caccioli et al. (2014), Duarte and Eisenbach (2018), Cont and Schaanning (2019), Roncoroni et al. (2019)).

Additionally, there are also theoretical models of interconnected networks, which can give relevant insights into the behaviour of interacting economic systems. Buldyrev et al. (2010) found that a broader degree distribution can amplify the vulnerability of coupled systems to random failures, which is opposite to how a single network behaves. Furthermore, Leicht and D'Souza (2009) showed that the percolation threshold in an isolated subnetwork can be significantly lower when edges to other networks are also present. Although these results were obtained in theoretical models with a very high abstraction level, they suggest, that accounting for the interconnected nature of economic networks can be crucial in systemic risk assessment.

Papers focusing solely on financial networks are also relevant to our work. The banking system block of our model is most similar in its spirit to Georgescu (2015), Idier and Piquard (2017), Covi et al. (2019) and Coen et al. (2019), however there are a vast amount of related papers concerning interbank contagions. E.g. Rogers and Veraart (2013) and Dietrich and Hauck (2020) focused on shock propagation in interbank networks, Gai and Kapadia (2010) and Gai et al. (2011) dealt with contagion through funding risk, and Bargigli et al. (2015), Poledna et al. (2015) and Montagna and Kok (2016) conducted research on contagion on multi-layer networks of banks. Upper (2011) and Jackson and Pernoud (2020) offer exhaustive summaries about further potential contagion channels. There are several other influential papers, which served as a starting point for many research projects in this topic: Furfine (2003) offered one of the first algorithmic solutions to the contagion mechanisms on a bank network, Eisenberg and Noe (2001)[5] managed to deal with the simultaneity problem of accounting for defaults and losses in a network, Battiston et al. (2012) offered a widely-used centrality measure to identify systemically important institutions and Barucca et al. (2016) improved on handling ex-ante valuation of claims among constituents of financial networks.

[5] Csóka and Herings (2018) shows a decentralized approach for the clearing in Eisenberg and Noe (2001), generalized to the discrete setup, while Csóka and Herings (2020) offers an axiomatization for the clearing process.

As we are taking into account the amplification of shocks in the production network of firms as well, our work is also connected to the supply chain contagion literature. Unlike in the case of banks, analysis of firm networks did not proliferate that much after the crises. However, some recent works have highlighted that systemic risk analysis should not be limited to financial networks. Bimpikis et al. (2018) and Bimpikis et al. (2019) have showed, that disruptions in the supplier network can result in suboptimal network formation which can amplify systemic risks. Baqaee (2018) showed in a general equilibrium model that shock propagation can be further amplified by the interconnectedness between industries. Luo (2019) establishes linkages between firms both using the production network and financial links due to delays in input payments, and shows that this multiplex network leads to the propagation of financial shocks in both upstream and downstream directions. further support for this mechanism using empirical data about the great east Japan earthquake. Barrot and Sauvagnat (2016) also uses natural disasters for the identification of firm-level shocks, and they found that suppliers can trigger considerable output losses for their customers. Further examples of supply chain disruption analyses can be Demir et al. (2018) and Boehm et al. (2019), but Carvalho and Tahbaz-Salehi (2018) and Bernard and Moxnes (2018) offer reviews of the broader literature on production networks.

Another important aspect of our model is its implementation on empirical data. Links between economic entities are very often confidential information and they are rarely accessible for academic institutions. In the case of bank networks a standard method is to reconstruct the topological structure using only aggregate observations. An often used procedure for reconstruction is the Maximum Entropy (ME) approach (Upper and Worms (2004), Elsinger et al. (2013)). Distributing each bank's total interbank lending as evenly as possible also means that ME results in an unrealistic, almost complete network. Drehmann and Tarashev (2013) enhanced ME by adding random perturbations to the maximum entropy output matrix to generate results with higher concentration mimicking more closely the sparse structure of empirical networks. Another variant of ME is the Minimum Density (MD) approach developed by Anand et al. (2015), which method creates an interbank lending network using as few links as possible by imposing a cost on link formation. Mastrandrea et al. (2014) takes into account the degrees of the nodes as well during the ME allocation. An alternative technique was applied by Baral and Fique (2012), which paper used copulas to construct the interbank lending network. ME was also applied to recover input-output matrices by Golan et al. (1994), however, reconstruction, or more generally even the use of granular entity-level linkages is much less prevalent in the case of firms than in the banking system. There are only very few countries in which fine-grained production network data is available. Watanabe et al. (2015) gave the first detailed description of a large, granular supplier network by considering relationships among 400,000 firms in Japan. However, probably the Belgian production network is used most often in studies dealing with firm-level trade connections Magerman et al. (2016), Tintelnot et al. (2018)). Additionally, Demir et al. (2018) used the Turkish, while Kumar et al. (2020) considered the Indian supplier network in their work.

3 Description of the model

In this section we provide intuitive description and justification for our work, while Section 4 will show the exact formulation of our simulations.

Our model can be divided into four theoretical blocks (Figure 1):

- In the first block, we model the adjustments and contagions in the banking system after an exogenous shock.
- As an adjustment mechanism of banks, a credit supply shock hits the real economy, which increases firms' probability of default (PD) on their loans.
- The amplification of the shock in the production network further increases firms' PD.
- As a feedback from the firm network, banks suffer losses on their corporate loan portfolios.

As the last three blocks are all parts of the process how credit supply shocks translate into an increased probability of firms becoming nonperforming on their loans, these can be handled together during the implementation as one modeling unit describing the real economy feedback. Before we describe the detailed formulation of the simulation steps, first we provide intuitive explanations for these theoretical blocks.

3.1 BANKING SYSTEM

Our model of the banking system contains two channels of contagion and several mechanisms that capture banks' adjustment. One source of contagion is happening through the interbank lending market: If a bank suffers a loss of a magnitude that results in its failure, and thus it becomes unable to repay the loans it borrowed in the interbank market, it causes losses to its partners. The second channel stems from the form of bank adjustment when a bank attempts to improve its position by selling assets whose price may change as a result of these transactions, and thus other banks also suffer losses because of the price change. (This mechanism is hereinafter referred to as 'fire sales'.) According to the logic of the model, contagion and adjustment mechanisms follow one another cyclically until the fixed point of the system is reached[6]. (Figure 3.1)

During running the model, first we examine whether the given bank meets the levels of the liquidity (Liquidity Coverage Ratio - LCR) and solvency (Capital Adequacy Ratio - CAR) indicators required by the regulatory authority. If not, to avoid bankruptcy, banks first try to adjust themselves until the required LCR and CAR levels are reached, in order to offset the impact of stress events. Our assumptions regarding the adjustment options are built on empirical findings in the European banking system: Brinkhoff et al. (2018) shows the results of the European Systemic Risk Board's macroprudential surveys that aim to assess banks' behaviour in macroeconomic stress scenarios. They have found that lowering credit risk exposures is the largest component of the expected reduction in their risk-weighted assets. Additionally, Behn et al. (2019) also showed that banks in danger of breaching regulatory requirements often choose socially detrimental adjustment strategies, most of all by reducing lending activity. The assumption that banks would even use balance sheet transformation which entail fire sales contagion to raise liquidity in a stress situation is supported by e.g. Allen and Carletti (2008), Adrian and Shin (2010) and Diamond and Rajan (2011). However, adjustment steps can differ between countries due to country- and bank-specific dissimilarities. As we could implement our model on Hungarian data, we fine-tuned the assumptions to the Hungarian experiences during the 2008 crisis. Furthermore, the exact adjustment opportunities can vary depending on the application as well. The assumed behaviors of banks in the model reflect these evidences and principles.

In order to improve the *liquidity* situation, banks in the model attempt to increase their liquid assets by liquidating those assets that cannot be taken into account in the LCR calculation or can only be taken into account with a high discount. This adjustment

[6] Eisenberg and Noe (2001) showed that a unique fixed point exists in the system, however, they only considered the interbank contagion channel without fire sales.

may take place in three stages. In the first step banks carry out operations that are feasible in a stress situation as well, do not cause a decline in reputation, do not entail large losses, and do not generate further contagion in the banking sector. Adjustment possibilities like this may include the drawing of nostro accounts (accounts that a bank holds in a foreign currency in another bank) and the non-renewal of just maturing deposits at the central bank. If no further adjustment is necessary, a given bank's reaction is evenly distributed across the above listed instruments. If carrying out the first level is not sufficient, the bank makes adjustments which do not meet the above listed considerations. In the second stage banks make the parts of the household and corporate loan portfolios which are just maturing on a cash flow basis expire[7]. Finally, if necessary, even those assets are liquidated (corporate bonds and mortgage bonds) whose selling may result in a fire sales effect as other banks whose balance sheet also contains the given security also suffer losses through the price change. The extent of the price change depends on the type, the overall amount and the liquidated amount of the given asset.

Improving the *solvency* position takes place along similar logic, with the difference that in order to improve a bank's position, asset restructuring is possible on the basis of the risk weights (which are taken into account during the calculation of the risk-weighted asset value), instead of the LCR discount rates. Accordingly, in this case the bank transforms the assets with high risk weight into assets with risk-free rating (e.g. into cash when making assets mature). According to our model specification, in the case of a solvency problem banks have somewhat fewer options to adjust as some assets in the first stage have practically zero risk weight, so their liquidation would not improve the CAR.

If even all these adjustments are insufficient to meet the requirements (LCR and CAR), the given bank goes bankrupt, and its interbank loans become nonperforming. We account simultaneously for the losses stemming from the interbank exposures vis-a-vis the banks that failed and the fire sales type price losses due to the asset fire sales. In the case of a default event, we differentiate in the LGD parameter based on the extent the given bank violated the requirements. After accounting for all the banks, if no change has taken place in the assets compared to the previous iteration, the process stops. Otherwise, if further loss occurred because of the contagion, some banks may have gone below the regulatory limit again, and the process restarts.

3.2 SHOCK TRANSMISSION FROM THE BANKING SYSTEM TO THE REAL ECONOMY

In the model of bank-firm network relationships the main mechanisms to transfer shocks from banks towards firms is the decline in credit availability from the supply side. Ivashina and Scharfstein (2010) offers an underpinning for this mechanism by showing that firms had difficulties during the recent financial crisis in renewing their credit lines. An important factor which can modulate this kind of vulnerability is the number of connections a given firm has to the banking sector. The ability for a bank to privately observe information and maintain a close relationship with its customer enables these firms to have increased access to capital with more complex and non-standard credit needs (Von Thadden (1995)). Based on this, it can be beneficial if a firm has more than one long-term, embedded connections with financial institutions.

This embeddedness is also useful during crisis times when firms often prefer to solve their financial problems privately in a credit relationship, rather than damaging their reputation on the financial markets. Jiangli et al. (2008) showed that banks are able to smoothen out shocks to firms by rescheduling payments or by the renegotiation of the terms of the credit contract. However, this effect seems to be much weaker during systemic crises situations. In this case, banks do not necessarily accommodate firms with new lending, rather they often refuse future lending. Puri et al. (2011) suggests that banks can smooth out idiosyncratic shocks but they amplify systemic shocks. They also showed that banks affected by a shock reject substantially more loan applications than non-affected banks.

In Hungary, the economy experienced a massive drop in lending after the 2008 crisis. Although Figure 3 and 4 do not distinguish supply and demand side factors, however, the extent of the disruption in the trends can still be considered as an obvious sign of credit retrenchment.

[7] We assumed that banks make 100 per cent of the household loans maturing within 90 days and 50 per cent of the corporate loans maturing within 90 days expire (however, this time window can vary based on the assumed initial shock and the application of the model). The difference between the retail and corporate portfolio is explained by the fact that reputation loss can be more severe in the case of corporate clients.

3.3 SHOCK AMPLIFICATION IN THE PRODUCTION NETWORK

Credit supply shocks can have an impact via the supplier network even on firms which were not affected directly. In this block of the model our objective is to assess also the indirect effect of shocks coming from the banking system. Our approach to deal with this challenge is different from the mechanical modeling style we applied for the banking system. As firms are extremely heterogeneous and their operation is much less regulated than that of banks, it would be extremely burdensome to work out the details of their behaviour. Instead, we used a spatial econometric approach to estimate the increase in the probability of default of firms on their loans after a credit supply shock hits some part of the production network they are indirectly connected to[8].

This solution is connected to the literature of supply chain contagions, which gained momentum after supplier information about firms became more and more often accessible. These studies supplied ample evidence that production networks are not resilient even to firm-level idiosyncratic shocks as firms are not capable to react flexibly enough[9]. Moreover, shocks can even be amplified through supplier links. E.g. according to the results of Barrot and Sauvagnat (2016), the reduction of sales by $1 at the supplier level causes a decrease of $2.4 in sales at the customer level.

Furthermore, this stream of the economic literature distinguishes between upstream and downstream shock propagations:

- If a firm experiences a credit supply shock, its production might fall on account of the financial distress, so the shock will affect intermediate input suppliers as well. In addition, suppliers might not be able to collect money from defaulting partners. This means that the shock travels to the upstream direction on the supply chain.
- Regarding the other direction, if a supplier defaults after a credit supply shock, the intermediate inputs it produced might not be easy to replace for its costumers, hence, the shock spreads to the downstream direction.

