UNIVERSIDADE DE SÃO PAULO
Instituto de Ciências Matemáticas e de Computação

Contagion in economic networks: a data-driven machine learning approach

Michel Alexandre da Silva

Tese de Doutorado do Programa de Pós-Graduação em Ciências de Computação e Matemática Computacional (PPG-CCMC)

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Data de Depósito:

Assinatura: ______________________

Michel Alexandre da Silva

Contagion in economic networks: a data-driven machine learning approach

Thesis submitted to the Instituto de Ciências Matemáticas e de Computação – ICMC-USP – in accordance with the requirements of the Computer and Mathematical Sciences Graduate Program, for the degree of Doctor in Science. *FINAL VERSION*

Concentration Area: Computer Science and Computational Mathematics

Advisor: Prof. Dr. Francisco Aparecido Rodrigues
Co-advisor: Prof. Dr. Thiago Christiano Silva

USP – São Carlos
May 2022

Ficha catalográfica elaborada pela Biblioteca Prof. Achille Bassi
e Seção Técnica de Informática, ICMC/USP,
com os dados inseridos pelo(a) autor(a)

A381c

Alexandre da Silva, Michel
Contagion in economic networks: a data-driven machine learning approach / Michel Alexandre da Silva; orientador Francisco Aparecido Rodrigues; coorientador Thiago Christiano Silva. -- São Carlos, 2022.
166 p.

Tese (Doutorado - Programa de Pós-Graduação em Ciências de Computação e Matemática Computacional) -- Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, 2022.

1. Redes complexas. 2. Economia. 3. Finanças. 4. Aprendizado de máquina. 5. Risco sistêmico. I. Aparecido Rodrigues, Francisco, orient. II. Christiano Silva, Thiago, coorient. III. Título.

Bibliotecários responsáveis pela estrutura de catalogação da publicação de acordo com a AACR2:
Gláucia Maria Saia Cristianini - CRB - 8/4938
Juliana de Souza Moraes - CRB - 8/6176

Michel Alexandre da Silva

Contágio em redes econômicas: uma abordagem de apredizado de máquina baseada em dados

Tese apresentada ao Instituto de Ciências Matemáticas e de Computação – ICMC-USP, como parte dos requisitos para obtenção do título de Doutor em Ciências – Ciências de Computação e Matemática Computacional. *VERSÃO REVISADA*

Área de Concentração: Ciências de Computação e Matemática Computacional

Orientador: Prof. Dr. Francisco Aparecido Rodrigues
Coorientador: Prof. Dr. Thiago Christiano Silva

USP – São Carlos
Maio de 2022

To Mirella.
Chiudi gli occhi e vedi il sole.

ACKNOWLEDGEMENTS

I would like to express my gratitude to the following people/institutions:

- My advisor, Prof. Dr. Francisco Aparecido Rodrigues, for the outstanding guidance he provided me throughout this project.
- My co-advisor, Prof. Dr. Thiago Christiano Silva, whose invaluable academic support was greatly appreciated.
- The Institute of Mathematics and Computer Science, University of São Paulo (ICMC/USP), for accepting me as a Ph.D. student and creating the ideal academic atmosphere for the development of this project.
- My parents, Ernesto and Marilene. I would never have imagined that their constant feeding of my curiosity would lead me so far.
- The Central Bank of Brazil, for providing me a relief from my professional duties and the financial support, which without I could not have carried out this project.
- The following colleagues who, each in their own way, collaborated with me on this project: Colm Connaughton, Solange Guerra, Gilberto Lima, José Méndez-Bermúdez, Krzysztof Michalak, Kauê Moraes, Luca Riccetti, Alberto Russo, and Benjamin Tabak.
- And, last but not least, to Vivian, who has kindly stood by me for the last months of this journey.

"Too large a proportion of recent 'mathematical' economics are merely concoctions, as imprecise as the initial assumptions they rest on, which allow the author to lose sight of the complexities and interdependencies of the real world in a maze of pretentious and unhelpful symbols."

(John Maynard Keynes)

"The world is a complex, interconnected, finite, ecological–social–psychological–economic system . We treat it as if it were not, as if it were divisible, separable, simple, and infinite. Our persistent, intractable global problems arise directly from this mismatch."

(Donella Meadows)

RESUMO

ALEXANDRE DA SILVA, M. **Contágio em redes econômicas: uma abordagem de aprendizado de máquina baseada em dados**. 2022. 166 p. Tese (Doutorado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2022.

A interconectividade é um traço onipresente em sistemas econômicos. Isso permite que diversas questões econômicas sejam analisadas por meio de ferramentas de redes complexas. A interconectividade pode ser benéfica aos agentes econômicos através, por exemplo, do compartilhamento de riscos em redes financeiras. No entanto, a turbulência financeira de 2008, cujo episódio principal foi o colapso do Lehman Brothers em setembro daquele ano, destacou a importância da interconectividade na propagação de choques — ou seja, *contágio* — através dos sistemas econômicos. Apesar de sua importância, ainda existem algumas questões em aberto relativas a contágio em redes econômicas, suas consequências e os processos que governam sua dinâmica. Nesta tese, nosso objetivo é lançar alguma luz sobre algumas dessas questões. Para realizar essa tarefa, contamos com ferramentas adequadas à análise de sistemas complexos — redes complexas, aprendizado de máquina (*machine learning* – ML) e modelagem baseada em agentes —, além de diversas bases de dados brasileiras. Nossas contribuições abordam três grandes questões: i) a identificação de agentes econômicos sistemicamente relevantes (bancos, empresas e ativos), ii) a dinâmica da propagação dos choques de política monetária e sua interação com a topologia da rede financeira, e iii) o impacto de mecanismos heterogêneos de distribuição de perdas no risco sistêmico (RS). Nossas principais conclusões são as seguintes: i) choques nas taxas de juros afetam a estabilidade financeira de forma não linear e esse efeito é mais forte em períodos de aperto da política monetária, ii) técnicas de ML podem identificar com sucesso determinantes de RS entre variáveis financeiras e topológicas, iii) a adoção de uma regra heterogênea de distribuição de perdas aumenta significativamente o RS, iv) características topológicas da rede de crédito banco-firma são significativamente afetadas por choques na taxa de juros, e v) a medida de centralidade recém-criada, a *risk-dependent centrality*, captura melhor a dinâmica do grau de risco externo do que outras medidas de centralidade.

Palavras-chave: Economia, Contágio, Risco sistêmico, Redes complexas.

ABSTRACT

ALEXANDRE DA SILVA, M. **Contagion in economic networks: a data-driven machine learning approach**. 2022. 166 p. Tese (Doutorado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2022.

Interconnectedness is pervasive in economic systems. This allows several economic issues to be analyzed through complex networks tools. Interconnectedness can be beneficial to economic agents through, for instance, risk-sharing in financial networks. However, the 2008 financial turmoil, whose main episode was the collapse of Lehman Brothers in September of that year, highlighted the importance of interconnectedness in the propagation of shocks – i.e., *contagion* – through economic systems. Despite its importance, there are still some open issues concerning contagion in economic networks, its consequences, and the processes governing its dynamic. In this thesis, we aim to shed some light on some of these open issues. To perform this task, we rely on tools suitable for the analysis of complex systems – complex networks, machine learning (ML), and agent-based modeling –, as well as several unique Brazilian databases. Our contributions address three broad questions: i) the identification of systemically relevant economic agents (banks, firms, and assets), ii) the dynamics of monetary policy shocks propagation and its interplay with the financial network topology, and iii) the impact of heterogeneous loss distribution mechanisms on systemic risk (SR). Our main conclusions are the following: i) interest rate shocks affect financial stability in a non-linear way and this effect is stronger in periods of monetary policy tightening, ii) ML techniques can successfully identify drivers of SR among financial and topological variables, iii) the adoption of a heterogeneous loss distribution rule significantly increases SR, iv) topological features of the bank-firm credit network are significantly affected by shocks to the policy interest rate, and v) the newly developed centrality measure, the risk-dependent centrality, captures better the dynamics of the external risk level than other centrality measures.

Keywords: Economic system, Contagion, Systemic risk, Complex networks.

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CHAPTER 1

INTRODUCTION

Interconnectedness is at the very heart of modern economic systems. A classical example is the interbank market, in which financial institutions are linked to each other through financial instruments like derivatives and repurchase agreements (repo). On the one hand, interconnectedness allows for diversification, reducing portfolio risk. On the other hand, it can also be a source of shock propagation. For instance, if a bank has its solvability negatively affected, it may be the case that it will not honor – total or partially – its debt commitments to other banks it is connected to in the interbank market. The solvability of these banks will be impacted too, and this process can go on until a large number of banks are affected. Such a process can also spread outside the financial system. For instance, the shrink of banks' solvability may engender a credit crunch, leading non-financial firms to reduce production and increasing unemployment.

Until recently, before the 2008 crisis, the conventional wisdom regarding interconnectedness in economic systems went hand in hand with the view expressed in Allen and Gale (2000) seminal paper. According to this paradigm, the benefits brought about by risk diversification overcome the contagion problems. Therefore, more interconnected economic systems would be more resilient. However, the 2008 financial turmoil defeated this view. The burst of the subprime mortgage bubble in the United States in 2007 led, through a network of complex financial linkages, to the collapse of big risk-taking banks, like that of Lehman Brothers in September 2008. This serious banking crisis rapidly spread to the real sector, causing an economic downturn in most of the world.

Two important lessons have come out from the crisis: i) economic agents interact in a nonlinear way so that small shocks are amplified and may have a great impact; ii) through complex interconnections, shocks may reach any part of the economic system. The crisis has also spawned severe criticisms to the traditional economic theory (e.g., Kirman (2010), Krugman (2009), Krugman (2011), Farmer and Foley (2009), Stiglitz (2015)). The general argument was that the traditional economic toolbox – whose backbone is the Dynamic Stochastic General Equilibrium (DSGE) model – was unable to explain, prevent, or even cope with the crisis. One of the main reasons for such failure is that existing economic models have a limited ability to deal with nonlinear interconnections between economic agents, as they are usually solved through log-linearization around a steady state. Nowadays, policymakers[1], as well as researchers, are aware of the importance of interconnectedness to the propagation of shocks throughout the economic system. Despite the increasing number of studies exploring this research field, the overall impact of interconnectedness in economic systems is still an open issue, as we will discuss below.

Contagion channels in economic networks Networks are ubiquitously present in economics: interbank markets (e.g., Allen and Gale (2000), Bardoscia *et al.* (2016)), bipartite bank-firm credit networks (e.g., Masi and Gallegati (2012), Lux (2016)), firms connected through trade credit operations (e.g., Alexandre and Lima (2020b), Burkart and Ellingsen (2004)), input-output networks (e.g., Acemoglu *et al.* (2016), Contreras and Fagiolo (2014)), international trade networks (e.g., Maeng, Choi and Lee (2012), Cepeda-López *et al.* (2019)), networks of correlated assets (e.g., Mantegna and Stanley (1995), Gabaix *et al.* (2003)), and so on. The type of node varies according to the network (e.g., banks in interbank networks, countries in trade networks), and so does the type of link (e.g., loans in bipartite bank-firm credit networks, return correlations in networks of correlated assets).

There are direct and indirect interconnections. The most representative example of direct interconnections refers to debt obligations (when, for instance, an agent grants a loan to another agent in the credit market). Economic agents can also be indirectly linked through some adjacent element. Three examples will be given here: i) common asset exposures, when agents hold investments in the same asset (Acharya (2009), Wagner (2010), Ibragimov, Jaffee and Walden (2011)), ii) ownership relationships, when agents own each others' shares (Vitali, Glattfelder and Battiston (2011)), and iii) derivative contracts (Glasserman and Young (2016), D'Errico *et al.* (2018)).

The contagion channels – i.e., the way negative shocks propagate through the economic agents – are closely related to the type of interconnections that exist among the agents. For instance, debt obligations give rise to two contagion channels: the *counterparty risk* (or *default cascade*) and the *funding risk*. In the first case, an agent negatively affected by a shock may not fully honor their debt obligations against their creditors (e.g., Upper (2011), Battiston *et al.* (2012c)). The counterparty risk may also occur through indirect interconnections as, for instance, in the derivatives market (Blavarg and Nimander (2001)). The funding risk refers to the fact that debtors of the affected agent may be negatively impacted through the partial loss of their funding. This effect can take place in two manners. First, agents hit by negative shocks may refuse to roll over short-term sources of funding, as loans and repo lending (López-Espinosa *et al.* (2012)). Second, they may anticipate the liquidation of assets (Allen and Gale (2000)). Through common

[1] See, for instance, the speech of the former FED president Janet Yellen, available at <http://www.federalreserve.gov/newsevents/speech/yellen20130104a.htm>.

asset exposures, shock propagation is engendered by fire sales (Kiyotaki and Moore (1997), Caccioli *et al.* (2014), Gangi, Lillo and Pirino (2018)). Agents facing the deterioration of their net worth may be forced to sell their external assets. If these assets are illiquid enough, they will be sold at a very discounted rate. It will cause a decrease in the assets price. As they must be marked to market, these losses have an immediate impact on the net worth of the other agents that hold investments in these assets.

Interconnectedness and systemic risk The propagation of shocks among different economic agents can lead to the collapse of a non-negligible part of the whole system. This risk is called *systemic risk* (SR). The complex network approach has spawned useful tools to the measurement of SR. For instance, in the *DebtRank* methodology (Battiston *et al.* (2012c), Battiston *et al.* (2012b)), the SR corresponds to the fraction of total agents' endowments (e.g., their net worth) lost as a consequence of the propagation of a given initial shock.

One of the main questions discussed in studies on SR is its relationship with the interconnectedness of economic networks. Interconnections are a channel for risk-sharing. However, they also propagate shocks. This is the risk-sharing–shock propagation trade-off and unveils the *robust–yet–fragile* nature of financial networks: interconnections serve as both shock–absorbers and shock–amplifiers (Chinazzi and Fagiolo (2015)). The impact of interconnectedness on SR depends on which one of these two effects prevails over the other.