Interestingly, shocks can reverse directions along the network, which means that in effect they can also spread horizontally. A popular example for this is the case of car manufacturing industry in the United States. In the fall of 2008, the president of Ford Motor requested government support for General Motors and Chrysler, but not for Ford. He wanted government support for his company's rivals because the failures of GM and Chrysler were predicted to result in the failure of many of the suppliers of Ford Motor. Namely, a shock to General Motors can trigger upstream shock propagation in the car-parts industry, which becomes a negative supply shock (downstream propagation) to Ford. One can imagine other scenarios for horizontal shock propagation as well. For instance, if a supplier is hit by a shock, its competitors can gain market share if the input is not too specific.

3.4 SHOCK TRANSMISSION FROM THE REAL ECONOMY TO THE BANKING SYSTEM

The parameters estimated for the direct and indirect impact of credit supply shocks on firms' PD can be applied directly to simulate firm defaults. If a firm becomes nonperforming, banks with loan exposures towards the firm will suffer losses on their corporate loan portfolio[10]. To handle the stochastic nature of this procedure we calculated with the expected value of 1000 realizations of credit losses.

The problem of nonperforming loan portfolios became one of the most pressing issues in several European countries. Rampant NPL portfolios are not only problematic for banks, but it cuts back lending activity even further creating a negative feedback loop in the economy (Accornero et al. (2017)). Figure 5 shows the devastating situation in Hungary following the 2008 crisis.

3.5 THE TIME SCALE OF THE MODEL

The processes described in this section so far must be synchronized in the time scale of the model. First of all, it is important to emphasize that even if the blocks of the simulation follow each other iteratively, this is often merely the practical representation

[8] The details of this estimation are discussed in Section 5.

[9] See for example Carvalho et al. (2016), Demir et al. (2018), Boehm et al. (2019).

[10] During most of the simulations we used either 50% or 100% as LGD parameters, which simplification conceals the vast difficulties of estimating LGD parameters specific to several relevant bank and firm characteristics.

of processes simultaneously reinforcing each other. Furthermore, the time scale of the simulations is highly dependant on the assumed initial shock and the application. As it can be seen on Figures 3-5, the effect of the shock in 2008 was rather drastic and immediate both in the case of the plummeting lending activity and the soaring delinquency ratio, and we also experienced that the situation worsened for several quarters at an almost constant rate. However, if we apply the model within the framework of a liquidity stress test, then the relevant time scale might be only 30 or 90 days.

To address this concern, we can adjust the model by tuning two types of parameters to match the time scale of the modeled phenomena. Firstly, the window in which banks can make their loan portfolio expire should be set to the time period applicable for the given run. Secondly, the parameters governing the probabilities of firms becoming non-performing on their loans can also be adjusted to manage the mismatch between the data frequency in the estimation and the application's time scale. It might arise as an additional concern, that we consider the shock propagation based on estimates coming from yearly data, which masks the differences between short-term and medium-term dynamics. On the one hand, one would assume that the production function is more similar to the Leontief function in the short run, but the opportunities for substitution become later gradually more and more relevant. On the other hand, firms' liquidity buffer can attenuate the propagation of shocks for a while. Unfortunately, we cannot measure which one of these impacts dominates in different time windows, so we opted for not making corrections to any direction based on these considerations, so we transform the yearly estimates simply proportionally to the time frame of the application.

Of course, similarly to any other model, the reliability of the results can be lower and lower as the time window increases and less and less elements of the economy can be assumed to remain constant. As this is only a partial model, it is not suited to incorporate long-term changes in the economy. For instance, during the years following the 2008 crisis the situation of the banks was heavily influenced by several factors including capital injections, extra taxes, restructuring of some banks by the state, introduction of new regulations, etc. This way, regarding the dynamics of contagions within the banking system, we can only make plausible assumptions for relatively short time periods.

3.6 DATA REQUIREMENTS OF THE MICROSIMULATION

To implement this microsimulation model on real data we obtained access to several detailed datasets at the Hungarian Central Bank and at the Hungarian Tax Authority. While detailed information about banks and bilateral exposures at the interbank market are part of the standard data reporting towards central banks in most countries, we could also access

- the central credit information database (KHR) containing all loan contracts between banks and firms,
- firms' balance sheet and profit and loss statements from corporate tax reports, and
- transaction level data about the supply chain connections among firms from VAT reports.

Although most of these datasets have been already preprocessed and have relatively high quality, the construction of the supplier network required several corrections. VAT reporting in Hungary contains information also about the trade partners of firms, where the tax content of all the trade transactions between two companies exceeds € 3000 in the given year. This information is available between 2014-2017[11], which made it possible to reconstruct the Hungarian production network with relatively high precision. By adding the location and financial reports of firms to the data we could utilize not only topological characteristics but also several node attributes. The most important shortcomings of this data are the missing observations stemming from mainly two sources: (i) international trade and (ii) connections below the value threshold. As a result of these, around 50% of the procurements is present in the observed system. The supplier network changes notably from one year to another, which is mainly due to the lot of one-off, incidental transactions. As these links are important from the point of view of shock propagation, we applied a filtering to keep only long-term supplier connections[12]. In 2017, only slightly more than half of the links are long-term, however, these cover around 93% of all the traded value.

A further distortion we had to handle is that firms belonging to the same ownership group sometimes report collectively, but very often it happens individually. To correct for this, we obtained access also to OPTEN's ownership connection database.

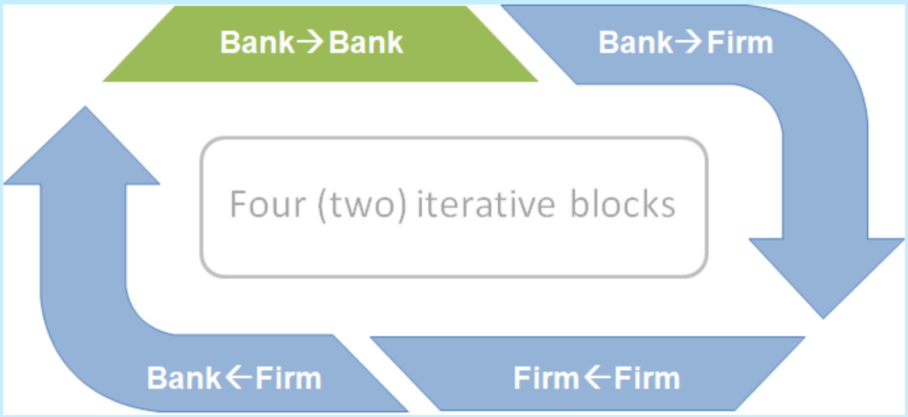
[11] Although the quality is very poor for 2014.

[12] We classified a connection as long-term if there were at least two transaction between the firms, and if there is at least one quarter time difference between the first and the last trade occasion between them.

Although we did not see global ultimate beneficiary owners, only local connections, we could still cover most of the relevant connections among firms. We also considered indirect ownership links by a calculation analogous to the Leontief inverse[13]. After all these corrections, our final network consists of yearly 80-100 thousand nodes and 200-250 thousand links.

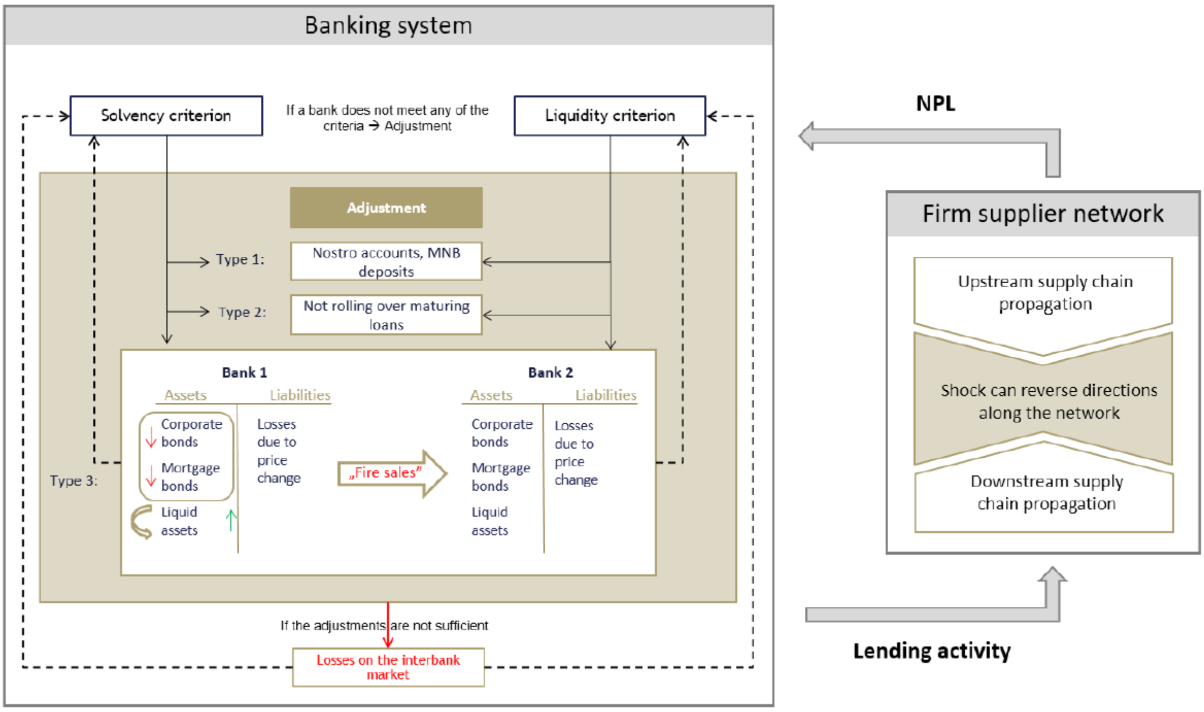
[13] More specifically, we computed the Neumann-series approximation of this version of the Leontief inverse.

Figure 1
Modeling blocks of the framework



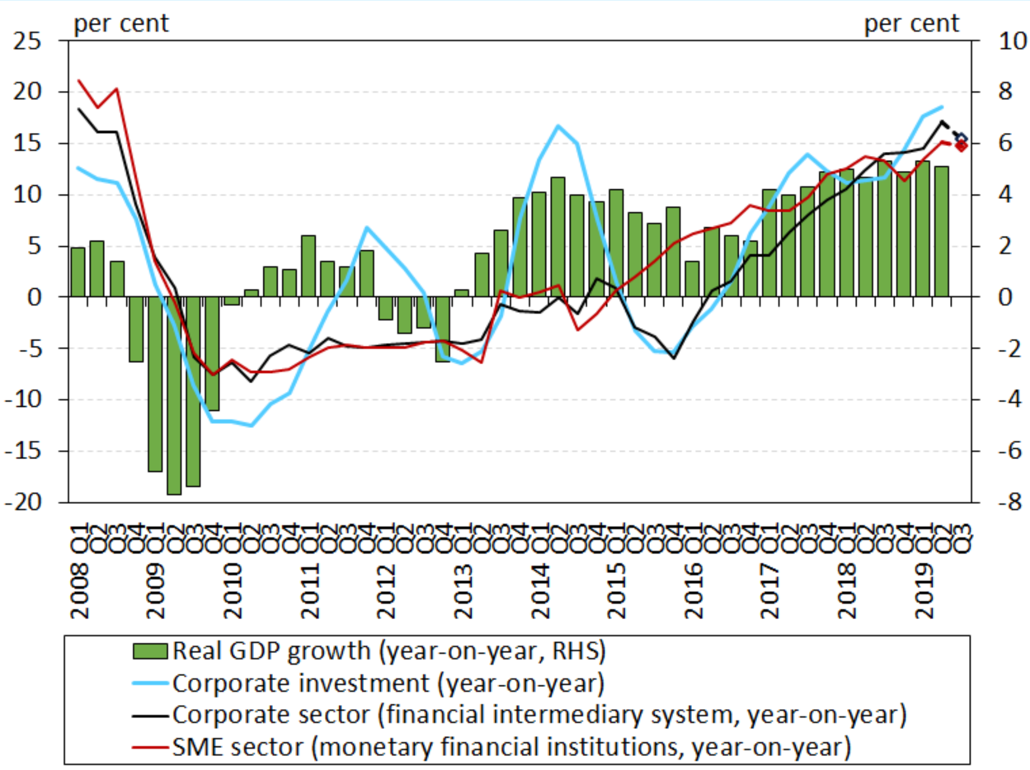
Our framework consists of four modeling blocks: (i) contagions in the banking sector, (ii) shock propagation from banks to firms, (iii) assessing the amplification of these shocks in firms' production network and (iv) feedback from firms to the banking system.

Figure 2
Schematic structure of the banking block



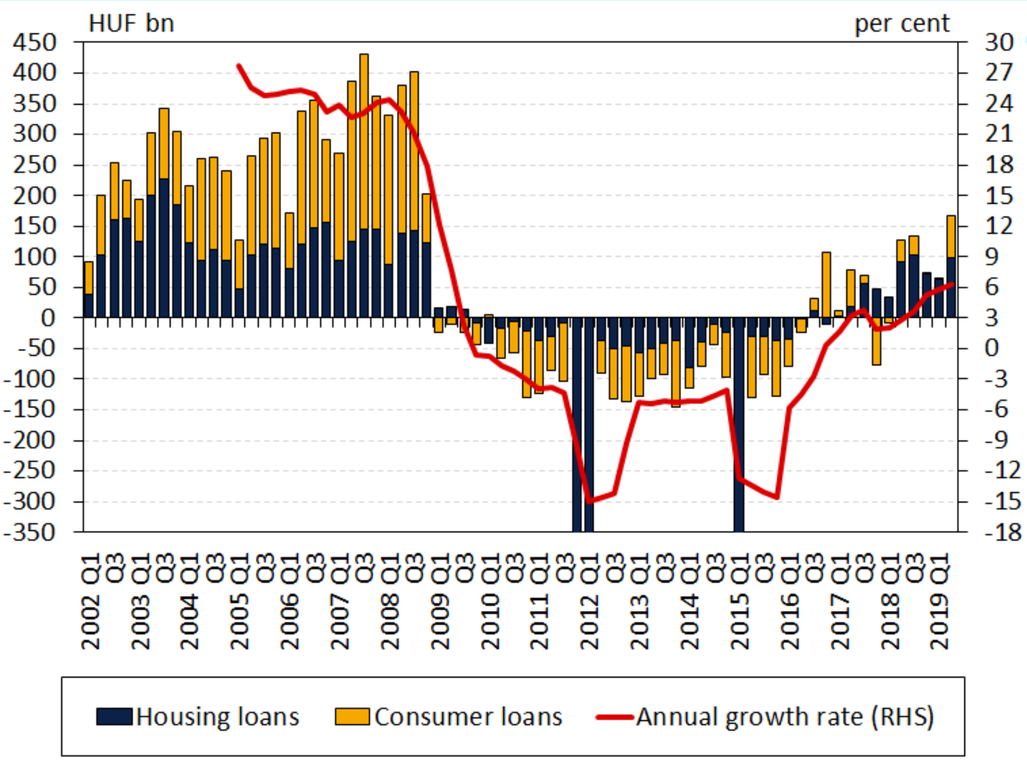
Regular arrows indicate adjustment options, while dashed arrows show occurrences of losses.

Figure 3
Growth rate of outstanding corporate and SME loans and indicators of the real economy



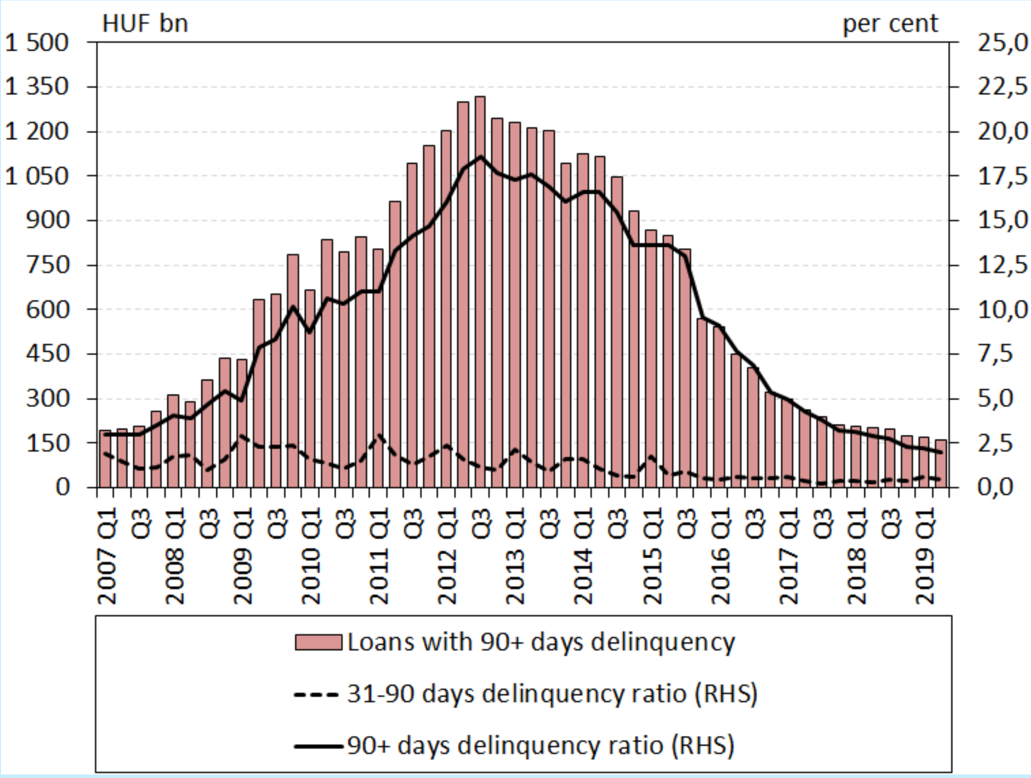
Source: Central Bank of Hungary.

Figure 4
Household (housing and consumer) loan transactions and its annual growth rate



Source: Central Bank of Hungary.

Figure 5
Ratio of non-performing corporate loans in the credit institution sector



Source: Central Bank of Hungary.

4 Details of the simulation

The banking system block and the real economy feedback part (which consists of the last three theoretical blocks) iteratively follow each other during the simulation. If any of the banks makes some adjustment in its lending activity (which exceeds a very low tolerance parameter in the model) the real economy feedback is triggered. If this feedback results in additional losses for the banking system (which exceeds the tolerance parameter), than the banking system's contagion mechanisms become active again. Within a "banking system block" there is a similar inner loop: If significant losses occur at any of the banks, its adjustment and/or its default can cause losses to the other banks as well, which can lead to further adjustments. Although the simulation runs in a sequential manner, this is often merely the technical representation of simultaneous events. When we denote the order of events (or states of variables) with the notation t, we refer to the iterative rounds of the simulation and not actual time. The logic of the simulation can be summarized by the following pseudocode:

In the following subsections we will give detailed formulation of the simulation steps.

4.1 BANKING SYSTEM CONTAGIONS

In the model we consider the nine largest Hungarian banks, which cover around 85% of the market[14]. At the Central Bank of Hungary we can observe banks' exact measures regarding their liquid assets, expected cash inflows and outflows, furthermore the equity instruments which are relevant for the CAR calculation and the risk-weighted assets.

Another crucial piece of information in the banking block is the representation of the interbank market. As the transactions here are usually very short-term, mostly overnight, a snapshot would not reflect a representative state of the market. Instead, we constructed the network by taking the average daily exposures in a month for each bank, which we then distributed in the proportion of the monthly average exposures towards the banks' partners.

Additionally, we consider further asset classes which are relevant for banks' adjustment processes. These are (1) short-term (within three month) claims towards the central bank, (2) nostro accounts, (3) government bonds, (4) corporate loans, (5) household loans, (6) corporate securities and (7) mortgage bonds. Each asset class has some parameters which govern their role during the adjustment decisions of banks (Figure 7)[15]:

- *LCR haircut* indicates that to what extent a given asset should be discounted during the calculation of liquid assets for LCR.
- *Risk weight* is the discount parameter to determine the risk-weighted assets of a bank.
- The *rank* parameter determines the order in which assets are used by banks to adjust their balance sheet to be able to meet the regulatory requirements. *Rank* is determined following the principles laid out in Section 3.1., and it can be considered as an externally given solution of banks' optimization problem. Assets can have the same rank parameter, in which situation the required adjustment is evenly distributed between those assets.
- *Minimum Price* denotes the lowest relative price in the scenario where all the banks in the model liquidate completely the given asset category. As there are other holders of those assets on the market, the banking system can have only limited impact on the price.

4.1.1 SOLVENCY ADJUSTMENTS OF BANKS

During modeling the solvency related behavior of the banks, firstly we have to test whether a bank meets the regulatory CAR requirement in every iteration. For a given bank i this test is given by Equation 1.

[14] The inclusion of smaller institutions, which often have in some aspect special operations would only add complications to the model without any significant benefit.

[15] The risk weights and the LCR haircuts are regulated in a very detailed way, which we did not follow in the model with the same level of precision.

$$\frac{(E_{i,t_0} - L_{i,t})}{RWA_{i,t_0} + \sum_j (rw_j \times p_{t,j} \times (A_{i,j,t} - A_{i,j,t_0}) + rw_j \times (p_{t,j} - p_{0,j}) \times A_{i,j,t})} < CAR_{reg} \tag{1}$$

where E_{i,t_0} is bank *i*'s original equity, $L_{i,t}$ is the cumulative loss occurred up until round *t* for bank *i*, RWA_{i,t_0} is the original risk-weighted asset of bank *i*, *rw* denotes the vector of risk weights associated with all the asset classes considered in the model, p_t is the vector of relative prices for all the asset classes[16] (the original price, p_0 is one in every case), and $A_{i,t}$ shows the assets of bank *i*. The change of the risk-weighed assets can be decomposed into the change due to asset liquidation ($\Delta RWA(A)$) and the change caused by price changes ($\Delta RWA(p)$). CAR_{reg} is the regulatory requirement of the capital adequacy ratio.

From this we can also calculate how much equity bank *i* lacks to comply with the regulation:

$$\begin{aligned} Missing\ Equity_{i,t} = [RWA_{i,t_0} + \Delta RWA(A) + \Delta RWA(p)] \times CAR_{reg} \\ -(E_{i,t_0} - L_{i,t}) \end{aligned} \tag{2}$$

We also have to assess how much assets are available for selling which could help to improve the solvency situation. In the case of solvency, banks first consider only one asset, sovereign bonds, with a rank parameter equal to 1 (Stage 1). Maturing household and corporate loans have a rank parameter equal to 2 (Stage 2), and corporate securities and mortgage bonds belong to Stage 3. The amount of available assets which can be used to improve solvency ($Assets\ for\ Adjustment_S$) in a stage is simply the sum of a given banks' assets in that category:

$$Assets\ for\ Adjustment_{S,i,t} = \sum_{j \in Stage_r} A_{ij,t} \tag{3}$$

where $Stage_r$ is the set of assets with rank *r*.

Then the actual solvency adjustment ($Adjustment_{S,i,t}$) is the minimum of the available adjustment opportunities and the necessary adjustment to reach the requirement. Even if a bank cannot meet the required CAR, it will try to approach it as much as possible.

$$Adjustment_{S,i,t} = min\left(Assets\ for\ Adjustment_{S,i,t};\ \frac{Missing\ Equity_{i,t}}{(rw_r) \times CAR_{reg}}\right) \tag{4}$$

where rw_r is the risk weight of assets with rank *r*.

If the required adjustment cannot be covered by Stage 1 assets, also Stage 2 and finally Stage 3 assets are needed. Adjustment within a given stage happens by selling the same percentage of each asset in that stage.

4.1.2 LIQUIDITY ADJUSTMENTS OF BANKS

During the testing of banks for their compliance with the CAR we accounted for the changes in the numerator and the denominator due to the adjustments in previous rounds. As the LCR has a more complicated formula (Equation 5) with more interactions with previous adjustments, we will present separately the alterations of LCR's components.

$$LCR = \frac{High\ Quality\ Liquid\ Assets\ (HQLA)}{Outflows - min(Inflows;\ 0.75 \times Outflows)} \tag{5}$$

[16] Accounting standards vary among countries and asset classes, but for the sake of simplicity, we generally follow the principles of mark-to-market evaluation in the model. Although the implications of this approach are often debated, it reflects realistically the fair value of the assets during crisis periods.

Bank *i*'s HQLA is computed as the sum of the amount of liquid assets at the current price plus the amount which was sold earlier possibly at a different price (both corrected by the vector of haircut parameters):

$$HQLA_{i,t} = HQLA_{i,t-1} + \sum_{j \in A_{LCR}} (A_{ij,t-1} - A_{ij,t}) \times (p_{j,t}) \times (1 - h_{LCR,j}) + \sum_{j \in A_{LCR}} (p_{j,t} - p_{j,t-1}) \times A_{ij,t-1} \times (1 - h_{LCR,j}) \quad (6)$$

where A_{LCR} is the set of assets which can be used for liquidity adjustment and $h_{LCR,j}$ is the LCR haircut parameter for asset *j*.

As opposed to the solvency examination, here we are calculating the difference between time t and $t-1$ instead of t_0. The reason for this is that now the time of the adjustment matters because prices can change during the simulation, and using different prices also means different change in the HQLA. The amount of cash received during liquidation has an important role for LCR (as it is part of the HQLA), but it was not relevant for the RWA as losses in the solvency block appeared in the numerator of the CAR.

Importantly, adjustments of banks aiming to improve their liquidity by increasing HQLAs can interfere with the denominator of the LCR as well. The usage of some of the adjustment options (short term central bank deposits and nostro accounts) influences the expected cash inflows as well, and this effect might distort the expression in the denominator. Additionally, losses on the interbank market also contribute to the reduction of the expected inflows:

$$\Delta Inflows_i = \Delta Nostro_i + \Delta CBclaims_i - L_{interbank,i,t-1} \quad (7)$$

where Δ refers to the change between t and $t-1$, while $L_{interbank,i,t-1}$ is the losses suffered by bank *i* in the previous round of the simulation.

The denominator of the LCR (LCR_{denom}) can be constructed now using the following expression:

$$LCR_{denom} = Outflows - min[max(Inflows + \Delta Inflows; 0);\ 0.75 \times Outflows] \quad (8)$$

After updating all the components of the LCR, we can also calculate the additional HQLA need if a bank is below the regulatory limit:

$$Missing\ HQLA_{i,t} = LCR_{denom,i,t} \times LCR_{reg} - HQLA_{i,t} \quad (9)$$

To get the required adjustment in a given stage we have to correct the *Missing HQLA* with the LCR haircut parameters and with the current weighted average prices.

$$Required\ adjustment^r_{L,i,t} = \frac{Missing\ HQLA_{i,t}}{\sum_{j \in A^r_{LCR}} h^r_{LCR,j} \times p_{j,t} \times \frac{A_{j,t}}{\sum A_{j,t}}} \quad (10)$$

where A^r_{LCR} is the set of assets which can be used for liquidity adjustment in stage *r* and h^r_{LCR} is the vector of LCR haircut parameters for assets with rank *r*.