The pioneer studies do not present a consensual view regarding this issue. Some of them argue that SR is smaller in more interconnected networks (e.g., Allen and Gale (2000)), while others support the opposite view (e.g., Freixas, Parigi and Rochet (2000), Brusco and Castiglionesi (2007)). Nowadays, there are two points broadly accepted in the literature concerning the impact of interlinkages on SR:[2]

- The relationship between interconnectedness and SR is non-linear. Some studies argue that shock transmission dominates at low connectivity, while shock absorption dominates for connectivity higher than a threshold level (Nier *et al.* (2007), Gai and Kapadia (2010). Therefore, the relationship between interconnectedness and SR is represented by an inverted U-shaped curve.

- How SR is impacted by interconnectedness depends on many other factors. Other studies point out that the impact of interconnectedness on SR depends on other elements. Heterogeneity, in many dimensions (e.g., agents' size, degree of connectivity, default probability), is deemed as a source of instability (Iori, Jafarey and Padilla (2006), Caccioli, Catanach and Farmer (2012), Amini, Cont and Minca (2016), Lenzu and Tedeschi (2012), Loepfe, Cabrales and Sánchez (2013)). The size of the initial shock is another key factor. Increasing interconnectedness has a negative (positive) impact on SR under sufficiently small (big) negative shocks (Acemoglu, Ozdaglar and Tahbaz-Salehi (2015)). Finally,

[2] For more details, see the excellent review in Chinazzi and Fagiolo (2015).

some simplifying assumptions of the models on SR, as the absence of misbehavior of agents (Brusco and Castiglionesi (2007)) and perfect information (Battiston *et al.* (2012a)), affects the relationship between interconnectedness and SR.

1.1 Objectives

The purpose of this thesis is to shed some light on some open issues concerning contagion and risk in economic networks. Specifically, we address three broad questions: i) the identification of systemically relevant economic agents (banks, firms, and assets), ii) the dynamics of monetary policy shocks propagation and its interplay with the topological features of the financial network, and iii) the impact of heterogeneous loss distribution mechanisms on SR. The contributions of this thesis to this theme are the following:

1. **Propagation of monetary policy shocks** (Chapter 2): Interconnectedness is of particular importance to economic policy. Due to the presence of complex interconnections between different economic agents, some policy instruments may engender undesirable side effects, in the sense they will negatively affect variables out of their set of target variables. For instance, a decrease in the interest rate – whose aim is to reduce unemployment in a recession scenario – cause loosening of borrowers monitoring, over-leverage, and higher risk-bearing, threatening financial stability (Claessens and Valencia (2013)). We will assess specifically the impact of monetary policy shocks on financial stability. We develop a network model which permits us to determine the short-run contagion effects of interest rate changes on both banks and firms. We apply this framework to a comprehensive database of Brazilian banks and firms from 2015 to 2020. We find that interest rate shocks affect more strongly financial stability in periods of monetary policy tightening. We also find notable asymmetric effects of positive and negative interest rate shocks in the Brazilian economy, with positive interest rate shocks affecting more financial stability. Finally, our results also suggest a non-linear relationship between interest rate changes and financial stability, reinforcing the need to mitigate monetary policy shocks through interest rate smoothing and adequate communication and transparency to society.

2. **Drivers of systemic risk** (Chapter 3): Identifying systemically relevant economic agents is crucial not only methodologically, but also from the economic policy viewpoint. Policy instruments aiming at addressing systemic risk have been headed towards systemically important economic agents. An example is the additional capital surcharge on domestic and global systemically important banks, required by the new Basel III agreement (BCBS (2012a), BCBS (2012b)). We assess the role of financial and topological variables as determinants of systemic risk (SR). The SR, for different levels of the initial shock, is computed for institutions in the Brazilian interbank market by applying the *differential DebtRank* methodology. The financial institution(FI)-specific determinants of SR are

evaluated through machine learning techniques: XGBoost, random forest, and Shapley values. We have found the importance of a given feature in driving SR varies with i) the level of the initial shock, ii) the type of FI (bank or credit union), and iii) the dimension of the risk which is being assessed – i.e., potential loss caused by (systemic impact) or imputed to (systemic vulnerability) the FI. The systemic impact is mainly driven by topological features for both types of FIs. However, while the importance of topological features to the prediction of the systemic impact of banks increases with the level of the initial shock, it decreases for credit unions. Concerning systemic vulnerability, this is mainly determined by financial features, whose importance increases with the initial shock level for both types of FIs.

3. **Homogeneous x heterogeneous loss transmission mechanisms** (Chapter 4): In network models of systemic risk, the loss distribution of a distressed debtor among its creditors follows a pro-rata fashion. It is proportional to the loan granted to the debtor. Despite its simplicity, this assumption is unrealistic. In this study, we create a framework for the computation of the systemic risk assuming a heterogeneous pattern of loss distribution, the *default pecking order*. Distressed debtors employ some criterion (equity, out-degree, or loan extended) to rank the creditors they are willing to default on first. Applying this framework to an extensive Brazilian data set, we found out the adoption of the default pecking order increases significantly the systemic risk. The rise in the systemic risk brought by the heterogeneous distribution over the homogeneous case decreases with the level of the initial shock and is higher for small-sized agents. This result can be interpreted in the light of the dual role of the financial network, which can be a channel for both risk-sharing and shock propagation. We test this hypothesis by assessing the role of interconnectedness (as measured by the network density) in driving the systemic risk. The results corroborate this hypothesis. When the homogeneous loss distribution (which maximizes risk-sharing) is abandoned, the density has a positive impact on the systemic risk. It suggests in this case the financial network acts mainly as a channel for shock propagation rather than for risk-sharing.

4. **The impact of interest rate shocks in the financial network topology** (Chapter 5): The propagation of shocks through economic networks depends on their topology. This process is driven not only by their interconnectedness but also by other topological features, such as assortativity and degree distribution. In network models of systemic risk, in which the potential loss of economic value generated by an exogenous shock is computed, the topology of the financial network is assumed to be fixed and exogenous. We pose the following questions: is the financial network topology affected by exogenous shocks? To answer this question, we develop an agent-based model (ABM) in which banks extend loans to firms. The bank-firm credit network is endogenously time-varying as determined by plausible behavioral assumptions, with both firms and banks being always willing to

close a credit deal with the network partner perceived to be less risky. We then assess through simulations how exogenous shocks to the policy interest rate affect some key topological measures of the bank-firm credit network (density, assortativity, size of largest component, and degree distribution). Our simulations show that such topological features of the bank-firm credit network are significantly affected by shocks to the policy interest rate, and this impact varies quantitatively and qualitatively with the sign, magnitude, and duration of the shocks.

5. **Risk-dependent centrality** (Chapter 6): As discussed above, the identification of systemically relevant nodes in economic networks is of key importance. The use of centrality measures has proved quite useful in identifying such nodes. However, the existent measures of centrality are based on a static view of the network. Bartesaghi *et al.* (2020) derived a new centrality measure called *risk-dependent centrality* (RDC). This node centrality measure depends on both the topology of the network and the external risk the whole network is submitted to. We calculate the RDC of the Brazilian stock market. We computed the RDC for assets traded on the Brazilian stock market between January 2008 to June 2020 at different levels of external risk. We observed that the ranking of assets based on the RDC depends on the external risk. Rankings' volatility is related to crisis events, capturing the recent Brazilian economic-political crisis. Moreover, we computed the RDC employing an empirically-computed external risk level, relying on the EMBI+ index. We show that some economic sectors (oil, gas, and biofuels and financial) become more central during crisis periods. Moreover, the volatility of the RDC is positively correlated to the external risk level.

1.2 Contributions: list of publications

- **Micro-level transmission of monetary policy shocks: The trading book channel** (Journal of Economic Behavior & Organization) (Silva *et al.* (2020)). Chapter 2.
- **The drivers of systemic risk in financial networks: a data-driven machine learning analysis** (Chaos, Solitons & Fractals) (Alexandre *et al.* (2021b)). Chapter 3.
- **Does Default Pecking Order Impact Systemic Risk? Evidence from Brazilian data** (Central Bank of Brazil Working Paper Series) (Alexandre *et al.* (2021a). Chapter 4.
- **The Financial Network Channel of Monetary Policy Transmission: An Agent-Based Model** (Available at SSRN 4039894) (Alexandre *et al.* (2022)). Chapter 5.
- **Risk-dependent centrality in the Brazilian stock market** (Journal of Complex Networks) (Alexandre, Moraes and Rodrigues (2022)). Chapter 6.

CHAPTER 2

MICRO-LEVEL TRANSMISSION OF MONETARY POLICY SHOCKS: THE TRADING BOOK CHANNEL

2.1 Introduction

The global financial crisis highlighted how monetary policy, banks' financial conditions, and the financial system structure interconnect in non-trivial ways. Existing research focuses typically on monetary policy transmission to the economy or the structure of the financial system as a driver of financial instabilities.[1] This paper lies at the intersection of both themes and documents on how monetary policy affects financial stability using network modeling with micro-level supervisory data. Network-based models have gained increased attention precisely because they offer a flexible and elegant way of constructing granular models with several heterogeneous agents while not abstracting away from their particularities, such as non-trivial connections patterns.

Monetary policy shocks impact the economy through a variety of transmission channels.[2] In this paper, we are concerned with adjustments in the accounting value of trading book exposures on banks' balance sheets that have to be marked to market when interest rates change. While existing research on agent-based models considers individual banks and firms that interact with each other as well as a central bank, in which monetary policy can affect the economy

[1] Research dealing with monetary policy transmission either use micro-level data in a reduced panel-data format Kashyap and Stein (2000) or a structural macroeconomic model Bernanke and Gertler (1995). The strand in the literature dealing with financial contagion and stability relies typically on the theory of complex networks to trace how shocks propagate throughout the network (Eisenberg and Noe (2001), Battiston *et al.* (2012c)).

[2] There are several well-documented channels through which monetary policy can influence the course of the financial and corporate sectors. Among them, we highlight Kashyap and Stein (2000), Bernanke and Gertler (1995), Diamond and Rajan (2012).

through a variety of channels,[3] none of them has explicitly incorporated the trading book channel. To evaluate how interest rate changes transmit to the entire economy through revaluation in banks' trading books, we build upon Silva, Alexandre and Tabak (2017) 's contagion model and extend it in three relevant ways. First, we add a policy-maker layer to allow for monetary policy shocks in the model. Second, we model bank-specific financial exposures to interest rate changes by recalculating the new fair value of the entire cash flow attached to the interest rate at different maturities in terms of banks' capitalization levels. Third, as banks may incur losses or profits due to interest rate changes, we adapt the Silva, Alexandre and Tabak (2017) 's inner stress transmission mechanism to accommodate positive and negative shocks.[4]

Our contagion model considers individual particularities of firms and banks, and also bilateral exposures among them. Banks that experienced trading book losses cut credit to the corporate sector due to macroprudential regulatory constraints and internal risk management. Depending on firms' current liquidity conditions and ability to substitute banks, they may not pay back the bank credit, leading banks into additional losses. These events create a vicious loss cycle fed by successive credit crunches and credit defaults. As output, the model permits us to determine the net worth reduction on every bank and firm due to these second-round (contagion) effects. This paper considers the net worth reduction as a proxy for economic agents' financial instability. With this tool, we can identify economic and financial sectors that would be more sensitive to sudden interest rate changes from the viewpoint of financial instability.

There are two broad channels through which interest rate shocks may directly affect banks (Kashyap and Stein (2000)): (i) the risk-taking channel[5] and (ii) the credit channel through bank lending[6] and balance sheet changes. In the short run, the balance-sheet channel works mainly through the revaluation of banks' trading books due to marking-to-market assets and liabilities. While the balance-sheet channel has an immediate impact on banks' net worth, the other channels take time to kick in because they involve changes in economic agents' behaviors and expectations. In this paper, we are concerned with the short-term consequences of monetary policy shocks to financial stability. Hence, we focus on the balance-sheet channel through trading book variations. As Basel III recommends that banks meet minimum capital requirements

[3] See Dawid and Delli Gatti (2018) for a comprehensive review on agent-based models.

[4] For instance, Silva, Alexandre and Tabak (2017) only study the effects of negative events in the economy, such as bank defaults. In contrast, trading book variations can generate profits or losses in such a way that banks can be better off after the interest rate change. We account for this particularity in the model by introducing a "better off" state for banks besides the traditional “distressed" and "in default" states found in stress-based contagion models.

[5] The risk-taking channel refers to the impact of prolonged accommodative monetary policy on the risk perception and tolerance of banks. It works through the "search-for-yield" mechanism and the impact on valuations, incomes and cash flows that may decrease the banks' probability of default and thus incentive more risky positions (Jiménez *et al.* (2014), Dell'Ariccia, Laeven and Marquez (2014)).

[6] The bank lending channel relates to the opportunity cost of bank liabilities. For instance, rises in the interest rate make government bonds more attractive than bank loans, which may ignite a substitution effect of loans to government bonds.

continuously (BCBS (2015)), trading book variations are of concern as banks may immediately run into insolvency following the shock and hence impair the stability of the entire financial system.

Trading book activities were one of the primary sources of financial losses in the 2008 financial crisis.[7] While accounting data on the trading book is scarce, the few data available attest to the non-negligible representativity of trading book positions. According to Ramon, Francis and Milonas (2017), the share of trading book assets increased over time since 1996 for the largest UK banks, reaching nearly 30% in 2013. The main German bank, Deutshce Bank (2014) reported that its trading book positions accounted for 56.7% (46.3%) of total assets (liabilities). In Brazil, the trading book position of commercial, investment, and development banks reached up to 35% (37%) of the total assets (liabilities) in 2015. Given the relevance of the trading book, the Basel Committee on Banking Supervision (BCBS (2013)) revised the capital framework for trading book exposures, recognizing the interest rate was one of its five broad risk factors (together with credit, foreign exchange, equities, and commodities). This normative change reflects the importance of understanding the impact of monetary policy shocks—which directly operate through revaluation of tradable instruments attached to the interest rate—on financial stability. For instance, interest rate changes caused considerable losses in the trading book of Indian banks after a rise in the yields of Indian benchmark securities in 2004–2005 (Saha *et al.* (2009)).

The trading book composition of banks is relatively rigid. Basel III strictly limits banks' ability to move instruments between the trading book and the banking book by their own choice after initial designation to bypass financial regulatory requirements and recover from accounting losses (BCBS (2015)). In practice, switching is rare and allowed by regulators only in extraordinary circumstances. This highlights the trading book channel's relevance as a potential medium of stress transmission in the economy that we explore in this work.