Similarly to the solvency part, we have to assess how much assets are available for selling to improve the liquidity situation. In a given adjustment stage *r* it follows the same logic as Equation 3.

$$Assets\ for\ Adjustment_{L,i,t} = \sum_{j \in Stage_r} A_{ij,t} \quad (11)$$

Finally, the actual liquidity adjustment ($Adjustment_L$) is the minimum of the available adjustment opportunities and the necessary adjustment to reach the requirement. Similarly to the CAR, even if a bank cannot meet the required LCR, it will try to approach it as much as possible.

$$Adjustment_{L,i,t} = min\Big(AssetsForAdjustment_{L,i,t}; Required\ adjustment_{L,i,t}\Big) \tag{12}$$

If the required adjustment can be covered by Stage 1 assets, only these will be utilized by selling the same percentage of each of them. If also Stage 2 or 3 assets are needed, the necessary adjustment will be distributed in the same proportional manner.

4.1.3 CLEARING OF THE LOSSES IN THE BANKING SYSTEM

After managing the solvency and liquidity situation of all the banks, we evaluate the state of the system. We consider a bank bankrupt, if even after all the adjustment opportunities it is unable to meet the regulatory criteria. However, we somewhat differentiate in the consequences of a default event based on the extent the given bank violated the requirements. In the case of the LCR, the loss given default (LGD) parameter was determined as 0% when the LCR is between 50-100%, and 100% for a requirement breach where the LCR goes below 50%. For the capital adequacy ratio a similar threshold is used at the 4% level of the CAR. A bank's LGD (lgd_k) is determined in every round based on their LCR and CAR levels:

$$lgd_{i,t} = max(lgd^S_{i,t}; lgd^L_{i,t}) \tag{13}$$

where $lgd^S_{i,t}$ is the LGD level which would be imposed based on the CAR of bank i, and $lgd^L_{i,t}$ is the LGD which would come from the LCR of bank i at round t.

Based on these parameters we update the interbank exposures following Equation 14.

$$W^B_t = W^B_{t-1} \times S_t \tag{14}$$

where W^B is the weighted adjacency matrix representing the exposures among K banks on the interbank lending market. A cell $w^B_{i,j}$ denotes the amount that bank i lends to bank j.

$$W^B = \begin{bmatrix} w^B_{11} & w^B_{12} & \cdots \\ \vdots & \ddots & \\ w^B_{K1} & & w^B_{KK} \end{bmatrix}$$

S is a diagonal matrix containing the surviving ratio of the interbank exposures based on the LGDs of each bank:

$$S = \begin{bmatrix} 1 - lgd_1 & & \\ & \ddots & \\ & & 1 - lgd_K \end{bmatrix}$$

The losses on the interbank exposures ($Loss_{ib}$) can be represented as the difference between the initial and the final state of the interbank matrix:

$$Loss_{ib} = W^B_t - W^B_0 \tag{15}$$

Finally, we are calculating the losses due to the change of the asset prices. The formula describing the functional form of price development is based on Georgescu (2015):

$$p_{j,t} = exp\Big(\alpha_j \sum_{i=1}^{K} s_{i,j,t}\Big) \tag{16}$$

where $p_{j,t}$ is the price of asset j at round t, $s_{i,j,t}$ is the sold amount of asset j until round t by bank i, and α controls the price elasticity. α is chosen such that when all of asset j in the system are sold, the price drops to the price level determined by the *minimum price* parameter of the given asset:

$$\alpha_j = ln(MinimumPrice_j) / \sum_{i=1}^{K} A_{i,j} \tag{17}$$

The losses due to fire sales ($Loss_{fs}$) can be calculated then as the difference in banks' asset values due to the price changes:

$$Loss_{fs} = (p_0 - p_t) \times A_0 \tag{18}$$

After accounting for all the banks, if the amount of the assets compared to the previous iteration changed more then the tolerance parameter ϵ, or some banks have gone below the regulatory requirements, the banking block part of the algorithm restarts. Otherwise, the banking block stops.

4.2 REAL ECONOMY FEEDBACK

Real economy feedback is triggered if any of the banks used corporate credit retrenchment during the adjustment process (similarly to Silva et al. (2018)). Firstly, we calculate the extent of the reduction of these loans in the case of all banks:

$$\Delta Loans_{corp,i} = \frac{(Loans_{corp,i,t_0} - Loans_{corp,i,t})}{Loans_{corp,i,t_0}} \tag{19}$$

where $Loans_{corp,i,t}$ is the size of the corporate loan portfolio (which is maturing within 30 days) of bank i at round t.

As establishing new bank connections is costly (see e.g. Kim et al. (2003)), and during a crisis the credit crunch can be general, bank i's credit retrenchment ($\Delta Loans_{corp,i}$) can be interpreted as a direct credit supply shock for firm j (css_j^0) who needs (re)financing from the given bank. [17]

After determining the credit supply shock experienced by firms directly, we assess the spillover effects happening via the supplier network. The simplest – although from a computational perspective sometimes inefficient – way to represent the firm network is using an *adjacency matrix* (A^F or in the case of weighted networks W^F). In this matrix, $W^F_{m,n}$ corresponds to the traded amount supplied by firm m to firm n.

To account for shock propagation to the upstream direction, we first normalize the weighted adjacency matrix by the output (revenue+activated own performance)[18] of firms in the row dimension:

[17] If a firm is connected to more than one banks, then the credit supply shock the firm faces will be some function of the shocks coming from the banks the firm has connections with. The choice of this functional form is not trivial: using the weighted mean (where the weights are coming from the lending history between the firm and the banks) would imply that firms would have demand towards their bank connections in the same proportion as in their pre-crisis credit mix. However, firms might try to switch between the existing bank connections during a crisis, so taking the minimum of the shocks coming from the existing bank connections seems to be a more realistic assumption.

[18] One could use the rowsums of the weighted adjacency matrix for normalization as well, however, using the output instead makes the interpretation of the results more intuitive.

$$\widetilde{W^F_{us}} = \Gamma \times W^F \tag{20}$$

where $\widetilde{W^F_{us}}$ is the row-normalized matrix representing the supplier network, and Γ is a diagonal matrix containing the reciprocal of the output of each firm.

By multiplying this row-normalized matrix with the vector of credit supply shocks experienced by each firm, we will have a vector representing the weighted sum of the credit supply shocks of the buyers (at one step distance in the network) of each firm css^1_{us}:

$$css^1_{us} = \widetilde{W^F_{us}} \times css^0 \tag{21}$$

where css^0 is the vector of direct credit supply shocks experienced by the firms.

To calculate higher order spillovers we can also determine weighted sum of the credit supply shocks of the buyers of the buyers (so at two steps distance downstream in the network) of each firm css^2_{us}:

$$css^2_{us} = \widetilde{W^F_{us}} \times css^1_{us} \tag{22}$$

We could go even further in the network, however, during the estimation of the coefficients for firms' PDs we have found only shocks coming maximum from two steps distance have significant effect. However, we can consider shock propagation from two steps distance to the downstream direction as well. To calculate these terms we have to make only a slight modification. We have to normalize the weighted adjacency matrix by the output of firms in the column dimension, which can be done by multiplying with the same diagonal matrix, but this time using the transpose of W^F:

$$\widetilde{W^F_{ds}} = \Gamma \times (W^F)^T \tag{23}$$

The calculation of the weighted sum of the shocks coming from the suppliers at distance one and two happens the same way as in the upstream case:

$$css^1_{ds} = \widetilde{W^F_{ds}} \times css^0 \tag{24}$$

$$css^2_{ds} = \widetilde{W^F_{ds}} \times css^1_{ds} \tag{25}$$

As we mentioned in Section 3.3., shocks can reverse directions along the network, which means that they can also spread "horizontally". If we consider only two steps distance again, we have to deal with two types of horizontal shock propagation: (i) In one situation the shock can come from the suppliers of my buyers, (ii) while in the second case it can come from the buyers of my suppliers. We can account for these shocks similarly to the previous calculations. As in the first case the shock goes first downstream and then upstream, it will be denoted by $css_{ds\rightarrow us}$, while the second case is the opposite: $css_{us\rightarrow ds}$. The calculation of each of them is shown by Equations 26-27 respectively.

$$css_{ds\rightarrow us} = \widetilde{W^F_{us}} \times css^1_{ds} \tag{26}$$

$$css_{us\rightarrow ds} = \widetilde{W^F_{ds}} \times css^1_{us} \tag{27}$$

As a next step, we translate the direct and indirect shocks hitting a firm into additional probabilities that a given firm becomes non-performing on its loans. This step is described by Equation 28.

$$\Delta PD_j = css_j^0 \times \beta_{css^0} + css_{us,j}^1 \times \beta_{css_{us}^1} + css_{us,j}^2 \times \beta_{css_{us}^2} + css_{ds,j}^1 \times \beta_{css_{ds}^1} + \\ css_{ds,j}^2 \times \beta_{css_{ds}^2} + css_{ds\rightarrow us,j} \times \beta_{css_{ds\rightarrow us}} + css_{us\rightarrow ds,j} \times \beta_{css_{us\rightarrow ds}} \tag{28}$$

where ΔPD_j is the increase in a firm's probability of becoming non-performing on its loans as a result of the direct and indirect consequences of the credit supply shocks[19]. The β parameters are coefficients showing the effects of one unit increase in the credit supply shock variables. The estimation of these coefficients will be described in Section 5.

To complete the feedback mechanism, we simulate the default of the firms based on their ΔPD and we calculate the losses for each bank on their loans belonging to the defaulted firms. As it is a stochastic procedure, we create 1000 realizations and use the average of them as the actual losses suffered by the banks[20]. Equation 29 shows the losses suffered by bank i on its corporate loan portfolio in one realization round ($Loss_{fb,i,t}$).

$$Loss_{fb,i,t} = \sum_{v=1}^{D} OP_{v\rightarrow i} \times lgd_f \tag{29}$$

where D is the number of firms becoming non-performing in the given realization, OP is the outstanding principal amount of the loan contract between bank i and firm v and lgd_f is the loss given default parameter for corporate loans.

After accounting for all the banks, if the loan losses of any of the banks exceeds the tolerance parameter ϵ, the banking block part of the algorithm is triggered again. Otherwise, the simulation ends.

[19] We concentrate now on the additional PD of banks' clients, as their base PD is accounted for during the normal operation of banks.

[20] We preferred to calculate here the average instead of the median, because the average reflects more the consequences of tail events which we did not want to ignore in the model.

Figure 6
Pseudocode describing the algorithmic structure of the simulation

Algorithm 1 The structure of the simulation

```
while additional feedback losses ≥ ε do

    Banking block:
    while additional losses ≥ ε do
        for banks do
            if (CAR_bank < CAR_regulation) then
                Solvency adjustments
            end
            if (LCR_bank < LCR_regulation) then
                Liquidity adjustments
            end
        end
        Calculating additional losses after bankruptcies
    end

    Feedback block:
    for firms do
        Calculating firm PDs after credit supply shock
        Simulating (1000 times) firms' defaults on their loans
    end
    for banks do
        Calculating additional feedback losses for banks
    end
end
```

Figure 7
Adjustment parameters of the relevant asset classes

	Risk weight	Rank (solvency)	LCR haircut	Rank (Liquidity)	Minimum Price
Central bank claims	0	0	10%	1	100%
Nostro account	0	0	10%	1	100%
Government bonds	20%	1	50%	1	90%
Household loans	50%	2	100%	2	100%
Corporate loans	50%	2	100%	2	100%
Corporate securities	50%	3	100%	3	50%
Mortgage bonds	50%	3	100%	3	50%

5 Estimation of the feedback parameters

The parameters controlling how credit supply shocks influence firms' probability of becoming non-performing would be difficult to determine reliably by expert judgment or based on the experiences of past crises, hence, we attempted to estimate them independently of the model. However, this task has two main challenges: Firstly, the identification of credit supply shocks is far from being trivial, and secondly, we want to estimate not only the direct effects, but also the spillovers via the production network. In the next two subsections we will describe our approaches to deal with these difficulties.

5.1 IDENTIFICATION OF CREDIT SUPPLY SHOCKS

Shocks can influence banks' credit supply and firms' credit demand simultaneously, thus, the observed change in lending amount cannot be considered the change of supply only. There are two typical strategies to handle this well-known endogeneity problem. When it is possible, researchers can use natural or quasi-natural experiments, such as an unexpected policy change, a nuclear accident or a natural disaster for identification. (See e.g. Khwaja and Mian (2008), Banerjee and Duflo (2014), Chodorow-Reich (2014) and Dörr et al. (2018).) The main advantage here is the strongly credible exogeneity of the shocks. However, it is often not possible to find or quantify such exogenous shocks, in which cases one can use only more indirect identification strategies. An indirect approach which gained popularity recently was developed by Amiti and Weinstein (2018). Their method uses matched firm-bank loan data, where the identification is based on the observation of firms with multiple bank connections in different time periods. Although this approach has weaker internal and external validity, it does not require to find a suitable instrument. Furthermore, by imposing adding-up constrains this procedure has the additional advantage to ensure consistency with the aggregate lending dynamics. This, or similar solutions were applied by e.g. Chava and Purnanandam (2011), Schnabl (2012), Jiménez et al. (2012), Dwenger et al. (2015), Amador and Nagengast (2016) and Degryse et al. (2017).