To show the applicability of the model, we use a comprehensive database encompassing Brazilian banks and firms, as well as their bilateral credit exposures. The Brazilian case is an interesting case study due to numerous reasons. First, the trading book of Brazilian banks is sizable and is mainly composed of instruments attached to the interest rate (roughly 70% of the trading book).[8] Therefore, interest rate changes can substantially affect banks' net worth. Second, capital markets are underdeveloped, and hence bank credit turns out to be a significant (or the only) funding option for firms.[9] Third, Brazilian experienced tremendous credit growth after

[7] In 2008, the Bank of America, the Royal Bank of Scotland, and the UBS Group AG reported trading book losses amounting to USD 5.9 billion, GBP 8.5 billion, and CHF 25.8 billion, respectively (Alexander, Baptista and Yan (2013)). Losses originated mainly from derivative instruments, such as credit default swaps (CDS) and collateralized debt obligations (CDO), in banks' trading book portfolios (D'Errico *et al.* (2018)).

[8] For further details, Figure 3d shows the composition of Brazilian banks' trading books in terms of instruments attached to the interest rate, foreign exchange rate, stocks, and commodities.

[9] As of March 2020, more than 21 million firms were operating in Brazil, of which less than 500 had

2008, making banks more exposed to firms and the business cycle. These two last characteristics increase firms' dependency on bank credit and enhance the way interest rate changes can transmit from the financial to the corporate sector through credit rationing. Fourth, Brazil has a comprehensive database containing detailed information on all loans made by banks to firms and between banks themselves and bank-specific net cash flows for maturities from 1 day up to 30 years. Such setup permits us to track how interest rate changes affect banks' net worth and how they transmit to the economy at a very granular level.

Overall, Brazilian banks have a positive net trading book (trading assets minus liabilities) and incur losses when interest rates increase. For the same interest rate shock, foreign private banks (state-owned banks) have the most (least) sensitive trading book to interest rates and thus lose/profit more (less) than other banks. We find that a 10% increase in the interest rate[10] can generate losses up to 5% of foreign banks' aggregate net worth only due to trading book variations.

We perform a sensitivity analysis of interest rate changes on banks and firms' financial instability, measured in terms of aggregate net worth losses originating from the trading book revaluation (direct impact) and financial contagion (indirect impact). In our model, while banks are subject to losses in both components, firms are only susceptible to financial contagion through credit rationing from the financial sector. We find strong asymmetric effects of interest rates on the financial instability of banks and firms. While negative interest rate shocks have a small impact on banks' capitalization and, therefore, on financial contagion, net worth losses become sizable for positive interest rate shocks. This effect is explained by the fact that Brazilian banks usually hold positive net trading books.

In our simulations, for a 10% increase in the interest rate, banks lose up to 5% of their aggregate net worth due to financial contagion (besides the 5% loss from trading book variations), while listed firms lose 0.8% of their aggregate net worth. This effect is heterogeneous across different banks and firms. While the least affected by trading book variations, state-owned banks endure losses amounting up to 12.5% of their net worth due to financial contagion. In contrast, foreign private banks (the most affected in terms of trading book variations) only lose up to 2.5%. State-owned banks are more susceptible to financial contagion because they are more exposed to the interbank market than foreign private banks. In the corporate sector, the agriculture and chemical sectors lose up to 10% and 15% of their net worth, respectively, for the same shock.

We analyze the period from the beginning of 2015 to March 2020. This time frame encompasses periods of high interest rates (14.25% at the beginning of the sample) and the historical lowest interest rates in Brazil (3.75% by the end of the sample). These opposing

access to capital markets.

[10] A 10% shock represents a percentage of the before-shock interest rate level and not an interest rate increase of an additional 10% per year. To exemplify, a 10% interest rate shock in a moment when interest rates are 5% would result in a stressed interest rate of 5.5%. In this case, the 10% interest rate shock corresponds to a 0.5 p.p. increase of the current interest rate.

pictures enable us to understand how monetary policy shocks affect financial stability during times of high and low interest rates. Our results reveal that interest rate shocks affect more financial stability during periods of monetary policy tightening, both in terms of direct and indirect impacts.

Our results point to a non-linear relationship between interest rate changes and financial stability, measured in terms of aggregate losses of the financial and corporate sectors.[11] This finding reinforces the conclusions of the classical work by Clarida, Galí and Gertler (1999), who advocate that central banks need to smooth interest rate changes to minimize disruptions in financial markets. By smoothing interest rate changes, the shocks tend to be smaller, and the impact becomes roughly linear. Managing expectations with proper communication and transparency to society also reduce the surprise component of changes in the interest rate.

2.2 Related literature

There is an ongoing debate on the role of interconnectedness in the amplification of shocks through contagion. Several papers have attempted to estimate different systemic risk measures using the information on financial networks. Methods that use financial networks to estimate systemic risk fall into two broad categories: loss-based methods (Eisenberg and Noe (2001)) or stress-based methods (Battiston *et al.* (2012c)). While the first evaluates real losses for a given shock, the second measures financial stress inside the network, which may not necessarily materialize. Loss-based methods are particularly useful for large initial shocks, such as significant bank defaults. In contrast, stress-based methods are more appropriate for small shocks and for capturing systemic risk buildup. Their complementary nature highlights that a set of systemic risk measures is often necessary to capture imbalances comprehensively. Our model is based on stress propagation because we are particularly interested in understanding the effect of small interest rate changes in the economy. Loss-based models would not be suitable in this setup because banks will most likely not default if these shocks occur.

The classical literature on systemic risk estimation using network-based models has focused on the traditional interbank market. Recently, after Glasserman and Young (2015)'s critique, there seems to be an effort in incorporating other sources of contagion into the analysis, such as the corporate sector (Silva, Alexandre and Tabak (2017)), common assets exposures (Poledna *et al.* (2021)), among other contagion transmission channels. In our case study using Brazil, due to the high dependency of the corporate sector with the financial sector, we use an adaption of Silva, Alexandre and Tabak (2017)'s model.

Papers dealing with monetary policy normally investigate its macroeconomic effects. For instance, Bernanke and Blinder (1992) target the macroeconomic aspect of monetary policy by

[11] Chinazzi *et al.* (2013) also find strong evidence of non-linear effects in a related study of the interbank financial network.

examining the strength of the federal funds rate as a tool of monetary policy to adjust output and price using a vector autoregression model. In turn, Jiménez *et al.* (2014), Dell'Ariccia, Laeven and Marquez (2014), and Maddaloni and Peydró (2011) study the effects of monetary policy on credit risk-taking in environments of prolonged low interest rates.

In contrast, research that mainly deals with financial stability focuses on the role that financial networks play in amplifying losses. For instance, Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) show that contagion in financial networks exhibits a form of phase transition. In this respect, more densely connected networks enhance financial stability as long as the magnitude of the negative external perturbation is sufficiently small. However, beyond a certain critical point, dense interconnections serve as a medium that favors the propagation of shocks, leading to more fragile financial systems. In the same vein, Elliott, Golub and Jackson (2014) study cascades of failures in financial networks and find that the effects of increasing dependence on counterparts (integration) and more counterparts per organization (diversification) have different and non-monotonic effects on the extent of financial contagion.

Network modeling enables us to trace how macroeconomic events disseminate through the economy at a very granular level. Notwithstanding recent advances in the literature, opening the black box of the monetary policy transmission mechanism with granular models to assess the heterogeneous effects on individual agents and understand how risks propagate in networks are still at the early stages. In this effort to link micro-founded models with macroeconomics, Dawid and Delli Gatti (2018) provide a comprehensive review of agent-based models used to analyze macroeconomic behavior. In turn, Ragot (2018) explore Heterogeneous Agent New Keynesian (HANK) models in incomplete markets. Our paper also deals with heterogeneous agents models with macroeconomic inspiration (monetary policy). However, our model significantly differs from them in that we study monetary policy transmission through the trading book channel. To the best of our knowledge, our work is the first to analyze such a channel using granular data of an economy.

Still in the agent-based modeling, Georg (2013) and Bluhm, Faia and Krahnen (2014) share similarities with our research, as they analyze the central bank as a liquidity provider in an interbank network. Liquidity provision makes banks more resilient to shocks. However, it is detrimental to financial stability because it encourages risk-taking and results in a more interconnected financial system, in which the shock transmission is facilitated. Our paper differs from these works in significant ways. First, we are interested in understanding the trading book channel through which monetary policy can operate. Second, they do not include the corporate sector, which is a relevant source of loss amplification Silva, Alexandre and Tabak (2017).

2.3 Methodology

In this section, we discuss the intuition and underpinnings of our methodology. As mentioned before, our model is closely related to Silva, Alexandre and Tabak (2017)'s model but adds three significant methodological contributions: (i) the inclusion of the policy-maker; (ii) the introduction of financial exposures of banks to the policy-maker, representing the sensitiveness to interest rate changes in their trading books; and (ii) the adaption of the stress transmission mechanism because the initial shock (trading book variation) can generate losses or profits for banks. While the first two are differences concerning the network structure (discussed in Section 2.3.1), the latter pertains to the stress transmission mechanism (see Section 2.3.2, the contagion component).

2.3.1 Network components

We design our framework using multilayer networks, in which each layer comprises a set of economic agents of the same nature and links connote bilateral financial exposures. Any multilayer network model dealing with stress propagation is completely described by defining the network layers, vertices, links, and stress transmission rules. We detail them the first three in this section and present the microfoundations of the last in the following section.

Network layers: Our model has three layers: the policy-maker layer, financial, and corporate sectors. Figure 1 exhibits an illustrative three-layer network, where the top, middle, and bottom layers constitute the policy-maker, financial sector, and corporate sector layers, respectively.

Network vertices: Each network layer contains economic agents of the same nature. The financial sector layer encompasses the collection of banks in the economy, the corporate sector layer includes firms, and the policy-maker layer embodies the central bank. As illustrated in Figure 1, banks, and firms can be of any numbers, are allowed to have heterogeneous balance sheet profiles, and can take any interconnection pattern to other members in the economy. The policy-maker layer, in contrast, has a single vertex.

Network links: a link originating in A (creditor) and ending in B (debtor) embodies bilateral financial exposure of the former to the latter. The link weight quantifies the magnitude of financial exposure. These financial exposures represent the contagion transmission channels through which stress propagates from one economic agent to another. Figure 1 illustrates the possible bilateral financial exposures. The policy-maker has no outgoing links and therefore has no vulnerabilities. Besides links connecting to the policy-maker, every other link is bidirectional because it models vulnerability in the asset side of the creditor's balance sheet and an associated vulnerability in the liability side of the debtor's balance sheet. We model counterparty risk in the asset side: if A lends to B, then a financial exposure arises in the asset side of A's balance sheet. We model funding risk in the (opposite) liability side: in the same example, B has a funding vulnerability to A in the case the loan is due in the short term. Both link weights need not be identical: while

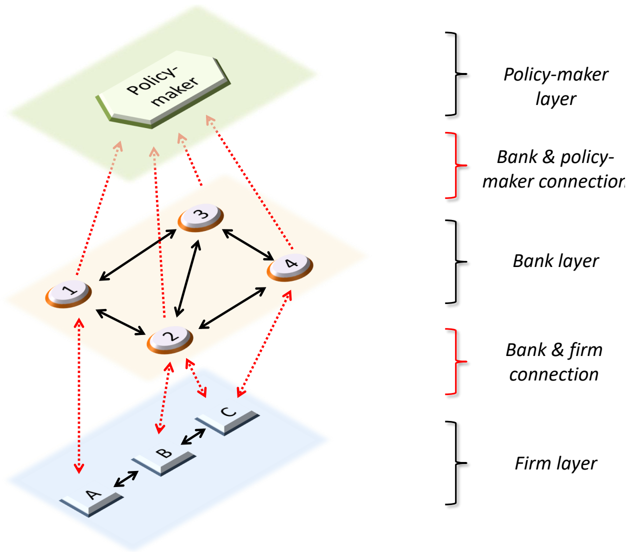


Figure 1 – *A schematic of the three-layer network representing our economy, containing the (i) policy-maker (diamond), (ii) bank (circle), and (iii) firm (square) layers. The policy-maker can apply interest rate shocks that, in turn, affect banks' trading books and hence their net worth. There are two interlayer connections: (i) banks to policy-maker (unidirectional), representing banks' sensitiveness to interest rate changes; and (ii) banks & firms (bidirectional), indicating banks' sensitiveness to loan defaults (vulnerability of banks to firms) and firms' sensitiveness to credit rationing (vulnerability of firms to banks). There are also intralayer connections: (i) bank-to-bank in the bank layer, representing banks' sensitiveness to credit default in the interbank market; and (ii) firm-to-firm connections, depicting firm's sensitiveness to defaults in trade credit relationships.*

Table 1 – *Types of network links in our three-layer network depicted in Figure 1. Links in the network express financial exposures between pairs of economic agents. Links are directed and follow the financial loss in the network, i.e., the link source is the risk origin and the link destination is the risk bearer.*

Economic Agents		**Vulnerability**	
A	**B**	**Asset side (transmission: B → A)**	**Liability side (transmission: A → B)**
Bank	Policy-maker	Sensibility of the net trading book volume to interest rate changes	—
Bank	Bank	Outstanding interbank loans	Credit crunch from other banks proportional to the short-term debt
Bank	Firm	Outstanding bank credit to the corporate sector	Credit crunch of the bank proportional to the short-term debt
Firm	Firm	Trade firm-to-firm credit	Firm's denial to rollover short-term trade credit

the vulnerability due to counterparty risk relates to the full loan/credit (outstanding short- and long-term loans/credit), that due to funding risk is proportional to the outstanding short-term loan/credit. Table 1 compiles all potential bilateral financial exposures among economic agents (policy-maker, banks, and firms).

The financial sector layer communicates with the policy-maker layer only unidirectionally. Banks are exposed to variations in the interest rate promoted by the central bank. These changes transmit instantaneously to bank balance sheets due to the daily mark-to-market updates on their tradable instruments attached to the interest rate. Examples include securities or derivatives attached to the interest rate, such as federal bonds and other fixed-rate contracts. In the interbank market, financial exposures arise from unsecured lending to other bank counterparts. Common instruments in the interbank market include interfinancial deposits, on-lending, and credit. Bank lending to the corporate sector includes non-collateralized earmarked and non-earmarked credit for general (e.g., working capital) and specific (e.g., financing to infrastructure, and exports & import operations) purposes. Firm-to-firm operations include trade credit transactions.