As the time window in which we observe both the Hungarian firm network and the loan contract data is relatively short, we had only very limited opportunities to find a suitable exogenous shock which we can use for identification. This period (2015-2017) was without major turbulences in the Hungarian banking sector, however, there were some policy measures which we attempted to exploit to identify the supply side of the corporate credit market.

The Hungarian Central Bank launched a program in 2015 called Market-based Lending Scheme (MLS) to stimulate economic growth by supporting banks' lending activity[21]. Within the framework of the MLS, the central bank offered two instruments: The first incentive was that the banks could hedge their lending-related interest rate risk by an interest rate swap (LIRS) offered by the central bank to incentivize banks to grant longer-term, fixed-rate SME loans. Additionally to the LIRS, a preferential deposit facility was also introduced to support banks' liquidity management.

However, there was a condition for banks if they wanted to participate in the MLS: By having recourse to the LIRS instrument, banks had to make an implicit commitment to increase their net lending to small and medium-sized enterprises by an amount equalling one fourth of the allocated LIRS. During the programme, the central bank concluded LIRS transactions amounting to a total € 2.2 billion with 17 credit institutions, which means the undertaking of an SME loan expansion of nearly € 550 million by the banks participating in the programme (Figure 8). As this means an ex ante dedication to future lending, it can be interpreted as a proxy for banks' credit supply. Banks made such commitments for 2016 and 2017 as well, which makes it possible to use this as a credit supply shock indicator in our estimation[22].

[21] The description of the MLS is based on Box 5 in the 2016 May *Financial Stability Report* of the Hungarian Central Bank, where further details can also be found. (https://www.mnb.hu/en/publications/reports/financial-stability-report/financial-stability-report-may-2016)

[22] Although the MLS program created a positive loan supply shock, we are assuming that a negative shock would have similar effect to the opposite direction.

A potential concern might arise due to the possibility that the variation in the commitment decisions of banks could be influenced to some extent by their anticipation of credit demand towards them. While this effect cannot be completely dismissed, it probably plays only a negligible role in the variation of the commitments. Although there are a few banks among the largest nine banks in Hungary (which were included in our model) which have some specialization (e.g. some banks are stronger in the household segment, others in the corporate market), however, even in their cases it is unlikely to experience very different demand from their SME clients as banks' specialization is not based on such firm characteristics (e.g. their industry) which could justify relevant differences in credit demand dynamics. Furthermore, the examined period can be considered free from serious economic turbulences in Hungary, thus, even if there were dissimilarities in banks' expectations concerning demand factors, these are more likely to be the result of the uncertainty of these kind of forecasts. However, as robustness check to the MLS shocks, we also performed the indirect method of Amiti and Weinstein (2018) following the implementation of Amador and Nagengast (2016). Further details of this methodology are described in Appendix A, where we also compare the outcomes of the regressions which are using different credit supply shock variables.

5.2 ESTIMATION OF DIRECT AND INDIRECT EFFECTS

To represent the network-based interactions among firms, we turned to estimation techniques coming from the spatial econometrics literature. This branch traditionally deals with spatially structured data, however, the same methods can be applied to capture more abstract interaction structures, such as the production network of firms. (For a detailed review of the field see e.g. Elhorst (2014).) Spatial estimation models usually display the dependence among the observations using the so-called spatial weight matrix (W), which makes it possible to represent units affecting each other mutually. In our case the spatial weight matrix is analogous to the normalized supplier exposure matrices.

Three basic types of spatial interaction models can be distinguished: (i) the spatial autoregreesive (SAR) model, (ii) the spatial error model (SEM) and (iii) the exogenous interaction (SLX) model. As the mechanisms modeled by each of these techniques can be present simultaneously, more complicated models were also developed to combine the different spatial interactions. Equation 30 shows a general formulation containing all of these potential spatial terms in matrix form:

$$Y = \rho WY + X\beta + WX\zeta + u \tag{30}$$

where Y is the dependent variable (e.g. the default of a firm's loans), W is the supplier exposure matrix, X is the matrix of explanatory variables (most importantly for us the credit supply shock) and

$$u = \lambda W + \epsilon$$

where

$$\epsilon \sim i.i.d.$$

The term ρWY represents the SAR part for which the interpretation would be that a given firms' probability of becoming non-performing depends on its buyers' or suppliers'[23] probability of becoming non-performing on their loans. The λW is the SEM term referring to shocks which would jointly affect firms that are connected to each other in the supplier network. Finally, $WX\zeta$ is the SLX term implying that firms' probability of becoming non-performing depends on its partners' independent variables, most importantly on their credit supply shock. As this last term is exactly what we are interested in for the model, we formulated a panel logit SLX specification without including the other types of spatial interactions (Figure 9). This way we assumed that (i) in the examined period there were no significant correlated shocks affecting firms based on their supplier connections, and (ii) the credit supply shocks did not spread through any other unobserved channels.

This relatively simple framework makes it possible to flexibly include further time and spatial lags, and even more than one spatial weight matrices. As $W_{i,j}$ is defined as firm i sells to firm j, than the matrix $W^k X$ would represent shock spreading to the upstream direction from distance k, while $(W^T)^k X$ would mean shock propagation to the downstream direction from distance

[23] It depends on whether we are using W, or W^T.

k. By including these matrices up to $k = 4$ in the estimation[24], we can have separate coefficients for different spatial lags for upstream, downstream and horizontal contagion as well.

To avoid any concerns about the potential endogeneity of the supplier exposure matrices, we are exploiting the time dimension of the data by using the one-year lagged versions of them. As we are considering only long-term supplier connections, the usage of the lagged versions does not cause significant information loss, but it can assure that the endogenous nature of link formation will not interfere with the spreading process.

A further difficulty which needs to be addressed is the handling of firms without loans. Ignoring them completely during the estimation would also mean their removal from the supplier network. However, even if a firm does not have any bank connection, and cannot experience credit supply shocks directly, it still can have a role in propagating shocks which were originated elsewhere in the production network. In order to preserve these pieces of information, we delete these firm only after calculating all the higher order matrices. This way we can retain all the indirect pathes between firms even if we disregard firms without loans during the estimation.

After taking into account all the considerations above, we arrive at our final specification, which gives estimates for all the parameters in Equation 31:

$$\begin{aligned} NP_t = \beta_0 + \beta_{css} CSS_t + \sum_{k=1}^{4} \left[\beta_{css^k_{us}} (\widetilde{W^F_{us,t-1}})^k CSS_t + \beta_{css^k_{ds}} (\widetilde{W^F_{ds,t-1}})^k CSS_t \right] + \\ \beta_{css_{ds\to us}} CSS_{ds\to us,t} + \beta_{css_{us\to ds}} CSS_{us\to ds,t} + X_t \beta_{controls} + \epsilon_t \end{aligned} \tag{31}$$

where NP_t is a dummy variable indicating whether a firm became non-performing (defined as more than 90 days delinquency) in the given year. In the estimation we included as controls firms' revenue, ROA, liquidity buffer, size category, the export share of their revenue and a dummy variable indicating state owned companies. Furthermore, we added fixed effects for firms' industry, regional location and for the year.

According to the results (Figure 10), the impact of credit supply shocks can be significant even two steps away in the supplier network. Although in the case of upstream propagation, p-values are a bit higher at distance two from the source of the shocks, we included even this level of spreading in the model as they are not that far away from the significance levels of the downstream case. However, in the case of distance three and four there is no indication of any effect of the credit supply shocks. Regarding the horizontal channels, our results indicate significant spreading only when the shock is firstly transmitted towards a supplier and then to another buyer of that supplier, but not for the reverse situation, so in the end we excluded the $css_{ds\to us}$ channel by setting its parameter to zero in the model.

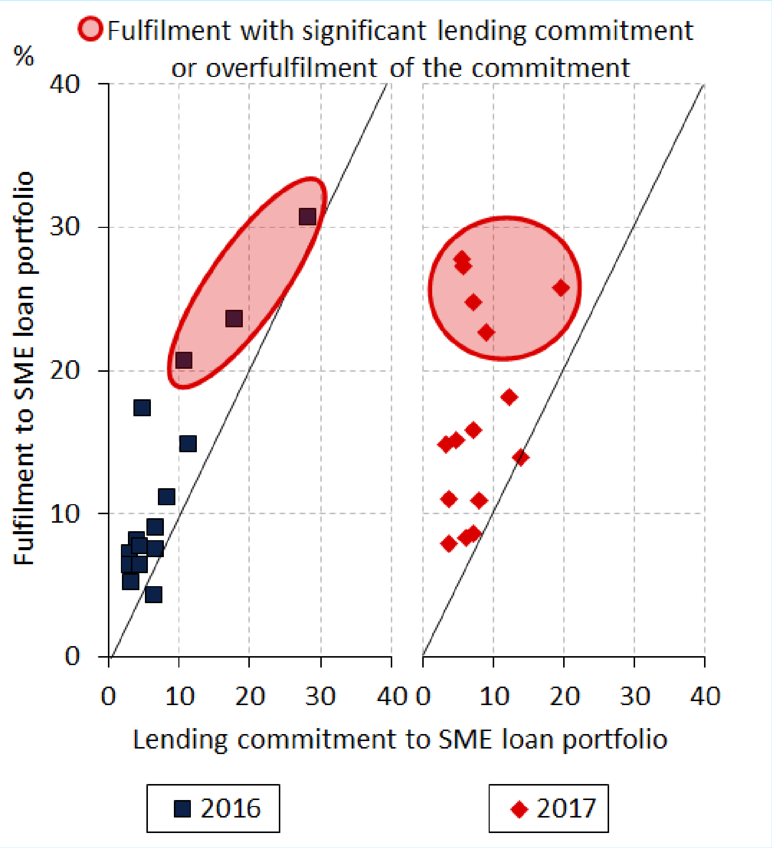
Since the coefficients of our estimation are odds ratios which cannot be used directly as parameters in the model, we had to calculate the marginal effects to obtain interpretable results. After this step, we arrive at the final feedback parameters (Figure 11):

As a robustness check, we performed the same estimation using the indirect credit supply shock variable as well. Although in this case we had significant results only for the one-step downstream shock spreading with the indirect shocks, and the marginal effects were somewhat different as well, the overall impact of the credit supply shocks were similar to that of the main specification. We show this in Appendix A using the application described in Section 6.1 as an illustration.

A further important consideration could be that the parameter values in Table 3 were estimated using data on yearly frequencies, however, some applications of the model might require a shorter time scale for the simulation. In these situations we adjusted the parameters proportionally; e.g. if we considered only a three months time window (for instance in the liquidity stress test in Section 6.1), we divided the parameters by four to handle the mismatch with the estimation.

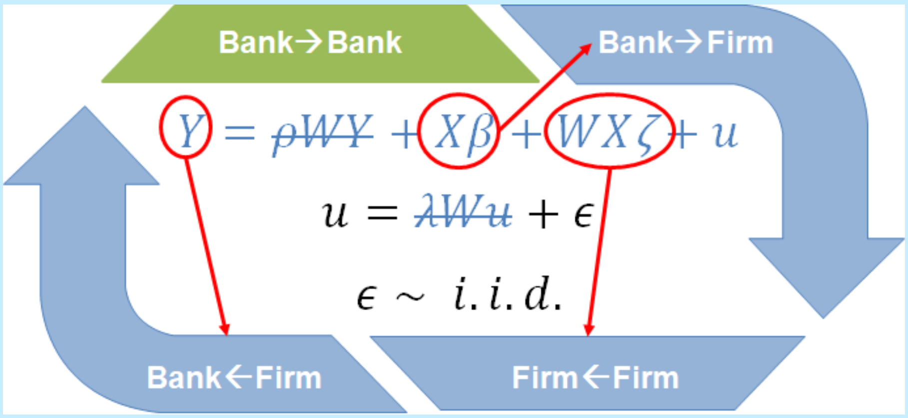
[24] As the average shortest path length of the production network is 4.9 with a standard error as low as 1.1, investigating four steps in both upstream and downstream directions is sufficient to cover the vast majority of potential shock propagation.

Figure 8
Banks' commitments and fulfillments in the MLS program



Source: Central Bank of Hungary.

Figure 9
Connections between the model and the estimated parameters



The different terms of the SLX model framework capture all the mechanisms which are relevant for the model. $X\beta$ refers to the direct effect of credit supply shocks, while $WX\zeta$ captures the spreading of the shock on the production network.

Figure 10
Regression results

	Dependent variable:					
	Probability of default on loans					
	Logit (1)	Logit (2)	Logit (3)	Logit (4)	Logit (5)	Logit (6)
css^0	−0.030** (0.012)	−0.028** (0.012)	−0.029** (0.012)	−0.028** (0.012)	−0.028** (0.012)	−0.028** (0.012)
css^1_{us}		−0.070*** (0.022)	−0.055** (0.023)	−0.058** (0.024)	−0.057** (0.024)	−0.060** (0.025)
css^1_{ds}		−0.121*** (0.033)	−0.068* (0.038)	−0.073* (0.039)	−0.065* (0.039)	−0.035 (0.042)
css^2_{us}			−0.079 (0.057)	−0.105 (0.068)	−0.111 (0.070)	−0.110 (0.072)
css^2_{ds}			−0.245** (0.105)	−0.307** (0.143)	−0.352** (0.145)	−0.306** (0.147)
css^3_{us}				0.099 (0.143)	0.113 (0.193)	0.098 (0.193)
css^3_{ds}				0.219 (0.336)	−0.153 (0.426)	−0.164 (0.431)
css^4_{us}					−0.058 (0.469)	−0.037 (0.469)
css^4_{ds}					1.088 (0.737)	1.137 (0.739)
$css_{ds\to us}$						0.030 (0.052)
$css_{us\to ds}$						−0.104* (0.055)
Constant	−5.124*** (0.405)	−5.119*** (0.407)	−5.125*** (0.408)	−5.126*** (0.408)	−5.128*** (0.408)	−5.117*** (0.409)
Year dummies	✓	✓	✓	✓	✓	✓
Industry dummies	✓	✓	✓	✓	✓	✓
Location dummies	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	91,528	91,528	91,528	91,528	91,528	91,528
Log Likelihood	-7,863.209	-7,847.722	-7,843.375	-7,842.913	-7,841.987	-7,839.985
Akaike Inf. Crit.	15,796.420	15,769.440	15,764.750	15,767.830	15,769.980	15,769.970
Note:	Clustered-robust standard errors is brackets. *p<0.1; **p<0.05; ***p<0.01					

Figure 11
Average marginal effects of the estimated feedback parameters

css^0	css^1_{us}	css^1_{ds}	css^2_{us}	css^2_{us}	$css_{us\to ds}$	$css_{ds\to us}$
0.0008	0.0013	0.0007	0.0010	0.0051	0.0900	0.0000

6 Applications

Since the primary objective of this model is to offer a versatile tool for various policy analyses, we present here three potential applications: (i) Firstly, we embedded the model into a liquidity stress testing framework, (ii) then we elaborated a way to use it for SIFI identification, and lastly (iii), we show an example of assessing the impact of shocks originated in the real economy.

6.1 EMBEDDING THE MODEL INTO A LIQUIDITY STRESS TEST

As one of the first applications, we embedded the model to the liquidity stress testing framework of the Hungarian Central Bank. This liquidity stress test has been featuring contagion channels in the banking system since 2016, however, we could add now a unified shock propagation modeling block with feedback mechanisms from the real economy. During the implementation we used the standard stress scenario of the liquidity stress test (presented in the central banks' biannual Financial Stability Reports), which is a complex exogenous shock calibrated to the 2008 crisis (Figure 12).

When we ran the stress test simulation using only a limited version of the framework which did not contain any contagion mechanisms, only one out of the nine largest banks was unable to comply with the LCR during the stress scenario. If we enabled for contagion channels in the banking block only, two out of the nine largest banks have become unable to comply with LCR even with using adjustment opportunities. In this case, an additional € 258 million fire sales loss and € 5 million interbank loss occurred in the banking system. After enabling the real economy feedback channels as well, 0.5% of the firms in the model went bankrupt causing € 184 million loss for banks on defaulting loans. Furthermore, losses due to fire sales further increased by € 41 million, and a third bank went below the regulatory requirement, but this time it happened due to solvency insufficiency. Although it is still the fire sales channel which is responsible for the largest chunk of banks' losses in the simulation, the real economy feedback contributes by almost the same extent. We also noticed that the loss-based ranking of the banks has changed as well after we enabled the feedback mechanisms. (Figure 13)

From the point of view of systemic risks and financial stability, it is clear that ignoring the feedback mechanisms can lead to the severe underestimation of risks and potential losses in this shock scenario. Furthermore, while the interlacing between the liquidity and the solvency problems was largely hidden in the reduced stress testing frameworks, the real economy feedbacks made this aspect also more pronounced. Additionally, by including the feedback channels we can gain some insight into the impacts of a banking sector liquidity shock on the non-financial firms as well. (Although we do not claim that the model is capable of giving a full picture about all the consequences of the stress scenario on the real economy.)

6.2 SIFI IDENTIFICATION BASED ON SHAPLEY VALUE

The problem of identifying systemically important financial institutions (SIFIs) has been dealt with by numerous papers, among which we relied in this exercise on those using the concept of Shapley value (Tarashev, Drehmann, et al. (2011), Bluhm et al. (2014), Aldasoro et al. (2017)). Shapley value is a concept originated in game theory, and it was developed to allocate the outputs generated in cooperative games among agents (Shapley (1953)).

The typical technique how the Shapley value is applied for SIFI identification is to calculate the difference between the system-wide losses occurring after a shock event with and without the participation of a given bank in the simulation of the banking system. We calculated this difference for the idiosyncratic default of each bank, however, Shapley value in its original form would require to repeat this calculation for all the possible subsystems of the banking system ($f(N^{SUB}) - f(N^{SUB} - i)$). The actual Shapley value would be then the average of the additional losses that a bank generates by participating in any subsystem of the bank network:

$$Shapley_i = \frac{1}{n} \sum_{n_s=1}^{n} \frac{1}{c(n_s)} \sum_{N^{SUB} \supset i} \left[f(N^{SUB}) - f(N^{SUB} - i) \right] \quad (32)$$

where $Shapley_i$ is the Shapley value of bank i, $N^{SUB} \supset i$ denotes all the subsystems that contains bank i, n_s means the number of banks in a given subsystem and $c(n_s) = \frac{(n-1)!}{(n-n_s)!}(n_s - 1)!$ is the number of subsystems containing bank i and are comprised of n_s banks.

Due to computational constraints, we did not perform the calculations for all the subsystems, only for the whole bank network[25]. This way, our Shapley-based measure for bank i is the average difference between the aggregate system-wide losses (caused by the idiosyncratic default of each bank occurring one by one) with and without the presence of the bank in interest[26]:

$$SIFI_i = \sum_{\substack{m,n \\ m \neq n}}^{N} S_{m,n} - \sum_{\substack{p,q \\ p \neq q}}^{N-1} S_{p,q}^{-i} \tag{33}$$

where S is an $N \times N$ matrix, in which N denotes the number of banks, and $S_{m,n}$ is the losses suffered by bank n after the exogenous default of bank m. S^{-i} is an $(N-1) \times (N-1)$ matrix which contains the losses occurring without the participation of bank i in the system. The main diagonals of these matrices are ignored in this application.

In order to gain more detailed insight in the sources of systemic risk for each bank, we present our SIFI measure decomposed into three factors:

- System-wide losses due to a given bank's default:

$$DamagingPotential_i = \sum_{n \neq i}^{N} S_{i,n} \tag{34}$$

- A given bank's losses due to other banks' defaults:

$$Vulnerability_i = \sum_{m \neq i}^{N} S_{m,i} \tag{35}$$

- Other banks' extra losses due to the amplification of the impact of other banks' defaults by bank i:

$$Amplification_i = \sum_{m \neq i}^{N} \sum_{n \neq i}^{N} S_{m,n} - \sum_{p=1}^{N-1} \sum_{q=1}^{N-1} S_{p,q}^{-i} \tag{36}$$

The importance of these factors can vary across the examined banks. (Figure 14) There are banks, whose systemic importance comes from their vulnerability to shocks. Other banks might be resilient from this aspect, but their default can cause severe damage in the banking system. The amplification component has notable role only in the case of one examined bank, which indicates that either the complexity of the Hungarian bank network was not high enough (in 2017) to make it possible for a bank to cause severe damage only by transmitting losses, or at least the assumed idiosyncratic shocks were too weak to trigger cascading failures.

6.3 IMPACT ASSESSMENT OF REAL ECONOMY SHOCKS

Our model contains elaborated details only for the banking system, but not about any other sector of the economy. However, in a limited form it might still be possible to examine the effects of shocks coming from the real economy if we keep in mind

[25] Castro et al. (2017) proposed a polynomial method using stratified random sampling with optimum allocation to estimate the Shapley value, however, for our purposes it is more advantageous to simply ignore the subsystems since we are more interested in the importance of institutions when the whole system is present.

[26] When a bank is deleted from the system, all the links attached to it will be removed as well. To avoid interference with the simulation of the model, we assumed that the banks which borrowed from the removed institution can replace their interbank funding with other financing sources offering the same conditions, while the assets of the removed bank are reallocated to agents outside of the model.

that in this framework, shocks have to be translated into the change in firms' probability of becoming non-performing. This way we can capture only the credit loss and the supply chain contagion aspects of real economy shocks, which is far from being a complete assessment. With this caution in mind, we attempted to assess the consequences of shocks originated in certain industries on the banking system. A recent example of an unexpected stress event can be the COVID-19 pandemic, which had very severe impact on some industries whose firms could transmit the shock to other industries, and to the banks as well.

As a first step in this analysis we identified the most vulnerable industries to this shock using four-digit NACE categories. Most of the affected sectors in Hungary belong to the manufacturing, wholesale and retail trade, transporting, storage, accommodation, food service activities, real estate activities, administrative and support service activities, arts, entertainment, recreation and other services activities. (A detailed table about the affected sectors can be found in Appendix B.) We assumed that these directly affected firms have 100% susceptibility for being hit by the shock, which means the maximum exposure to the shock.

After the identification of the most involved sectors, we calculated the indirect exposures (up to four steps) to these industries in each firm's revenue. (E.g. if 20% of firm A's revenue comes from buyers belonging to the directly affected sectors, then firm A's exposure will be 20%. If there is another buyer of this firm, which is responsible for another 20% revenue and it has 50% exposure, then the vulnerability of firm A will be $20\% + 10\% = 30\%$.) During this procedure we did not include the directly affected firms as they have reached already the maximum level of involvement with the crisis[27]. To acknowledge some heterogeneity among firms, we corrected their exposure with firms' potential liquidity buffers[28]. We calculated these buffers in the proportion of their revenue as well, so we could simply subtract it from the exposure measure.

As we estimated only the parameters governing shock spreading and feedback in the case of credit supply shocks (which would not be applicable here), we had to make some assumptions about the connection between this shock and firms' probability of becoming non-performing. If the final value of the exposure was 100%, or a firm operates directly in some of the affected sectors, we increased the probability of becoming non-performing by ΔPD percentage points. If the vulnerability was below 100%, we decreased the ΔPD parameter proportionally. These PD values could be directly fed into the model as inputs to simulate the effects of this shock. As we do not know the exact value of ΔPD, we ran the simulation ten times increasing it by five percentage points each time.

Figure 15 shows the number of lost jobs due to the defaulting firms, and the losses of the banking sector in the case of different values of the ΔPD parameter. Figure 16 illustrates the losses separately for the nine largest Hungarian banks[29]. If one considers the direct scenario, the banking system could suffer a loss of more than € 1.1 billion, which is equivalent to almost 13% of the equity in the banking system.

Other shocks coming from the real-economy could be included in a similar fashion, however, for the sake of reliable interpretation of the results, it is necessary to thoroughly explore the connection between firms' exposure to the shock and their probability of becoming non-performing on their loans. In the case of the COVID-19 crisis, we do not have yet the necessary statistics to make confident assumptions in this aspect, however, the results can still indicate a plausible range for the expected consequences.

[27] It also means that directly affected firms cannot amplify shocks further. E.g. if a firm has a buyer belonging to one of the directly hit industries, and this buyer is responsible for 10% of the firm's revenue, then there cannot be second, or higher order contagions through the same buyer, as the whole 10% exposure has been already taken into account as vulnerability.

[28] We calculated basically the quick liquidity ratio with a slight modification: We took the difference between the numerator and the denominator from the original formula.

[29] Since our data are about 2017, the results should also be interpreted as if the shock had happened in 2017.

Figure 12
Components of the liquidity stress scenario of the Hungarian central bank

Assets			Liabilities		
Item	Degree	Currencies affected	Item	Degree	Currencies affected
Exchange rate shock on derivatives	15 per cent	FX	Withdrawals in household deposits	10 per cent	HUF/FX
Interest rate shock on interest rate sensitive items	300 basis points	HUF	Withdrawals in corporate deposits	15 per cent	HUF/FX
Calls in household lines of credit	20 per cent	HUF/FX	Withdrawals in debt from owners	30 per cent	HUF/FX
Calls in corporate lines of credit	30 per cent	HUF/FX			

Figure 13
Results for the nine largest banks in Hungary (based on 2017 data).