2.3.2 Stress transmission mechanism

Our model is particularly useful for understanding the short-term consequences of interest rate shocks in the economy, in that it assumes that the network topology does not change after the shock.[12] However, the model allows for simple actions by firms. For instance, when firms experience credit rationing by the financial sector, they may replace the bank rationing credit for a counterparty willing to lend outside the network.

The model has two sequential steps:

1. *The risk-taking component* (initial shock): the risk-taking component represents the change in banks' trading books when a policy-maker enacts an interest rate change. The mechanism is immediate and works through marked-to-market accounting of tradable assets/liabilities. Such changes reflect directly in banks' net worth and represent the initial shock to the next step of the model. The risk-taking component is a contribution of this work to existing models.

2. *The financial contagion and amplification components* (second-order effects): due to the financial exposures (links) among banks and firms, losses/gains arising from the trading book in view of an interest rate shock do not dissipate entirely on the directly affected banks. Financial frictions, such as internal risk management and regulatory limits, enable stress transmission to other economic agents. These frictions allow trading book changes to propagate to the corporate sector.

2.3.2.1 The risk-taking component

The risk-taking component shapes the sensitivity of banks' net worth to interest rate variations. Banks' net worth changes according to trading book gains and losses arising from the tradable instruments attached to the interest rate. The marking-to-market of trading books is crucial for the validity of our results. In our application to Brazil, the *Circular* 3,354, 27/6/2007 enacted by the Central Bank of Brazil enforces daily marking-to-market of the trading book.

[12] To understand the medium- and long-term effects of monetary policy shocks in the economy, we would have to consider the network topology as endogenous. In that configuration, each bank and firm would be allowed to create and sever links to each other based on their utility functions. As a robustness check, we analyze the resilience of our results to random reattachment of links in the interbank market during the stress propagation mechanism in Section 2.5.3.

Otherwise, banks could keep the value fixed until a convenient moment and only then revalue their trading book, invalidating our analysis of the short-term effects of interest rate changes on financial stability.

To capture a comprehensive view of banks' sensitiveness to interest rate changes, we consider the present value of the balance between cash inflows and outflows attached to the interest rate maturing at the following twelve vertices of the interest rate term structure: 1 day, 1 month, 2 months, 3 months, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 10 years, and 30 years. Following BCBS (2013), if a financial instrument's maturity does not fall into any of these vertices, we decompose their constituent cash flows and assign it to the nearby vertices on a proportional basis.

An interest rate shock causes an immediate change in the present value of banks' balance of cash inflows and outflows. Net cash flows with longer maturities are more sensitive to interest rate changes. If the policy-maker changes the interest rate to i_{stressed} from the original value of i_{original}, bank i recalculates the new fair present value of its net flow of cash maturing v days ahead $r_i^{\text{stressed}}(v)$ as follows (BCBS (2013)):[13]

$$r_i^{\text{stressed}}(v) = \frac{r_i^{\text{original}}(v)\left(1+i_{\text{original}}\right)^v}{\left(1+i_{\text{stressed}}\right)^v}, \tag{2.1}$$

in which $r_i^{\text{original}}(v)$ is the present value of the net cash flow evaluated with the original interest rate $r_i^{\text{original}}(v)$ maturing v days ahead. If $i_{\text{stressed}} > i_{\text{original}}$, then the new cash flow is smaller than the original value. In this situation, when inflows (assets) surpass outflows (liabilities), i.e., when $r_i^{\text{stressed}}(v) > 0$, the bank incurs losses in the net cash flow maturing v days ahead. When outflows (liabilities) are larger than inflows (assets), i.e., when $r_i^{\text{stressed}}(v) < 0$, then the bank profits at the net cash flow maturing v days ahead.

We compute the *total gain/loss* of the trading book attached to the interest rate of bank i by summing the differences of the fair net present value after the interest rate change (according to Eq. (2.1)) and the original net present value over all vertices (maturing days). Mathematically, bank i's total gain/loss is given by:

$$\Delta r_i = \sum_{v \in \mathscr{V}} \left[\frac{r_i^{\text{original}}(v)\left(1+i_{\text{original}}\right)^v}{\left(1+i_{\text{stressed}}\right)^v} - r_i^{\text{original}}(v)\right], \tag{2.2}$$

in which $\mathscr{V}$ stands for the set of vertices with the following maturing days: 1 day, 1 month, 2 months, 3 months, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 10 years, and 30 years.

[13] In general terms, the interest rate could also depend on the maturity of the cash flow. In this paper, we assume that both the original and stressed interest rates are independent of the vertex. However, the proposed model can encompass such dependency provided that data is available.

The change in bank i's net worth Δr_i is used as input to the next step of our framework, detailed in the following.

2.3.2.2 The financial contagion and amplification component

We treat banks and firms indistinctively as economic agents. After banks revalue their tradable instruments following the interest rate shock, we remove the policy-maker because: (i) it is not exposed to any economic agents and, hence, it is insensitive to second-order (contagion) effects; and (ii) we are dealing with the short-term consequences of the interest rate shock, in such a way that we can assume that the rate remains fixed during the financial contagion and amplification process. Putting these facts together, the central bank is an exogenous entity in the model. The model then reduces to describing the net worth dynamic of banks and firms following the interest rate shock.

Although our model consists of a single-period economy, we represent the shock propagation process as a dynamic system that may take several iterations before converging. We notate as t the current iteration of the dynamic system. For mathematical convenience, we assume that $t = 0$ represents the economy's state before the interest rate change. At $t = 1$, the policy-maker changes the interest rate, and banks revalue their trading books, recognizing losses or profits in their net worth according to Eq. (2.2). At $t > 1$, the net worth change transmits forward in the network in the form of downward investment repricing (counterparty risk) and increased financing costs (funding risk). Since economic agents hold positive equities, the shock always dissipates as it travels along with the network. Hence, the dynamic system has a contracting map as the update rule, and therefore it converges to a fixed point.

The balance sheet of economic agent i at iteration t consists of three elements: assets $(A_i(t))$, liabilities $(L_i(t))$, and net worth $(E_i(t))$. In the case of firms, the net worth is $E_i(t) = A_i(t) - L_i(t)$. In the case of banks, it is the capital buffer, which is the net worth parcel that is above the minimum capital requirements established by the regulator (more details in Section 2.4). In both cases, the economic agent default at t when $E_i(t) \leq 0$. We split the economic agent assets and liabilities in the following disjoint quantities: inside-network assets $(A_i^{(\text{in})}(t))$, outside-network assets $(A_i^{(\text{out})}(t))$, inside-network short-term liabilities $(L_i^{(\text{in-st})}(t))$, inside-network long-term liabilities $(L_i^{(\text{in-lt})}(t))$, and outside-network liabilities $(L_i^{(\text{out})}(t))$.

Losses due to counterparty and funding risks: We decompose net worth losses of economic agent i by using a differential version of the fundamental accounting equation:

$$\Delta E_i(t) = \Delta A_i^{(\text{in})}(t) + \left[\Delta A_i^{(\text{out})}(t) - \Delta L_i(t)\right] = \Delta E_i^{(\text{ct})}(t) + \Delta E_i^{(\text{f})}(t) \tag{2.3}$$

in which $\Delta E_i^{(\text{ct})}(t) = \Delta A_i^{(\text{in})}(t)$ and $\Delta E_i^{(\text{f})} = \Delta A_i^{(\text{out})}(t) - \Delta L_i(t)$ indicate potential losses due to counterparty risk and funding risk, respectively.

Counterparty risk losses arise from the repricing of inside-network assets due to decreased creditworthiness of debtors. Fluctuations in the probability of default lead to changes in debtors' creditworthiness. When economic agents monitor these changes, they register accounting losses in their balance sheets due to changes in their debtors' riskiness. The model proxies the economic agent's probability of default proportionally to the amount of its net worth loss relative to the initial net worth. Under this repricing mechanism, Silva, Alexandre and Tabak (2017) demonstrate that losses due to counterparty risk of i are:

$$\Delta E_i^{(\mathrm{ct})}(t+1) = \sum_{j \in \mathscr{A}(t-1)} \frac{A_{ij}^{(\mathrm{in})}(0)}{E_j(0)} \left[E_j(t) - E_j(t-1)\right] \tag{2.4}$$

in which $A_{ij}^{(\mathrm{in})}(0)$ and $E_j(0)$ are exogenous variables representing initial exposure of i to j and the net worth of j, respectively. The term $\mathscr{A}(t-1)$ indicates the set of economic agents that have not defaulted up to iteration $t-1$.

Funding risk losses arise from the inability to rollover short-term debt, forcing the fire selling of illiquid assets. Gai, Haldane and Kapadia (2011) document that banks hoard liquidity to control their uncertainty over their ability to roll over their debt or even to survive. Therefore, we assume that economic agents ration credit proportionally to their amount of net worth loss relative to the initial net worth (our proxy for probability of default).[14] Under such hypothesis, Silva, Alexandre and Tabak (2017) demonstrate that losses due to funding risk of economic agent i are:

$$\Delta E_i^{(\mathrm{f})}(t+1) = \sum_{j \in \mathscr{A}(t-1)} \frac{\alpha_{ij} L_{ij}^{(\mathrm{in\text{-}st})}(0)}{E_j(0)} \left[E_j(t) - E_j(t-1)\right], \tag{2.5}$$

in which $L_{ij}^{(\mathrm{in\text{-}st})}(0)$ is the initial short-term liabilities of i to j that is exogenous to the model and $\alpha_{ij} \geq 0$ modulates the funding risk arising from the short-term liability. When economic agent i is liquid or can replace the funding counterparty j easily, then α_{ij} is small. Otherwise, this coefficient is larger. This coefficient is estimated using past data.

Shock propagation rule: Our model also departs from Silva, Alexandre and Tabak (2017)'s in how shocks propagate throughout the network. In their model, since only negative events

[14] In our application to Brazilian data, we also observe this behavior within the analyzed period (2015–2020). Brazil had a deep recession in 2015–2016 with substantial increase in delinquency rates and therefore credit losses to banks. Concurrent to that, we observed an increase in the average Liquidity Coverage Ratio (LCR) of large banks of 24.86% in 2016 compared to 2015. Large foreign private banks performed a more pronounced precautionary liquidity hoarding, with an average increase of 27.73% in 2016 compared to 2017. When conditions improved in 2017, the LCR of these banks decreased 8.22% in that year when compared to 2016.

are studied, banks cannot have net worth larger than their initial values by construction. In our case, banks can potentially profit from the interest rate shocks. In this way, we use the following propagation model for economic agent i:

$$s_i(t+1) = \min\left[1, s_i(t) + \sum_{j \in \mathscr{S}} V_{ij}(\text{AS}) \max\left[0, \Delta s_j(t)\right] + V_{ij}(\text{LS}) \max\left[0, \Delta s_j(t)\right]\right], \tag{2.6}$$

in which $\mathscr{S}$ is the set of all economic agents and $s_i(t)$ represents the financial stress of economic agents that we evaluate as:

$$s_i(t) = \frac{E_i(0) - E_i(t)}{E_i(0)}. \tag{2.7}$$

and $V(\text{AS})$ and $V(\text{LS})$ are the vulnerability matrices that numerically translate how financial contagion spills over and impacts economic agents from their asset and liability sides, respectively. These matrices are exogenous to the model and are computed as follows:

$$V_{ij}(\text{AS}) = \frac{A_{ij}^{(\text{in})}(0)}{E_i(0)}, \tag{2.8}$$

$$V_{ij}(\text{LS}) = \frac{\alpha_{ij} L_{ij}^{(\text{in-st})}(0)}{E_i(0)}. \tag{2.9}$$

In our framework, we monitor how financial stress of economic agents in Eq. (2.7) increases as shocks propagate across the network. Note that the numerator in Eq. (2.7), $E_i(0) - E_i(t)$, quantifies the losses of economic agent i up to iteration t. It can happen that banks profit from the interest rate shock, in a way the banks' stress levels become negative. In-between values represent partial financial distress. Default occurs when $s_i(t) = 1$, which denotes an upper limit due to the $\min[.]$ operator in Eq. (2.6).

Economic agents in the network model can attain three different states that are important in terms of stress propagation. We depict them in the state machine illustrated in Figure 2. We can identify them simply looking at the current stress levels of economic agents in Eq. (2.7). A description of the states is given below:

- *In default state* ($s_i(t) = 1$): the net worth of economic agents in this state has been completely depleted. Economic agents cannot propagate any further stress throughout the network when they default.
- *Distressed state* ($s_i(t) \in [0, 1]$): economic agents in this state have positive net worth but smaller than its original value *ex-ante* the interest rate shock. They propagate losses

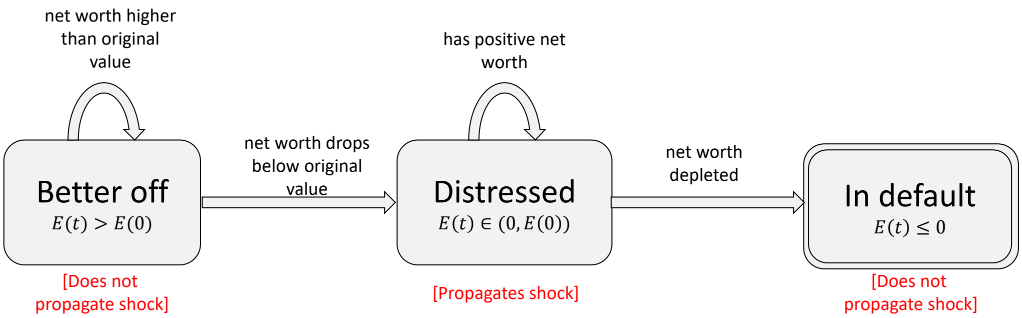


Figure 2 – *State machine representing the states that economic agents in the network model can attain during the stress propagation rule described in Section 2.3.2.2. Economic agents can start off either in the "better off" or "distressed" state. "In default" is a sinking state (double borders).*

through the network in accordance with Silva, Alexandre and Tabak (2017)'s contagion mechanism.

- *Better off state* ($s_i(t) < 0$): economic agents attain this state when their net worth is larger than their original values *ex-ante* the interest rate shock. Only banks can attain this state when they receive trading book profits following the interest rate shock.