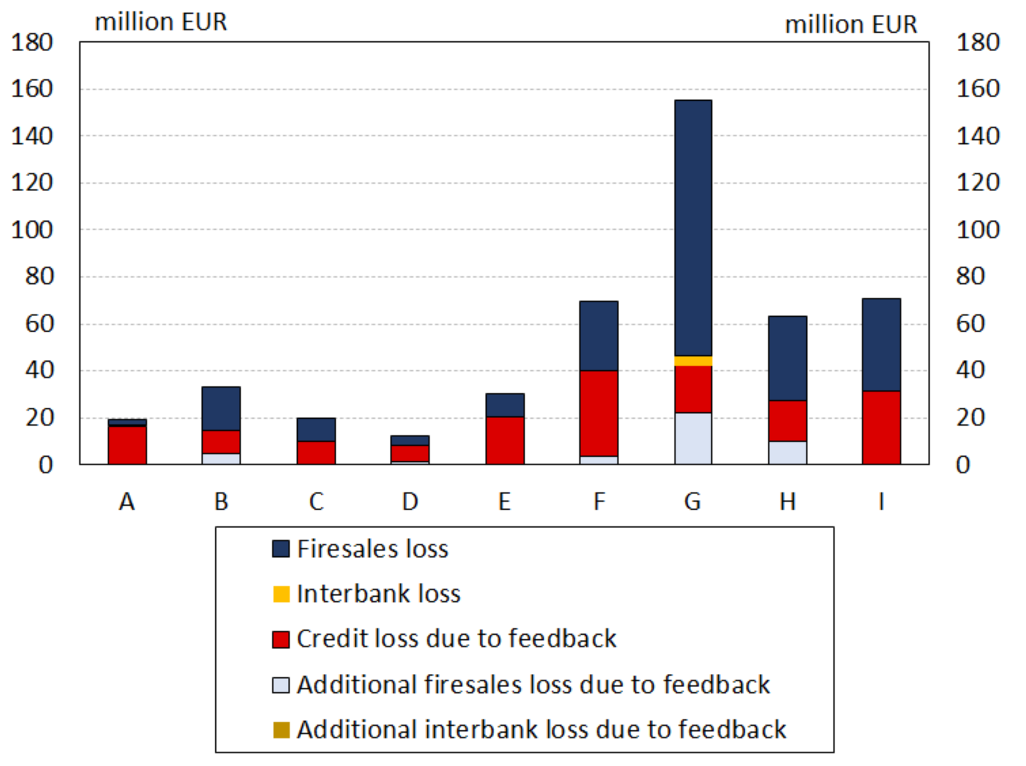
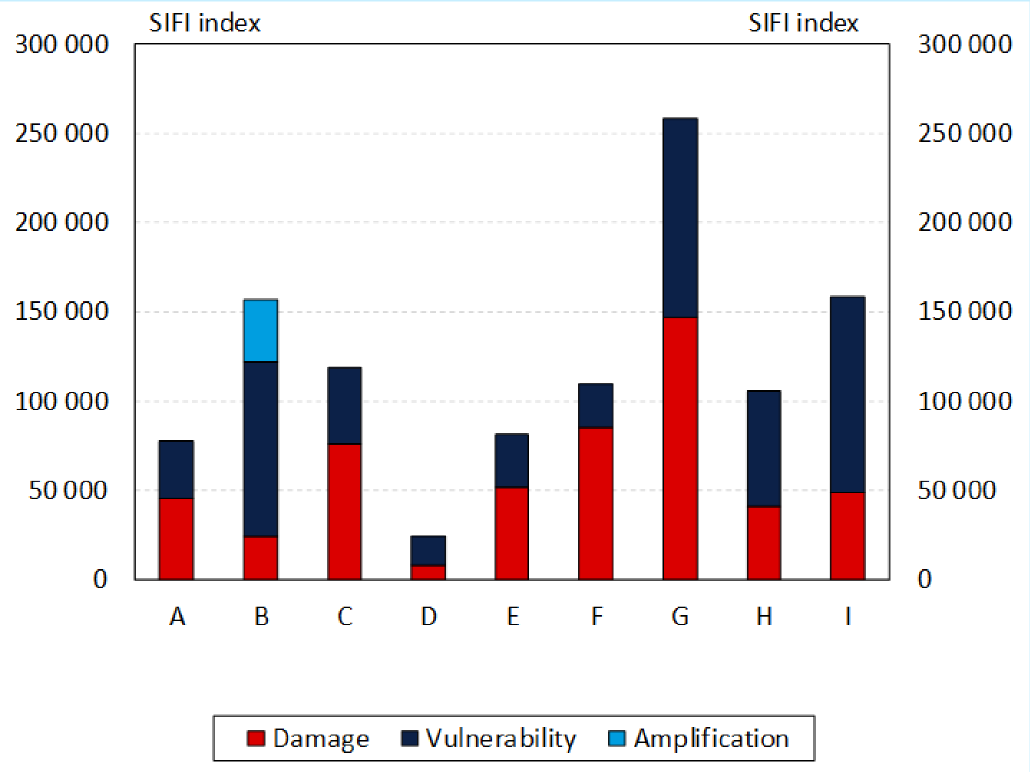


Figure 14
Decomposed SIFI index of the nine largest banks (2017)



Although the units of this SIFI index are expressed in Hungarian Forint, they would be difficult to interpret as amounts of money since they are the sums of the differences between aggregate losses in the case of multiple scenarios.

Figure 15
The number of lost jobs and the losses of the banking sector in the case of different values of the Δ*PD* parameter.

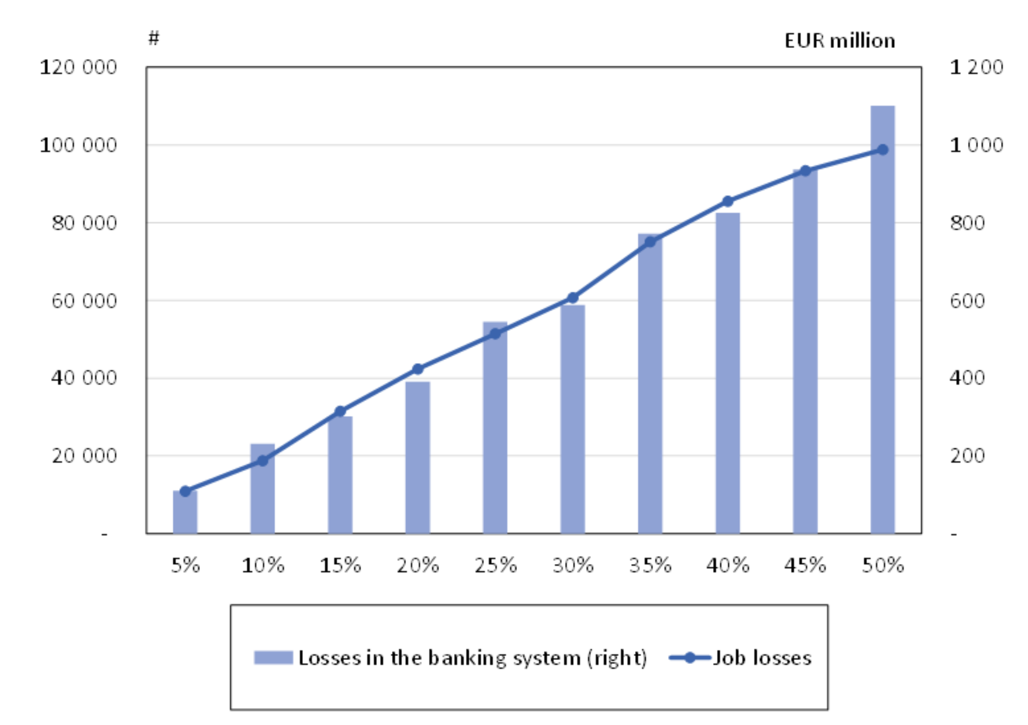
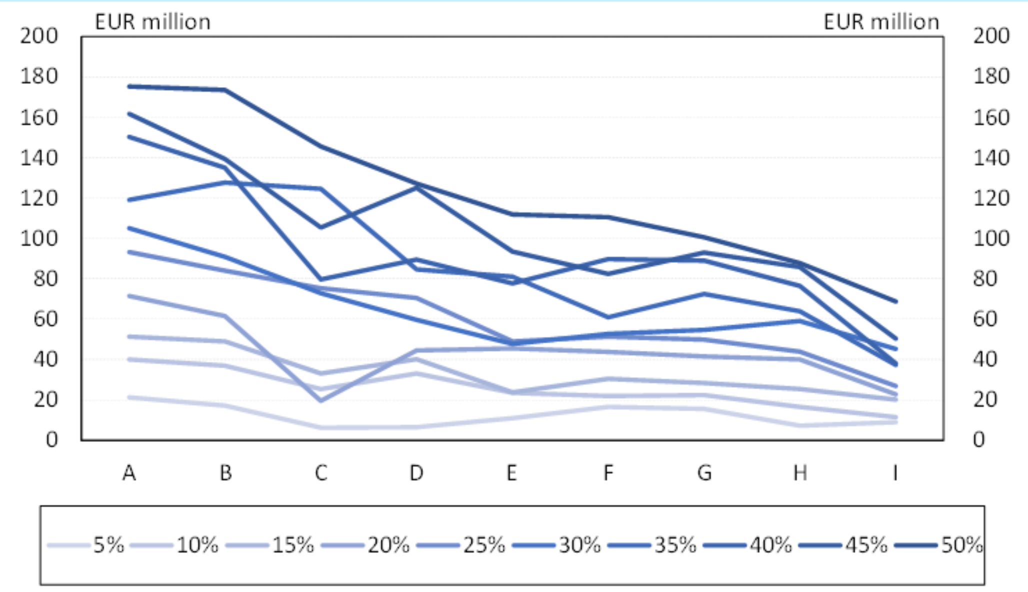


Figure 16
Losses of the nine largest Hungarian banks in the case of different values of the Δ*PD* parameter.



7 Conclusion

The main objective of this research project was to create a modeling framework to analyse the financial stability of an economy in a microsimulation environment which is suitable to capture contagious mechanisms in an interconnected system of economic networks. More specifically, we were focusing on the interactions between the network of banks (exhibiting contagious mechanisms among them) and the network of firms (transmitting shocks to each other along the supply chain) which systems are linked together primarily via loan-contracts.

In order to build an implementation of this microsimulation environment we obtained access to several detailed datasets describing the links, nodes and attributes in these economic networks. Among these rarely available pieces of information the most unique is probably the transaction level data about the supply chain connections between Hungarian firms, which made it possible to model shock propagation even on the production network.

Our hypothesis was, that the feedback mechanisms in these coupled networks could amplify the losses in the economy beyond the shortfalls expected when we consider the interacting subsystems in isolation. As a first test for this, we embedded the model into the liquidity stress testing framework of the Central Bank of Hungary, and our results proved the importance of the real economy feedback channel, without which systemic risks could potentially be severely underestimated. The inclusion of this feature did not only doubled the system-wide losses, but it also made the connection between liquidity and solvency problems more pronounced. To illustrate the versatility of this modeling framework, we presented two further applications for different policy purposes. (i) Firstly, we elaborated a way to use it for SIFI identification, which showed us that the source of the systemic importance of banks can greatly vary between the damaging potential of their default and their vulnerability to shocks coming from other banks, and (ii) secondly, we showed an example of assessing the impact of shocks originated in the real economy. By using the example of the COVID-19 pandemic as a shock to some industries, we calculated that in the worst scenario the losses in the banking sector can reach up to more than € 1.1 billion, while almost 100 thousand jobs could be lost in the economy.

Given the wide range of potential further applications, a more elaborated embedding of the financial system in the real economy would be desirable. Our framework could be extended in several directions. Regarding the financial sector we only included banks but no other financial institutions (such as the insurance sector, investment funds or central clearing counterparties), which can contribute greatly to the complexity of the economy. However, our representation of the real economy was even more simplified. A significant upgrade would be to model the operation of firms more mechanistically instead of our statistical approach. It would make it possible to reflect on the now missing credit demand component, and one could also include shocks coming from outside the financial sector more realistically. In a more general model it would even be possible to generate endogenous shocks[30]. However, in parallel with these opportunities one should also be aware of some pitfalls during the elaboration of more and more details of the economy in this data-driven simulation environment. This line of research would lead to the territory of agent-based macroeconomic models, for which one of the greatest challenges is to create detailed models, but preserve their tractability to avoid becoming unfathomable "black boxes". Furthermore, as it is apparent in our work, the development of these models should go hand in hand with the advancement of the empirical literature which produces vital inputs for essential parameters.

[30] Nowadays researchers usually impose exogenous stress calibrated to a crisis event to see how the modelled mechanisms respond. However, in reality, these mechanisms are also responsible for the shocks growing to the observed extents.

8 Appendix

8.1 APPENDIX A – INDIRECT CREDIT SUPPLY SHOCK IDENTIFICATION

For the sake of tractability we start the description of this estimation by showing a general modeling specification for the problem. If one assumes that the credit demand of a multi-bank firm changes the same way towards all of its partner banks, than the percentage difference between the changes in the amounts of credits can be attributable to supply side factors (Figure 17).