This state machine contrasts with the economic agents' dynamics of Silva, Alexandre and Tabak (2017)'s model. Therein, since the authors only study negative events, such as bank defaults, economic agents are only allowed to attain the "distressed" or "in default" states. In our extended model, banks (but not firms) can assume the "better off" state, representing the case in which they end up more capitalized after the interest rate change. In this state, they do not cut lending nor propagate any stress to the interbank market. Instead, they stay latent in the model and are only susceptible to receiving stress from other bank and firm counterparts. Only when their net worth drops below the original values *ex-ante* the interest rate shock they will transit to the "distressed" state and will start propagating losses. The mechanism of enabling or disabling stress propagation of economic agents creates a non-linear behavior in the model that will become evident in our empirical section.[15]

Systemic risk estimation: We evaluate systemic risk in terms of the aggregate net worth loss experienced by economic agents. Take a sufficient large iteration $t = t_c \gg 1$ in a way that the dynamic system settles down after the interest rate shock. Then, the systemic risk SR arising from an interest rate shock is:

[15] The main difference of our shock propagation rule in Eq. (2.6) from the Silva, Alexandre and Tabak (2017)'s model is the introduction of the $\max[.]$ operator in the stress differentials Δs. In their model, $\Delta s \geq 0$ by construction because only negative events are considered. However, if banks profit from the interest rate change, we could have $\Delta s < 0$. To prevent this, we take the $\max[.]$ operator. This construction is also important to guarantee the convergence of the dynamic system. While the economic agents' financial stress has clear upper bounds—represented by their default—there is no clear lower bound, in such a way that the convergence of the model would be compromised. By restricting negative stress propagation of "better off" banks, we guarantee convergence because stress levels take a non-decreasing behavior and have an upper limit.

$$SR = \sum_{i \in \mathscr{S}} s_i(1)E_i(0) + \sum_{i \in \mathscr{S}} \left(s_i(t_c) - s_i(1)\right) E_i(0) = SR_{\text{risk-taking}} + SR_{\text{contagion}}, \tag{2.10}$$

in which $SR_{\text{risk-taking}} = \sum_{i \in \mathscr{S}} s_i(1)E_i(0)$ and $SR_{\text{contagion}} = \sum_{i \in \mathscr{S}} \left(s_i(t_c) - s_i(1)\right) E_i(0)$. Observe that both $SR_{\text{risk-taking}}$ and $SR_{\text{contagion}}$ are in monetary values, since stress levels are normalized by the net worth *ex-ante* the interest rate shocks. The systemic risk due to the systemic risk-taking component is evaluated only at $t = 1$, which is the instant that we apply the exogenous monetary policy shock. The systemic risk due to financial contagion and amplification is the additional system-wide financial stress caused by the negative spillovers to the economy.

Linking the interest rate change as the initial shock of the contagion model: As discussed before, $t = 0$ represents the current economy's state. At $t = 1$, the policy-maker changes the interest rate, causing changes in banks' trading books. We need to translate such losses in terms of financial stress relative to their initial net, as defined in Eq. (2.7). Therefore, we set:

$$s_i(1) = \begin{cases} \min\left[1, -\frac{\Delta r_i}{E_i(0)}\right], & \text{if } i \text{ is a bank} \\ 0, & \text{if } i \text{ is a firm} \end{cases} \tag{2.11}$$

in which Δr_i is the net trading book variation, which we evaluate in accordance with Eq. (2.2). If the interest rate generates losses to bank i, then $s_i(1) > 0$; otherwise, $s_i(1) \leq 0$. If the bank loses more than its initial net worth, then the minimum operator caps the financial stress at $s_i(1) = 1$, indicating that it has defaulted.

2.4 Data

We collect, pre-process, and match several unique Brazilian databases with supervisory and accounting data. We extract monthly information from January 2015 through March 2020 in all data sources.[16] Next, we discuss how we build the network components using the terminology exhibited in Figure 1.

[16] The sample period is defined due to data availability. The lower limit occurs due to a substantial change in how financial institutions started to consolidate and report their balance sheets in 2015 brought by the *Carta-Circular* 3,687, 26/12/2014, issued by the Central Bank of Brazil. With this regulatory change, financial institutions had to consolidate all controlled firms' balance sheets regardless of whether they were regulated or unregulated (such as consortium administrators, payment institutions, credit society, and securitizer over which the institution had direct or indirect control). These were termed as *prudential conglomerates*, as opposed to *financial conglomerates* before the entrance of this regulatory change, in which balance-sheet consolidation was limited to controlled financial firms directly supervised by the Central Bank of Brazil. Therefore, data on conglomerate-level market exposures became more comprehensive since 2015.

2.4.1 Bank & policy-maker connection

This represents the interlayer connections between banks and the policy-maker. Connections are unilateral from banks to the policy-maker and represent banks' net trading book sensitiveness to interest rates changes. Brazil adopts Basel III recommendations regarding the treatment of the trading book. In this way, the Central Bank of Brazil has established rules that oblige banks to mark-to-market any tradable instrument daily. We take monthly supervisory data from the Risk Market Statements database (*Demonstrativo de Risco de Mercado* - DRM) maintained by the Central Bank of Brazil. The DRM contains bank-specific information on cash flows (in and outflows) subject to market risk at different maturity dates ranging from one day to 30 years (twelve vertices).

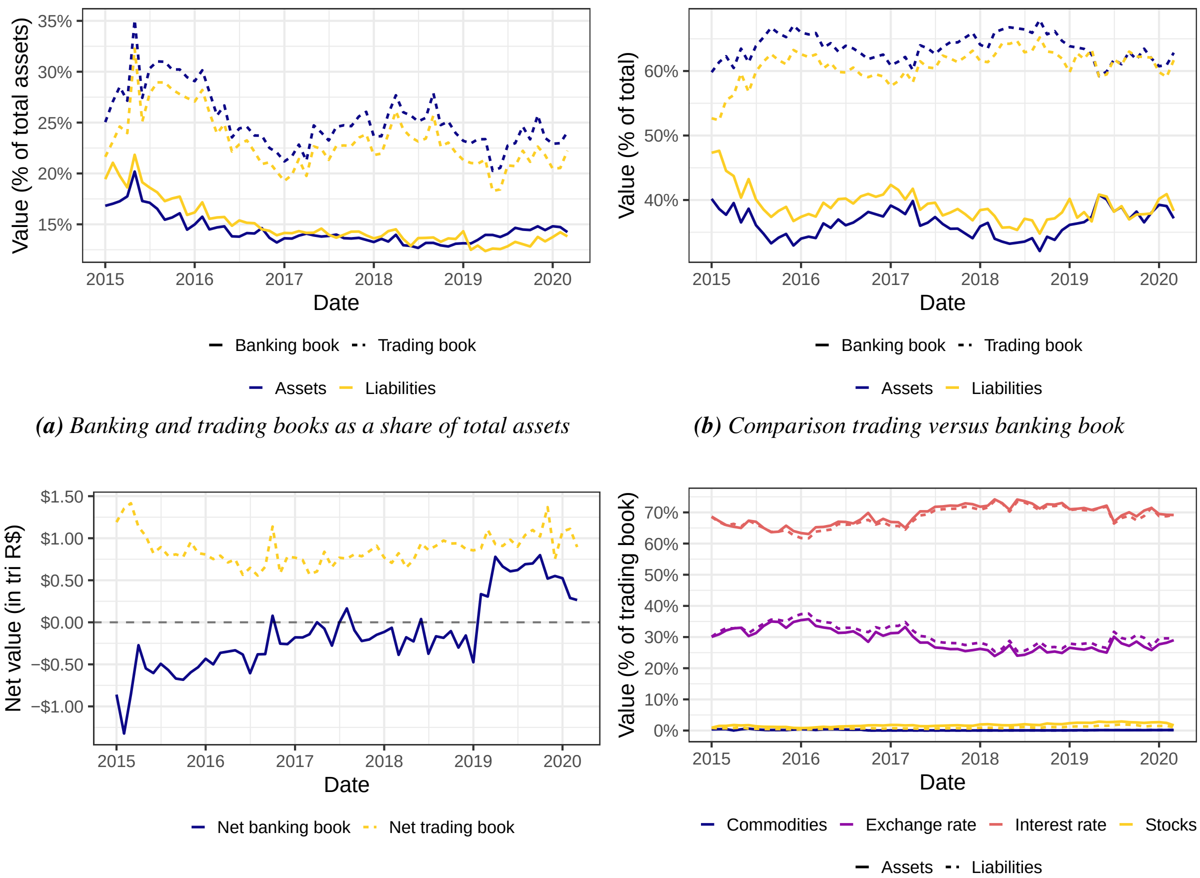
Figure 3a shows the aggregate size of the banking and trading books in terms of the total assets of the entire financial sector from 2015–2020. Trading assets and liabilities are more representative and correspond to 25% and 22%, respectively, of the financial system's total assets. The net trading book is positive, suggesting that increases in interest rate generate losses to banks. At the beginning of the sample, when interest rates were high, the trading book was slightly larger due to the attractiveness of federal bonds attached to the interest rate. When interest rates decreased, the trading book size reduced as well. Figure 3b portrays the trading and banking books as a share of the sum of both books.[17] The trading book takes 60% of the size of both books during the period. Figure 3c shows monetary values of the net trading and banking books (assets − liabilities) of the entire financial system. The net trading book remains stable in the period with a net positive position of R$ 1 trillion (about 14% of the Brazilian GDP in 2019). In contrast, the banking book seems to change from a net short position to a long position in the period.

In this paper, monetary policy shocks transmit to banks' balance sheets through the revaluation of tradable instruments attached to that rate rather than the entire trading book. Figure 3d breaks down the components of banks' trading books in terms of instruments attached to the interest rate, foreign exchange rate, commodities, and stocks. Values are in shares of the total tradable assets/liabilities. Interest rates are the most representative portion of both the trading book's asset and liability sides, with an average share of 70% in 2015–2020. Foreign exchange rates follow with an average share of 30%. Most of the foreign exchange exposures are overhedge operations to offset the difference in taxation between hedging in Brazil and foreign investment. The shares of tradable assets/liabilities representing commodities and stocks held by Brazilian banks are negligible. Monetary policy changes transmit through the tradable instruments attached to the interest rate, which are the most important parcel held by Brazilian banks.

The interest rate shock effect will depend on the portfolio formed by tradable instruments,

[17] The total assets contain elements that are not classified neither in the trading nor banking books, such as cash, permanent assets, deferred tax credit, and other assets that do not have a market risk component. By eliminating these terms, we can compare the relative sizes of both books.

the net position, and the duration gap, defined as a difference between the weighted maturity of the portfolio's assets and liabilities. *Ceteris paribus*, the greater the difference in duration, the greater the variation in the portfolio value.[18]



(a) Banking and trading books as a share of total assets

(b) Comparison trading versus banking book

(c) Comparison net trading versus net banking book

(d) Composition of banking trading book

***Figure 3** – Aggregate size of the banking and trading books of Brazilian banks from January 2015 to March 2020. (a) Representativeness of the aggregate trading and banking books as a share of the total assets of the financial system; (b) trading and banking books as a share of the sum of both books; (c) net monetary values of the trading and banking books; (d) trading book broken down by risk factors.*

2.4.2 Bank layer

The Brazilian interbank market is composed of secured and unsecured financial operations. Due to domestic regulatory norms, financial institutions must register and report all securities and credit operations to the Central Bank of Brazil, which reinforces the data representativeness and quality. From January 2015 to March 2020, 86% of the financial operations were not collateralized. Most of the unsecured lending are on-lending (91.4% of the total unsecured lending in the period), followed by credit (6.1%), and interfinancial deposits (1.7%).

[18] Bluhm, Georg and Krahnen (2016) argument that the interbank book in Germany shrinks the underlying client book, like a mirror image. In Brazil, this case is also possible, as changes in the trading portfolio may indirectly affect the interbank market. The direct variation of the interbank market due to the revaluation of the trading book is negligible, as banks have little exposure to instruments attached to the interest rate in the interbank market.

The most common secured lending operations among banks are short-term re-purchase agreements (repos) collateralized with Brazilian federal bonds (99.8% of the total secured lending). Since the vast majority of secured lending are backed by federal bonds—which are very liquid—creditors could sell off these bonds with roughly no losses even in the very short term if debtors default. Therefore, we remove secured lending during the contagion transmission process as they are unlikely to convey counterparty risk.[19]

The Brazilian interbank market has significantly changed since 2015. Before, most transactions were collateralized with federal bonds, and the primary transactions were repos, on-lending, interbank deposits, financial bills, and debentures. This structural change may be partly due to the onset of the Brazilian recession in 2015, which may have led banks to redirect credit from the real sector to the interbank market. According to Bluhm, Georg and Krahnen (2016), the inflow and outflow of non-bank customers are correlated with the interbank market.

These operations are registered and controlled by different custodian institutions, which raises the complexity of gathering, pre-processing, and matching the data across different systems. Among the custodian institutions, we extract data from the Cetip[20], which holds operations with private securities, the Central Bank of Brazil's Credit Risk Bureau System (SCR)[21], which registers credit-based operations, and the Brazilian stock exchange (BM&FBOVESPA)[22], which records swaps and options operations. On March 30th, 2017, BM&FBOVESPA, and Cetip merged into a new company named B3.

[19] While this argument holds for Brazil, in which secured lending is mainly through repo operations collateralized by federal bonds, counterparty risk does exist, in general, in secured lending. A clear example is the global financial crisis. Gorton and Metrick (2012) argue that the 2008 financial crisis was a system-wide bank run in the "securitized-banking" system, rather than in the traditional banking system. They find that securitization and repo financing were at the core of the crisis. The contagion led to *en masse* withdrawals, causing high haircuts in the repo markets. Unlike the US case, in which repo markets are more developed and diversified with private securities used as collateral, repo operations in Brazil mainly take place with federal bonds, which are guaranteed by the federal government and hence much less prone to haircuts.

[20] Cetip is a depositary of mainly private fixed income, state and city public securities, and other securities. As a central securities depositary, Cetip processes the issue, redemption, and custody of securities, and, when applicable, the payment of interest and other related events. Eligible institutions that participate in Cetip include commercial banks, multiple banks, savings banks, investment banks, development banks, brokerage companies, securities distribution companies, goods, and futures brokerage companies, leasing companies, institutional investors, non-financial companies (including investment funds and private pension companies) and foreign investors.

[21] SCR is a comprehensive data set that records every single credit operation within the Brazilian financial system worth R$200 or above. Up to June 30th, 2016, this lower limit was R$1,000. SCR has the tax identifier of the bank and client, the loan's maturity, modality, interest rate, risk classification, origin (earmarked or non-earmarked), and the parcel that is overdue.

[22] BM&FBOVESPA is a privately-owned company created in 2008 through the integration of the São Paulo Stock Exchange (Bolsa de Valores de São Paulo) and the Brazilian Mercantile & Futures Exchange (Bolsa de Mercadorias e Futuros). As Brazil's central intermediary for capital market transactions, the company maintains electronic systems for trading equities, equity derivatives, fixed-income securities, federal government bonds, financial derivatives, spot FX, and agricultural commodities.

We consider financial exposures among different conglomerates or individual financial institutions that do not belong to conglomerates. In Brazil, conglomerates must account for all the counterparty risk of their branches, subsidiaries, and other entities within the group, such as consortia. Therefore, we remove intra-conglomerate exposures in the analysis as they are more related to internal liquidity management and less to risky operations. We contemplate all banking institutions in Brazil, encompassing commercial banks, investment banks, development banks, federal savings banks, and universal banks. There are, on average, 131 active banking institutions in our sample for the analyzed period. We do not include non-banking institutions, such as credit unions, because their contribution to stress transmission is negligible.[23]

Following Silva, Souza and Tabak (2017), we take as bank capital only that fraction above the minimum capital requirements that Brazilian banks must continuously hold (the capital buffer). That is, the bank defaults when its total capital buffer relative to its risk-weighted assets (RWA) falls below the 8% Basel regulatory requirement. Since the total RWA also accounts for the interest rate risk held in the trading book (inside the market risk component), our capital buffer also includes the capital requirements arising from banks' risk-taking component besides the counterparty risk in the interbank and corporate markets.

2.4.3 Firm layer

In this section, we only describe the set of firms used in the analysis. We do not model firm-to-firm links (trade credit) due to data unavailability.

Our model requires firms' accounting data. Unlike the financial sector in which we have complete information on bank exposures, data on the corporate sector is scarcer and is available only for listed companies in BM&FBOVESPA. Due to legal enforcement, listed firms must report balance-sheet data, such as financial statements and financial indicators, quarterly. We use Economatica to extract consolidated balance sheet information from these firms. Table 2 reports the number of firms in each economic sector that we use in our analyses. Although firms can coexist with negative equities, such as those facing judicial recovery, we remove them because our model uses equities as the primary resource of loss absorption.

To facilitate the reading, we limit our discussion to six sectors that we select by the extent of the interest rate shock effect. We choose the three most affected (agriculture, chemical, and electric electron) and least affected sectors (mining, oil & gas, and technology). Firms in these six sectors have high relevance to the Brazilian economy, such as those in the mining, oil & gas, and agriculture sectors. As for the impact of negative shocks, as will be discussed in the results Section 2.5, contagion is low and negligible for financial stability.

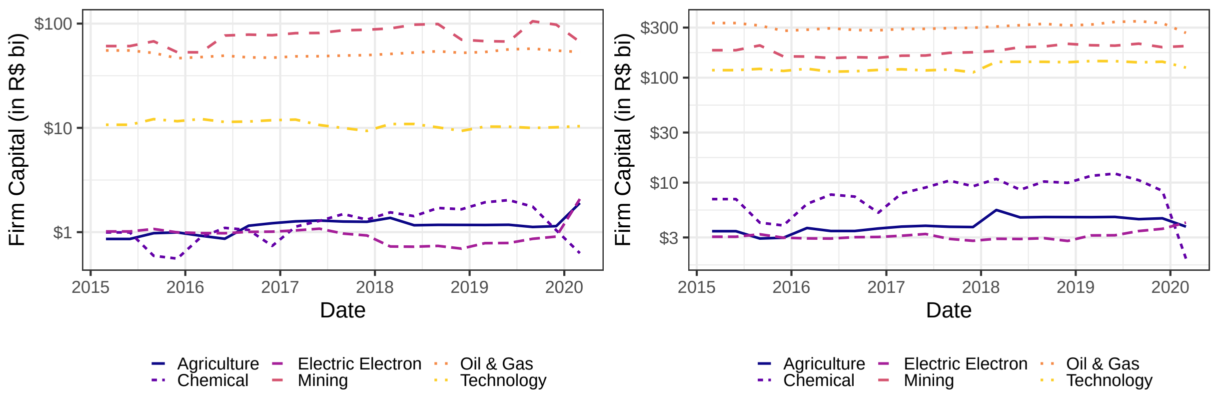
Figures 4a and 4b depict the average net worth (equities) and total equities of the six

[23] For more details, we refer the reader to Silva, Souza and Tabak (2016), who study the structure and systemic risk issues of the Brazilian interbank market in terms of the type of the financial institution (credit unions, commercial, investment, development banks).

Table 2 *– Number of firms by economic sector representing the firm layer in Figure 1. Because the model requires firm balance-sheet information, we restrict our analysis to listed firms in the BM&FBOVESPA. We also remove firms with negative equities.*

Economic sector	Number of firms	Economic sector	Number of firms
Trade	33	Chemical	9
Electric Energy	26	Oil & Gas	7
Construction	24	Industrial Machine	6
Fabricated Metal	18	Agriculture	5
Textile	18	Electric Electron	5
Technology	16	Mining	5
Food & Beverage	13	Pulp & Paper	3
Vehicle & Parts	13	Non-Metallic Mineral	2
		TOTAL	203

selected economic sectors from January 2015 to March 2020. During the COVID-19 crisis in 2020, total sector-level capitalization mainly dropped, especially for the chemical sector. As firm capitalization serves a loss-absorption mechanism, these firms in the chemical sector become more exposed to credit rationing from the financial sector. The technology sector has a higher heterogeneity regarding firm size since the total capital is high, and the average capital is relatively low.



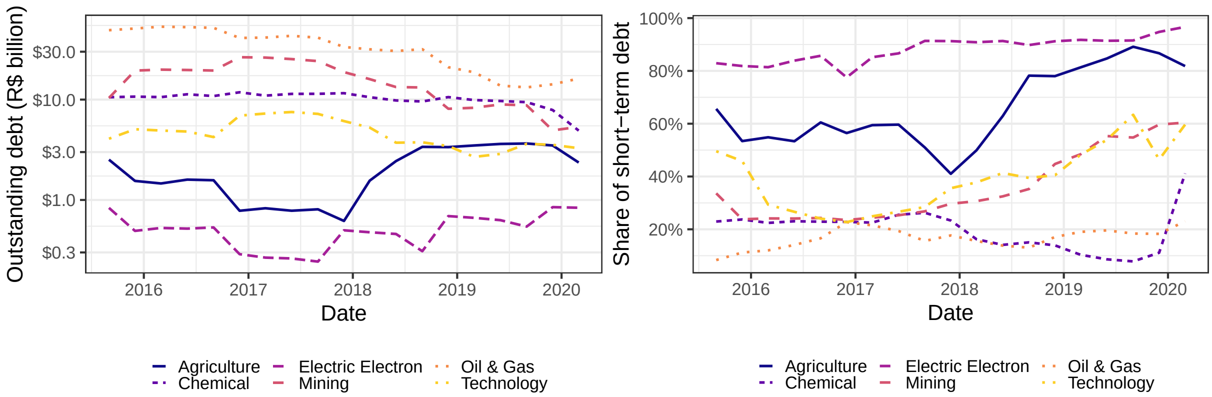
(a) *Average capital* ***(b)*** *Total capital*

Figure 4 *– Average net worth (equities) of Brazilian selected economic sectors from January 2015 to March 2020. For the sake of readability, we plot these quantities for the three most and least affected sectors by the interest rate shock. Panel (a) shows the average firm capital for each selected sector (agriculture, chemical, electric electron, mining, oil & gas, and technology), while panel (b) shows the total firm capital for the same sectors.*

2.4.4 Bank & firm connection

For each firm, we identify its economic conglomerate, which encompasses all controlled firm branches of the listed firm. We then extract the outstanding bank credit of each firm economic conglomerate from January 2015 to March 2020 monthly using the SCR. We also consider the maturity of the loans, such as to identify the short- (less than one year) and long-term bank funding. This division is important because funding risk operates through short-term loans, while counterparty risk works through total outstanding loans (short + long).

Firm perspective: Figures 5a and 5b portray the outstanding (short and long term) bank debt and the average share of short-term bank debt of firms, respectively. Sectors with the highest share of short-term debt, chemical and agriculture, have the lowest bank credit volume and are most prone to credit rationing (funding risk). Overall, firms increased their short-term debt during the COVID-19 crisis mainly by borrowing working capital to withstand potential liquidity constraints, as capital markets were facing high volatility.

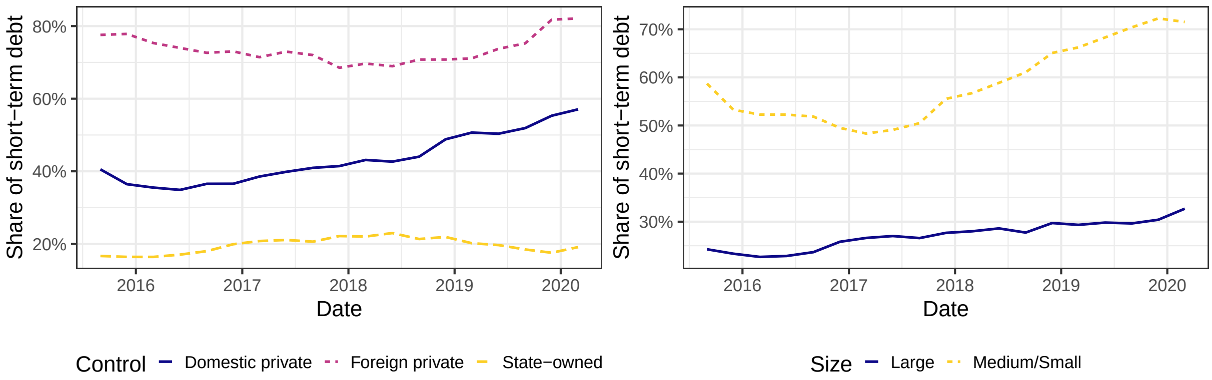


(a) Firm outstanding debt *(b) Firm short-term debt*

Figure 5 – *Firms' average total outstanding debt and credit share due in the short term (less than one year) from January 2015 to March 2020 in terms of their maturity. For the sake of readability, we plot these quantities for the three most and least affected sectors by the interest rate shock. Panel (a) shows the total outstanding debt of selected economic sectors (agriculture, chemical, electric electron, mining, oil & gas, and technology), while panel (b) shows the share of short-term bank debt for the same economic sectors. We apply a smoothing filter of three months to remove seasonality and facilitate reading.*

Bank perspective: We now look at how economic sectors are connected to banks. In our model, banks that endure large losses in view of changes in interest rate are those that will restrain more credit to the corporate sector. Thus, firms that are connected to these banks will be the ones most affected. Since financial stress transmits from banks to firms through credit rationing, we focus on short-term bank credit.

Due to the importance of state-owned banks for the Brazilian economy and financial system, we depict in Figure 6a the share of bank credit that is due in the short term to the corporate sector broken down by bank control (domestic private, foreign private, and state-owned). Most of the short-term bank credit to Brazilian listed firms comes from foreign private banks (roughly 80%). Hence, if foreign private banks endure large trading book losses due to interest rate changes (risk-taking component), firms relying on their credit will be most affected by credit rationing. State-owned credit is mainly long term, as they aim to finance long-term infrastructure projects from listed firms. We also report the share of short-term bank credit to the corporate sector in Figure 6b broken down by bank size (large, and medium/small). The bank size component is important because larger banks are the most important institutions for the financial stability.[24] Firms that borrow from medium/small size are more susceptible to bank funding risk and, therefore, to contagion.



(a) Bank control type *(b) Bank size*

Figure 6 – *Share of short-term debt granted by banks to firms broken down by bank type: (a) bank control (state-owned, domestic private, and foreign private); and (b) bank size (large and medium/small). We apply a smoothing filter of three months to remove seasonality and facilitate reading.*

2.5 Empirical results

We start this section by performing a sensitivity analysis of economic agents' financial stability to interest rate shocks. After, we present a more granular view of interest rate consequences on financial stability. Finally, we report some robustness tests.

2.5.1 Sensitivity analysis of the financial stability of economic agents to interest rate shocks

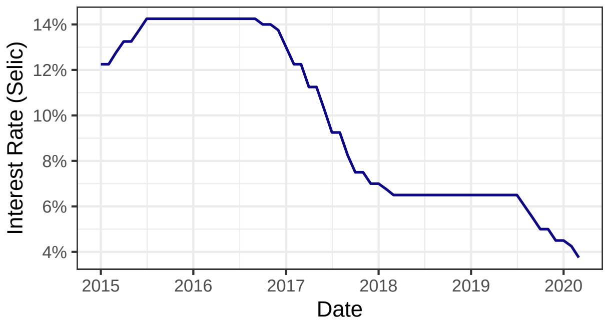
We start this section by performing a sensitivity analysis of the potential net worth loss of banks and firms to different interest rate shocks. Our exercise consists of three sequential and independent steps: (i) vary the interest rate from -90% to 90% relative to its true nominal rate at that time, with steps of 10 percentile points, (ii) revalue the stressed cash flow attached to the interest rate of banks using the methodology in Section 2.3.2.1, and then (iii) estimate potential net worth losses—i.e., our proxy for the financial stability of the economic agent—of every bank and firm in the economy through financial contagion using the guidelines in Section 2.3.2.2.

Figure 7a depicts the trajectory of Brazil's policy rate (Selic rate). Our sample covers an interesting period in Brazil. It starts with a period of monetary tightening (January 2015 to May 2017), followed by a period of significant reduction in the interest rate until it entered a

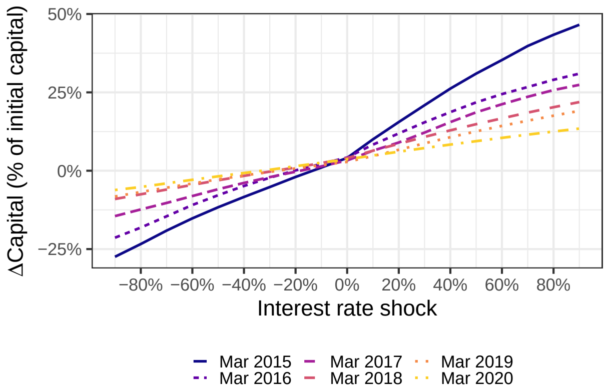
[24] We classify banks as large or medium/small as follows. We first construct a cumulative distribution function (CDF) on the banks' total assets and classify them depending on the region in which they fall in the CDF. We consider as large those banks that fall in the 0% to 75% region, and as medium/small, otherwise.

period of monetary easing (March 2018 to March 2020). In this last period, the Selic rate reached 3.75%—its lowest historical value since the beginning of the time series in 1996 up to March 2020. Our sample also encompasses the beginning of the COVID-19 crisis in Brazil, which led to further monetary easing.