In this case, the lending Ψ_{fbt} between bank b and firm f at time t can be decomposed into supply (β_{bt}) and demand factors (α_{ft}):

$$\frac{\Psi_{fbt} - \Psi_{fb,t-1}}{\Psi_{fb,t-1}} = \alpha_{ft} + \beta_{bt} + \epsilon_{fbt} \tag{37}$$

where we assume that the expected value of the error term is zero, $\mathbf{E}[\epsilon_{fbt}] = 0$. α_{ft} captures all firm-specific characteristics and shocks which can affect its borrowing, while β_{bt} comprises all the bank-specific factors which can have an impact on the credit supply of a given bank. Although Equation 37 could be directly estimated on our data coming from the credit registry, Amiti and Weinstein (2018) highlighted that this formula ignores the aggregate equilibrium on the lending market. That is, firms can only obtain new loans if a bank is willing to provide that credit; and similarly, banks can increase their lending activity only if there are firms soaking up the additional supply. They offer an alternative formulation which corrects for this inefficiency and allows us to consider newly formed loan contracts as well. According to this, the growth in a given bank's lending D^B_{bt} can be expressed as the supply of the bank plus the weighted sum of its client firms' demand, where the weights are the share a given firm had in the bank's lending in the previous period:

$$\begin{aligned} D^B_{bt} &= \sum_f \left(\frac{\Psi_{fbt} - \Psi_{fb,t-1}}{\Psi_{fb,t-1}}\right) \times \frac{\Psi_{fb,t-1}}{\sum_f \Psi_{fb,t-1}} \\ &= \beta_{bt} + \sum_f \phi_{fb,t-1} \times \alpha_{ft} + \sum_f \phi_{fb,t-1} \times \epsilon_{fbt} \end{aligned} \tag{38}$$

where

$$\phi_{fb,t-1} = \frac{\Psi_{fb,t-1}}{\sum_f \Psi_{fb,t-1}} \tag{39}$$

Analogously, the growth in a given firm's borrowing D^F_{ft} is the composition of its own demand and the weighted sum of the supply of its partner banks:

$$\begin{aligned} D^F_{ft} &= \sum_b \left(\frac{\Psi_{fbt} - \Psi_{fb,t-1}}{\Psi_{fb,t-1}}\right) \times \frac{\Psi_{fb,t-1}}{\sum_b \Psi_{fb,t-1}} \\ &= \alpha_{ft} + \sum_b \theta_{fb,t-1} \times \beta_{bt} + \sum_b \theta_{fb,t-1} \times \epsilon_{fbt} \end{aligned} \tag{40}$$

where

$$\theta_{fb,t-1} = \frac{\Psi_{fb,t-1}}{\sum_b \Psi_{fb,t-1}} \tag{41}$$

As $\phi_{fb,t-1}$ and $\theta_{fb,t-1}$ are determined directly from the data, we can make similar assumptions about the error terms as before: $\mathbf{E}\left[\sum_f \phi_{fb,t-1} \times \epsilon_{fbt}\right] = 0$ and $\mathbf{E}\left[\sum_b \theta_{fb,t-1} \times \epsilon_{fbt}\right] = 0$. With these moment conditions we arrive at a system of linear equations with α_{ft} and β_{bt} as unknowns:

$$D^B_{bt} = \beta_{bt} + \sum_f \phi_{fb,t-1} \times \alpha_{ft} \tag{42}$$

$$D^F_{ft} = \alpha_{ft} + \sum_b \theta_{fb,t-1} \times \beta_{bt} \tag{43}$$

Although this system consists of the same number of equations and unknowns (which is equal to the number of banks plus the number of firms) in every year, the system is still under-determined as the sum of the shares in lending are equal to one ($\sum_f \phi_{fb,t-1} = 1$ and $\sum_b \theta_{fb,t-1} = 1$). To be able to find a unique solution, we have to impose an additional constraint, which can be handled analogously to the dummy variable trap problem by choosing a reference category. To obtain economically interpretable results, we transformed α_{ft} and β_{bt} by subtracting their median respectively in every year. (This implies, that banks' credit supply shocks can only be compared to each other within the given year. However, since we also include time fixed effects, this concern is not problematic as the time-specific components are removed from the banks' shocks.) The transformation gives us the following expression for the banks:

$$D^B_t = (\bar{A}_t + \bar{B}_t)\iota_B + \Phi_{t-1}N_t + \Phi_{t-1}\widetilde{A}_t + \widetilde{B}_t \tag{44}$$

where D^B_t is a vector containing the loan growth rates of banks at time t, $(\bar{A}_t + \bar{B}_t)$ are the median firm and bank common shocks, which would affect all firm-bank pairs the same way in year t. ι_B is a vector of ones, N_t is the vector of the average industry-level shock for all the firms, and Φ_t is the matrix of weights of all the loans of every borrowers:

$$\Phi_t = \begin{bmatrix} \phi_{11,t} & \cdots & \phi_{F1,t} \\ \vdots & \ddots & \\ \phi_{1B,t} & & \phi_{FB,t} \end{bmatrix}$$

The first term in Equation 44 represents common shocks, e.g. a change in the key interest rates by the central bank, which would affect all lending connections. The second term shows industry-level shocks to a given banks' clients. It captures changes in a bank's lending coming from its specialization to some industries, which can make its lending activity differ from the general trend. The third term can be interpreted as the change in the bank's lending due to idiosyncratic firm-level demand shock. Lastly, the fourth term represents the credit supply shock of a bank which is independent from all the above listed influences, so we can use it as a credit supply shock variable in our estimation of feedback effects. Since this term was expressed as the deviation from the median bank's supply shock in year t, its interpretation is also relative to this median. This way, the zero value of the credit supply shock does not mean unchanged lending activity, but rather the median change in the system in a given year. If a bank decreases its lending by 20%, but all the other banks' lending drops only by 15%, than the credit supply shock of the given bank will be 5%.

The described methodology of Amiti and Weinstein (2018) is based on firms with multiple bank connections, regarding which we made a slight modification following Degryse et al. (2017). As only a small portion of Hungarian firms have multiple bank connections (Figure 18), we wanted to enhance the external validity by including also firms with only one bank link. If the vast majority of the firms were excluded from the estimation, β_{bt} might not reflect the representative credit supply shocks of banks, but only those experienced by firms with more bank connections. Since Hungarian firms show strong heterogeneity especially along the dichotomy of large, productive foreign-owned companies and small, inefficient SMEs, representativeness might be essential in gaining correct estimates.

The main idea of Degryse et al. (2017) is that firms with similar size, operating in the same region and in the same industry can have similar dynamics in their credit demand as well. To exploit this information we replaced the *Time* $\times$ *Firm* fixed effects with *Location* $\times$ *Industry* $\times$ *Size* $\times$ *Time* fixed effects as control to demand-side factors in a given a year[31].

The results of the parameter estimation using this indirect credit supply shock variable are summarized below:

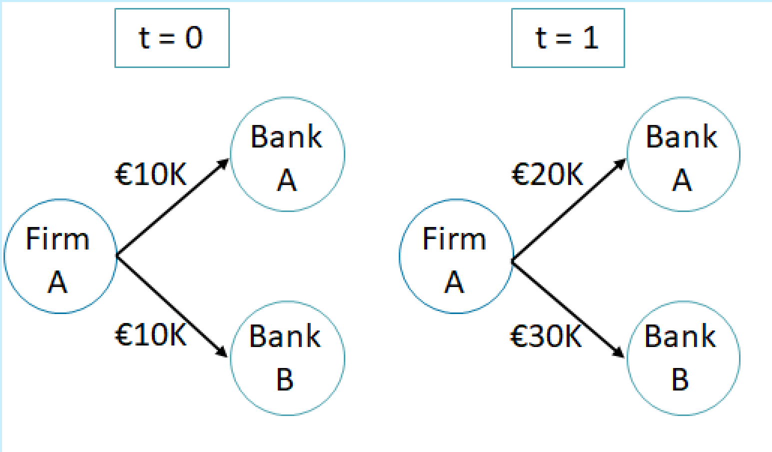
To assess the sensitivity of our model to the differences between the feedback parameters estimated using direct and indirect credit supply shocks, we used the application in Section 6.1 as an illustration. After enabling the real economy feedback channels in the model, 0.51% of the firms in the model went bankrupt (as opposed to 0.53% in the main specification) causing € 175 million loss for banks on defaulting loans (which is only slightly differ from the € 184 million in the original results). Furthermore, losses due to fire sales further increased by € 48 million (instead of € 41 million), and a third bank went below the regulatory requirement the same way due to solvency insufficiency.

Based on these results, the main difference between the two specifications seems to be that in the case of the indirect credit supply shock estimates the role of the direct effect of the shocks is somewhat weaker, and the role of the contagion among firms is stronger. However, the overall impact is basically identical from the point of view of the losses in the banking system.

8.2 APPENDIX B – LIST OF DIRECTLY AFFECTED INDUSTRIES

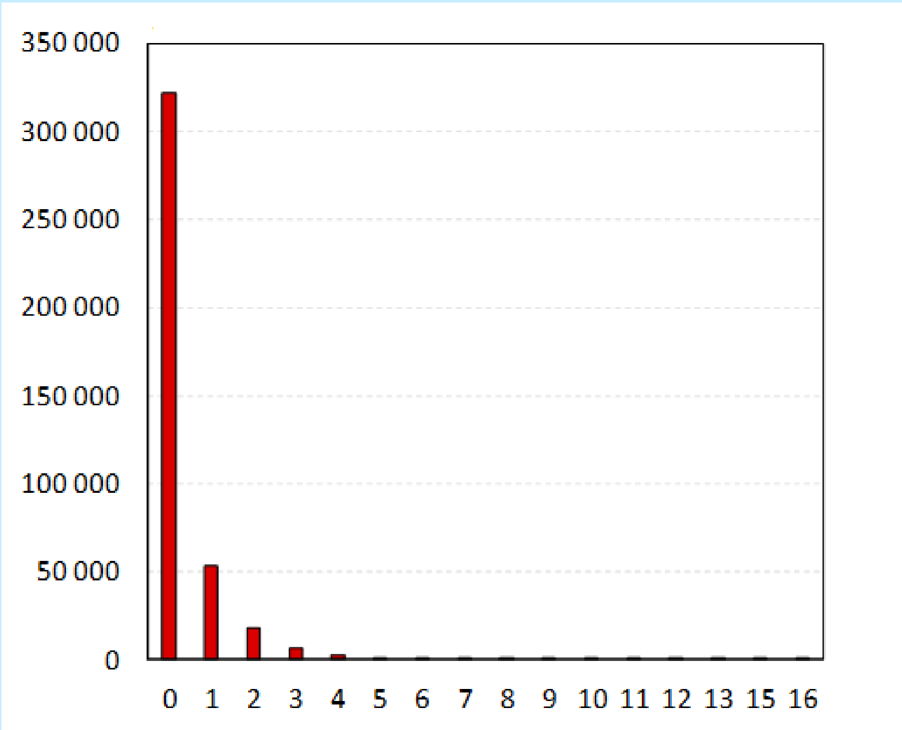
[31] The industry classifications are based on the two-digit NACE categories, location is determined by the town of the headquarters of firms, while size categories are given by the Hungarian XXXIV. SME regulation.

Figure 17
Intuitive illustration of the indirect credit supply shock identification



The amount of credits between firm A and bank B increases more than towards bank A. If one assumes that the credit demand of the firm changes uniformly towards both of its partner banks, then this difference can be attributed to supply side factors.

Figure 18
Distribution of Hungarian firms based on the number of bank connections.



Bank connections are defined by credit contracts or financial leasing. (Based on 2017 data.)

Figure 19
Regression results

	Dependent variable:					
	Probability of default on loans					
	Logit (1)	Logit (2)	Logit (3)	Logit (4)	Logit (5)	Logit (6)
css^0	−0.047	−0.031	−0.032	−0.032	−0.033	−0.007
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.125)
css^1_{us}		−0.957**	−0.928**	−0.910**	−0.905**	−0.846*
		(0.424)	(0.427)	(0.429)	(0.429)	(0.433)
css^1_{ds}		−0.819	−0.892	−0.607	−0.596	−0.563
		(0.706)	(0.716)	(0.740)	(0.741)	(0.747)
css^2_{us}			−1.057	−1.088	−1.057	−0.966
			(1.128)	(1.145)	(1.187)	(1.187)
css^2_{ds}			1.697	2.424	2.192	2.340
			(2.162)	(2.139)	(2.324)	(2.320)
css^3_{us}				1.032	1.180	1.270
				(2.993)	(3.082)	(3.052)
css^3_{ds}				−8.499	−9.214	−9.415
				(5.441)	(5.945)	(5.938)
css^4_{us}					−2.380	−1.576
					(10.274)	(10.153)
css^4_{ds}					4.982	6.801
					(15.479)	(15.720)
$css_{ds\to us}$						−1.244
						(1.358)
$css_{us\to ds}$						−0.393
						(1.297)
Constant	−4.491***	−4.487***	−4.487***	−4.485***	−4.485***	−4.485***
	(0.230)	(0.230)	(0.230)	(0.230)	(0.230)	(0.230)
Year dummies	✓	✓	✓	✓	✓	✓
Industry dummies	✓	✓	✓	✓	✓	✓
Location dummies	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	156,110	156,110	156,110	156,110	156,110	156,110
Log Likelihood	-16,639.930	-16,636.460	-16,635.750	-16,634.680	-16,634.620	-16,634.140
Akaike Inf. Crit.	33,351.870	33,348.930	33,351.500	33,353.360	33,357.250	33,360.270

Note: Clustered-robust standard errors is brackets. *p<0.1; **p<0.05; ***p<0.01

Figure 20
Marginal effects of the estimated feedback parameters

css^0	css^1_{us}	css^1_{ds}	css^2_{us}	css^2_{us}	$css_{us\to ds}$	$css_{ds\to us}$
0.0002	0.0190	0.0126	0.0216	0.0000	0.0090	0.0280

Figure 21
List of directly affected industries

Manufacturing	22xx, 25xx, 28xx, 29xx, 30xx
Wholesale and retail trade	4511, 4719, 4751, 4752, 4753, 4754, 4759, 4761, 4762, 4763, 4764, 4765, 4771, 4772, 4775, 4777, 4778, 4779, 4782, 4789, 4799
Transporting and storage	4930, 4932, 4939, 5010, 5030, 5110, 5223
Accommodation and food service activities	55xx, 56xx
Real estate activities	6810, 6820, 6831, 6832
Administrative and support service activities	7711, 7721, 7722, 7729, 7911, 7912, 7990
Arts, entertainment and recreation	9001, 9002, 9311, 9321
Other services activities	9511, 9512, 9521, 9522, 9523, 9524, 9525, 9529, 9601, 9602, 9604, 9609

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