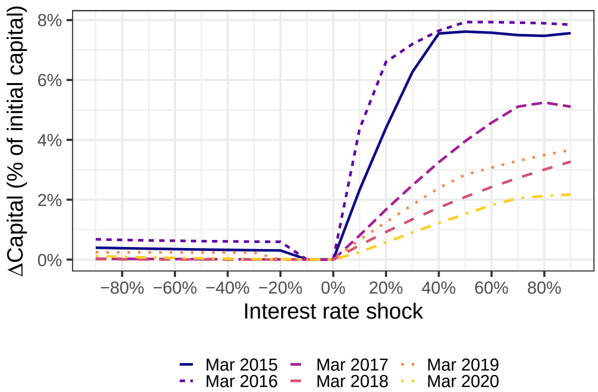
Figure 7b shows the direct impact of interest rate shocks on banks' trading books due to the immediate revaluation of their cash flows attached to the interest rate. In turn, Figures 7c and 7d show the indirect impact on the financial and corporate sectors due to financial contagion. We report losses/profits as a fraction of the current net worth of economic agents. We only report curves with data from March of each analyzed year.



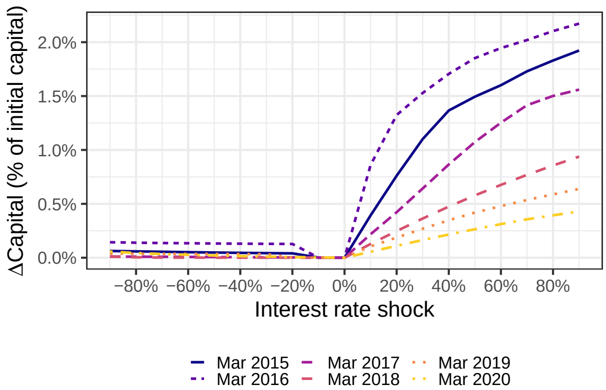
***(a)** Brazil's policy rate (Selic)*



***(b)** Direct impact in the financial sector (trading book variation)*



***(c)** Indirect/Network impact in the financial sector (contagion losses)*



***(d)** Indirect/Network impact in the corporate sector (contagion losses)*

Figure 7 – *Brazil's interest rate curve and sensitivity analysis of banks' and firms' net worth variations to different interest rate shocks (from −90% to 90% of the current nominal interest rate). (a) Brazil's interest rate curve (Selic). (b) Direct impact of interest rate shocks on banks' net worth due to the revaluation of their net trading book (without using the network model). (c) Indirect impact of interest rate shocks on the financial sector due to financial contagion & amplification. (d) Indirect impact on the corporate sector through credit rationing of short-term bank credit.*

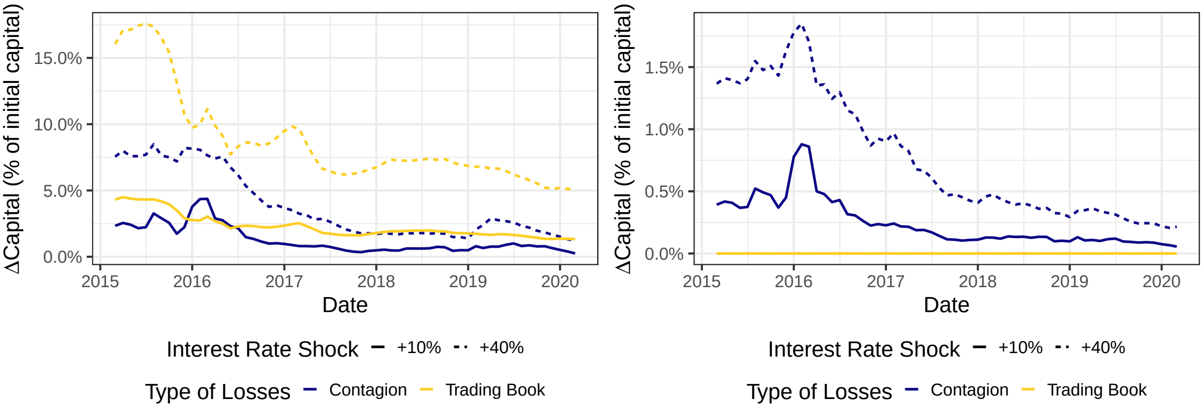
Our sensitivity analysis points to a piece-wise linear relationship between trading book losses and interest rate shocks (Figure 7b). The sign of the interest rate shock separates the linear segments of this relationship. The trading book's sensitivity to interest rates is more pronounced for positive shocks, as we can observe from the larger curve slopes for positive interest rate shocks when compared to negative shocks. Roughly, the slope relationship between the positive and negative segments is 2. Interest rate shocks cause substantial variations of banks' net worth, especially in periods of high interest rate (March 2015). For instance, in March 2015, a 10% shock would cause a 10% decrease in the capitalization of the entire financial system. In turn, in a period of low interest rates such as March 2020, the same shock would cause a 4% reduction. For comparability, the delinquency rate of 3% observed in 2015 corresponded to about 22% of the financial system's net worth. While losses arising from credit default are aggregate within the year, the interest rate shock must be registered within the day. Therefore, these observed net worth losses are relevant.

In contrast, we observe a non-linear relationship between interest rate changes and contagion & amplification losses for both financial and corporate sectors (Figures 7c and 7d). While the impact of negative shocks is stable, the impact of positive interest shocks on net worth losses grows non-linearly as we distance from the current state of the economy (no interest rate shock). The non-linearity arises from the network topology among economic agents. Some banks may lose, and others may profit from the interest rate shock. The way they interconnect with other banks and firms will determine how shocks will propagate. The marginal sensitiveness of economic agents' net worth to interest rate shocks due to the indirect impact decreases for larger shocks because there are important banks to which firms/banks are exposed that end up better off due to the large interest rate shock. Therefore, they attenuate the overall contagion effect.

We also highlight an interesting observed feature. Even though interest rates in March 2016 were higher than in March 2015, the effect of interest rate changes on banks' trading books (direct impact) is higher in the former date. One explanation is that Brazil was in a phase of increasing (already high) interest rates, which incentives position-taking in tradable instruments attached to the interest rate. However, we observe a different profile for indirect impact, with contagion being higher than trading book losses in 2016. This fact occurs because some foreign private banks are more affected by interest rate shocks in 2016 than in 2015. Since they are the main drivers of funding risk to the corporate sector (see Figure 6a), they end up transmitting more financial stress to the entire economy.

To better exemplify the relevance of monetary policy shocks to the financial stability, Figures 8a and 8b exhibit aggregate net worth losses of the financial and corporate sectors for +10% and +40% interest rate shocks. We do not consider negative interest rate shocks when analyzing the financial contagion because net worth losses are negligible during 2015–2020 (see Figure 7b). We choose the +10% and +40% shocks due to the significant interest rate variations in the analyzed period. Although shocks of 10% over the nominal interest rate are feasible over the entire sample period, the magnitude of this shock becomes irrelevant at the end of our sample, when the Selic rate reached 3.75%. Therefore, we also investigate the financial stability implications of a 40% interest rate shock, which would be feasible at the end of the sample, given the historical changes in the Selic rate promoted by the policy-maker.

We can see that the financial and corporate sectors are more sensitive to interest rate



***(a)** Financial sector* ***(b)** Corporate sector*

Figure 8 – *Trajectory of the short-term sensitiveness of the (a) financial and (b) corporate sectors' aggregate net worth to +10% and +40% interest rate shocks from January 2015 to March 2020. Higher sensitivities imply larger losses in their net worth when interest rate changes.*

shocks in periods of monetary tightening. The direct impact of a +40% interest rate shock reaches up to 4 times the net worth variation caused by a +10% interest rate shock from 2015 to 2017. After this period, there is greater stability in the net worth variation caused by these two shocks, even though Brazil's policy rate decreased during the period. Overall, the net worth variations caused by the +40% interest rate shock is about 3 times greater than the +10% interest rate shock after 2017. Regarding the indirect impact, we observe the same phenomenon for both the financial and corporate sectors. Also, capital losses from financial contagion are higher than from the trading book in the first half of 2016. These results indicate that, in addition to the interconnections in the real and financial sectors, macroeconomic conditions are relevant to the relationship between monetary policy and financial stability.

We can also draw some policy implications given this non-linear relationship between monetary policy and financial stability. First, policy-makers should be aware of the financial system's current capitalization levels when conducting monetary policy. Big swings in the interest rate can cause considerable adverse consequences for banks' net worth through trading book variations and the network effect, which could spillover to the corporate sector. Second, our findings reinforce the conclusions of the classical work by Clarida, Galí and Gertler (1999), who advocate that central banks need to smooth interest rate changes to minimize disruptions in financial markets. By smoothing interest rate changes, shocks tend to be smaller, and the impact becomes roughly linear.

2.5.2 A more granular view on the consequences of monetary policy shocks to financial stability

The previous aggregate analysis is useful for a system-wide view of the financial system's resilience to monetary policy shocks. However, it does not allow us to identify particularities arising from banks' and firms' financial conditions and the network structure. This section analyzes the effects of interest rates on these economic agents in a more granular way.

2.5.2.1 Interest rate sensitiveness of banks by control and size

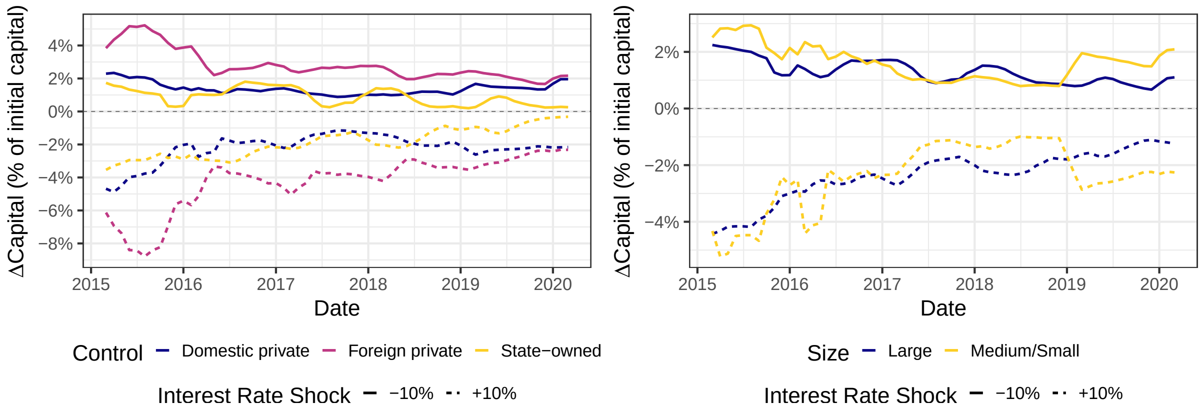
In this section, we break down the effects of interest rate shocks on the financial sector by looking at which banks are more susceptible to these shocks in terms of control and size.

Direct effects: Figures 9a and 9b display the average banks' net worth variation caused by the direct effect when we simulate a $+10\%$ and -10% interest rate shock broken down by bank control and bank size, respectively. Foreign private banks are more sensitive to both positive and negative interest rate shocks. While in the aggregate analysis (Figure 8a) losses from trading book variations are less than 5% of the financial system's net worth, losses for foreign private banks reach almost 9% for a $+10\%$ interest rate shock (Figure 9a). Private foreign banks are also the ones that show the greatest capital gain in the event of a negative interest rate shock, reaching almost double the earnings of other types of banks. A possible explanation for these results is the business niche of these banks. Many are investment banks and, therefore, operate with a larger trading book and act more strongly when interest rates are high in Brazil.

In contrast, state-owned banks experience fewer losses and gains in the trading book mainly because of their institutional purposes. State-owned banks are conduits of public policies in Brazil and tend to have smaller net trading books. For instance, in Brazil, they operationalize subsidized and long-term credit programs to mitigate market failures in certain sectors. Domestic private banks, in contrast, have in-between losses comparatively to state-owned and foreign private banks. However, at the end of the sample, domestic and foreign private banks have similar losses/gains, possibly because they increase their position-taking as a result of the reduction of Brazil's policy rate. This fact highlights the importance of having a more detailed view of the financial system so that a shock does not cause unintended imbalances.

We do not observe sizable differences on the trading book variation by bank size until 2019. In this year, medium/small banks show high sensitiveness to positive and negative interest rate shocks (Figure 9b). Finally, in case of a -10% interest rate shock, there will be capital gains on average for banks. Roughly speaking, the potential capital losses trajectories due to positive and negative 10% shocks are very similar. However, they start at different levels. In 2015, the potential capital gains for a -10% interest rate shock were about half of the potential losses for a positive shock of the same magnitude. At the end of the sample period, both percentages of potential gains and losses on average are similar.

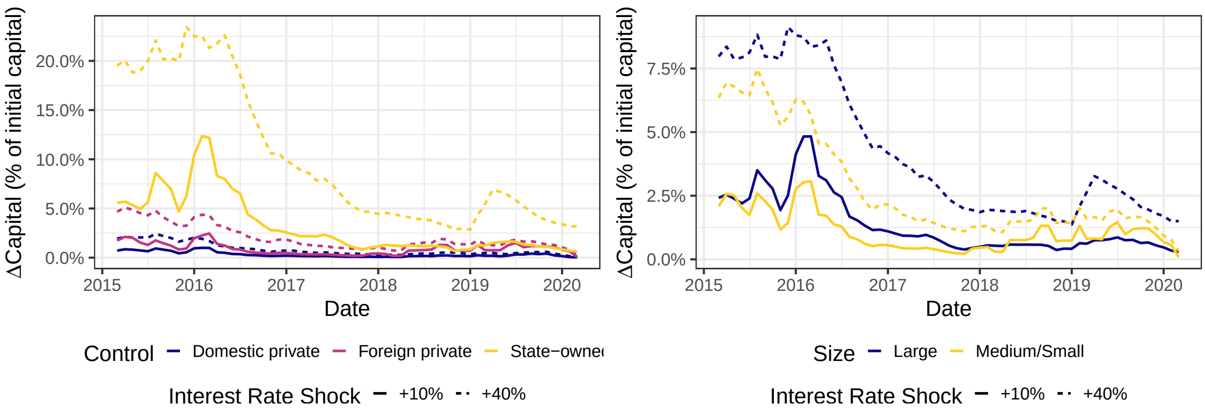
Indirect effects: We now analyze the indirect short-term consequences of interest rate shocks in the corporate and financial sectors. We take the trading book variations explored in the previous in this section as input to the network model. As discussed in the previous section, we analyze contagion regarding shocks of $+10\%$ and $+40\%$ on interest rate due to the negligible indirect impact of negative interest rate shocks.



(a) Potential capital loss by bank control type *(b) Potential capital loss by bank size*

Figure 9 – *Short-term consequences on banks' net worth caused by $+10\%$ and -10% interest rate shocks (risk-taking component). Interest rate changes force the immediate revaluation of banks' trading instruments, directly reflecting on banks' net worth. We report the aggregate net trading book variation (assets − liabilities) by: (a) bank control type (state-owned, domestic private, and foreign private); and (b) bank size (large and medium/small).*

As in the case of direct impact, we note that net worth losses are smaller when monetary policy is looser. This fact reinforces the perception that the policy-maker must also take contagion into account when establishing monetary policy interest rates. Unlike trading book variations, state-owned banks and large banks are more susceptible to contagion (Figures 10a and 10b) because they are the largest creditors of listed firms and play a central position in the interbank market. Therefore, the likelihood of receiving financial stress from any other agent in the network is higher.



(a) Potential contagion loss by bank control *(b) Potential contagion loss by bank size*

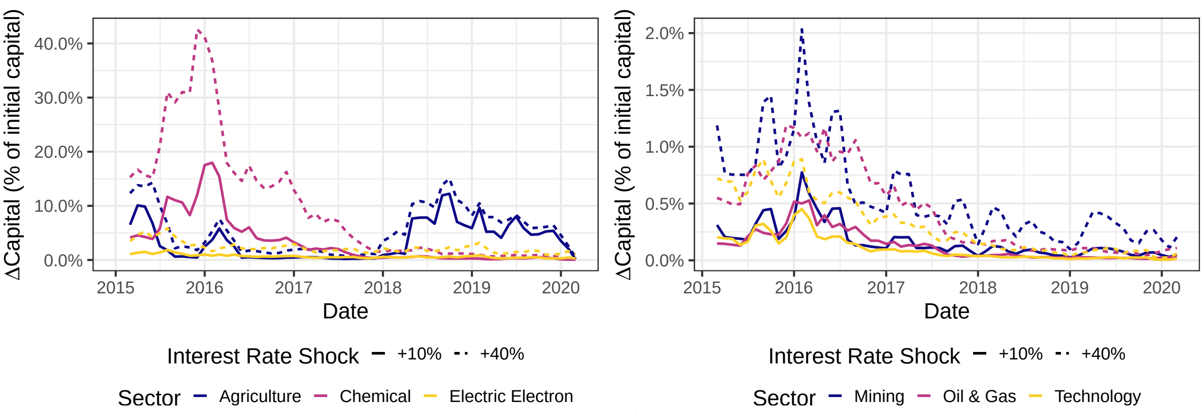
Figure 10 – *Short-term consequences on banks' net worth in view of contagion caused by $+10\%$ and $+40\%$ interest rate shocks (contagion and amplification component). Contagion arises due investment repricing (counterparty risk) and credit rationing (funding risk). We report the aggregate potential net worth loss due to contagion by: (a) bank control type (state-owned, domestic private, and foreign private); and (b) bank size (large and medium/small).*

2.5.2.2 Interest rate sensitiveness of firms by economic sector

In this part, we evaluate the corporate sector's short-term sensitiveness to $+10\%$ and $+40\%$ interest rate shocks. Recall that firms are exposed to interest rate shocks in the model through credit rationing from the financial sector. Therefore, they only have a non-zero indirect effect (financial contagion).

Figure 11a portrays the short-term sensitiveness of the three most affected economic sectors to $+10\%$ and $+40\%$ interest rate shocks (indirect effect). All losses are in terms of the sector-specific total net worth. The granular analysis reveals that losses in some economic sectors can be significantly higher than those estimated by the aggregate analysis. While in the latter net worth losses were limited to a maximum of 1% and 2% of the entire corporate sector's net worth for $+10\%$ and $+40\%$ interest rate shocks, respectively, sector-specific net worth losses can be substantially higher. For instance, the chemical sector would lose up to 40% of its total capitalization. Even though total losses in the granular analysis must coincide with the aggregate analysis if we sum across all economic sectors, our results evidence the high level of heterogeneity that monetary policy can affect the corporate sector through credit rationing. We can also notice that the aggregate losses are similar to the losses of the sectors least affected by contagion (Figure 11b).

Unlike other sectors and even the financial sector, whose net worth sensitivity follows Brazil's policy rate, the agriculture sector becomes more sensitive when the Selic rate is at its lowest levels. One possible explanation is the increase in bank loans taken by firms in the sector, as shown in Figure 5, especially short-term credit. The sectors least affected by interest rate shocks are the most capitalized.



***(a)** Most sensitive sectors to $+10\%$ and $+40\%$ interest rate shocks*

***(b)** Least sensitive sectors to $+10\%$ and $+40\%$ interest rate shocks*

***Figure 11** – Trajectory of the short-term sensitiveness of economic sectors to $+10\%$ and $+40\%$ interest rate shocks from January 2015 to March 2020 (contagion and amplification component). (a) Most sensitive sectors and (b) least sensitive sectors.*

The granular analysis of the firms' net worth sensitiveness to interest rate shocks reinforces the idea that the policy-maker has to make a comprehensive analysis before taking monetary policy decisions. In addition to assessing the impact on the financial sector, one has to estimate second-order effects, such as on the corporate sector. Monetary policy and financial stability have a non-trivial relationship, with ties that depend on the conditions of economic agents in the corporate and financial sector, and also the underlying network structure that defines the relationships among them. Our methodology applied to Brazil highlights a potential expressive financial contagion in the agriculture sector through credit rationing in periods of monetary policy easing. The agriculture sector is heavily dependent on bank financing and is of great importance for the Brazilian economy. Although the aggregate analysis indicates a low effect of monetary policy on the financial stability of the corporate sector, the agriculture sector has a significant loss of capital in a period when the model indicates decreasing losses in an aggregate manner.

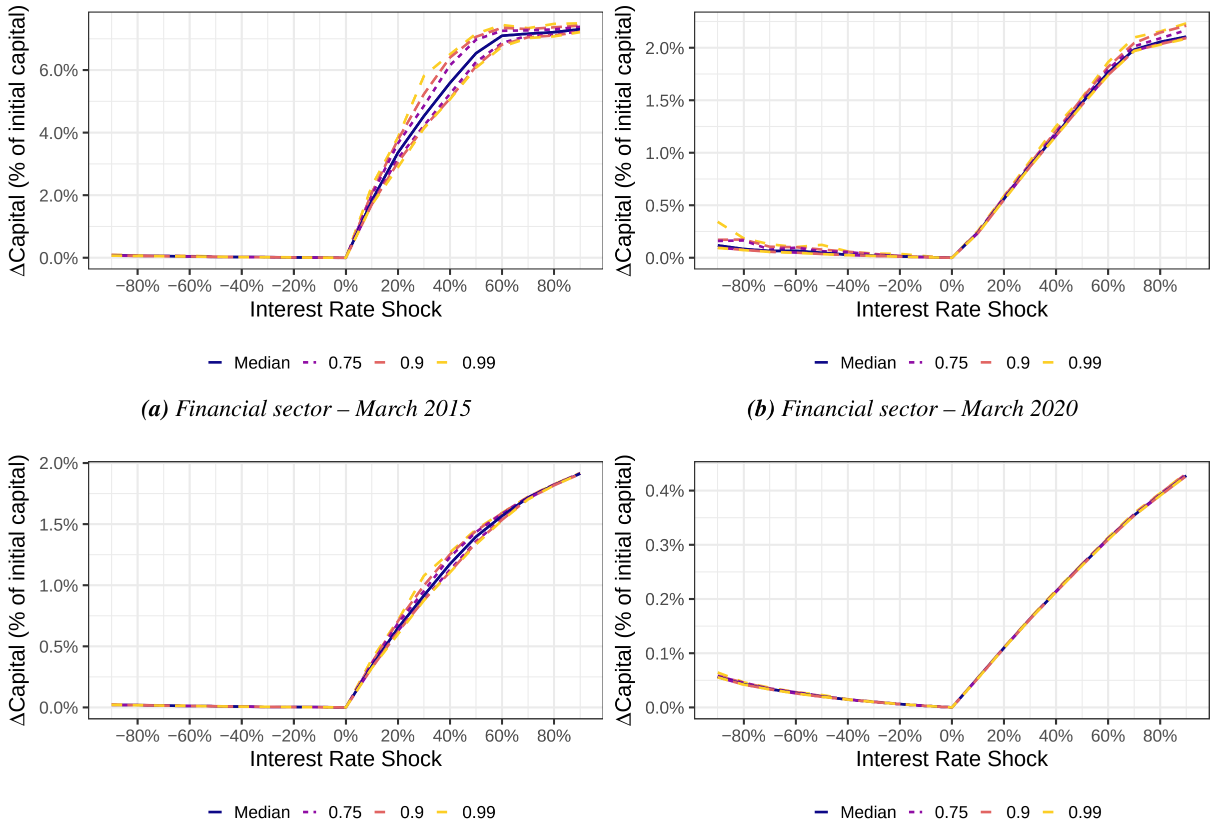
2.5.3 Robustness tests

Mutable network structure: our financial contagion & amplification model assumes the network structure as fixed. Even in the short term, links among banks/firms may be created or severed, depending on several factors. In this section, we perform a simple exercise in which we allow links in the interbank market to change stochastically while shocks transmit across the network. Following the interest rate shock in the economy, we perform a random reattachment of all interbank links before each iteration of the shock transmission rule in Eq. (2.6). We use a uniform distribution to reassign the links, but we prevent the creation of self-loops. Figure 12 displays a sensibility analysis of the aggregate net worth losses to interest rate shocks, similar to the setup in Figure 7. For each date and interest rate shock, we perform 100 independent runs and report the quantiles 0.50 (median), 0.75, 0.9, and 0.99 of the aggregate net worth loss distribution of (a) the financial sector in March 2015; (b) the financial sector in March 2020; (c) the corporate sector in March 2015; and (d) the corporate sector in March 2020. The random reattachment of links does not seem to interfere with our results in qualitative terms. However, we should note that link reattachments are not random and rather strategic in reality. Despite this, our results provide a first idea of the robustness of our results to different network structures.

Paying out profits from interest rate shocks: banks may be tempted to pay out gains from re-valuation caused by interest rate changes, thus eliminating any positive effects on their net worth. To simulate this behavior, we assume that banks' initial net worth does not increase when they profit from an interest rate shock as they immediately pay out their gains to shareholders. Hence, they do not enter the "better off" state as in Figure 2. Our results remain qualitatively and almost quantitatively the same as in Figure 7.

2.6 Conclusions

This paper investigates how monetary policy shocks transmit to the economy, considering a very granular model comprising each individual bank and firm and their connection patterns.



***(a)** Financial sector – March 2015*

***(b)** Financial sector – March 2020*

***(c)** Corporate sector – March 2015*

***(d)** Corporate sector – March 2020*

***Figure 12 –** Robustness test. We allow random reattachment of links in the interbank market as the shock transmits throughout the economy. We perform a sensitiveness analysis similar to that in Figure 7. For each date and interest rate shock, we perform 100 independent runs and report the quantiles 0.50 (median), 0.75, 0.9, and 0.99 of the aggregate net worth loss distribution of (a) the financial sector in March 2015; (b) the financial sector in March 2020; (c) the corporate sector in March 2015; and (d) the corporate sector in March 2020.*

Though there are several transmission channels through which monetary policy operates, we are concerned with adjustments in the accounting value of trading book exposures on banks' balance sheets that have to be marked to market when interest rates change. While there are increasing efforts in linking macroeconomic behavior with granular models in the literature, primarily through network models, none of them has explicitly incorporated the trading book channel that we explore in this work. Such a detailed understanding of how monetary policy is transmitted can help decision-makers design better policies to steer the economy and mitigate financial imbalances.

To evaluate how interest rate changes transmit to the economy, we extend Silva, Alexandre and Tabak (2017)'s model by encompassing a policy-maker and introducing the trading book channel. Interest rate changes can generate losses or profits for banks, depending on their trading book exposures and duration gap. Profiting banks increase their capitalization levels while banks registering losses become financially distressed. The extended granular model permits us to open the black box of the monetary policy transmission and to determine the effects on every bank and firm in the economy and any second-round (contagion) effects. With this tool, we can identify economic sectors and banks that would be more sensitive to sudden interest rate changes. We use a comprehensive database of Brazilian banks and firms to show the applicability of the model. Our results reveal that interest rate shocks affect more financial stability during periods of monetary policy tightening, both in terms of direct and indirect impacts.

Our granular network model also abstracts away from some contagion transmission channels. For instance, interest rate increases not only affect firms' cost of funding but also reduce consumer demand. While our model indirectly captures the first component through successive credit crunches as a function of the firm creditworthiness, we do not integrate the second risk channel. As future work, we could apply a similar model to study potential capital outflows. In general, this is an existing risk in emerging markets, such as Brazil.

CHAPTER 3

THE DRIVERS OF SYSTEMIC RISK IN FINANCIAL NETWORKS: A DATA-DRIVEN MACHINE LEARNING ANALYSIS

3.1 Introduction

This paper is related to the literature on network-based models of systemic risk (SR). In these models, SR is the result of a shock propagation throughout a network of interconnected financial institutions (FI). Here, we apply machine learning (ML) techniques to assess the role of financial and topological variables as determinants of SR. ML techniques are able to capture complex non-linear relationships among variables. We believe such a feature is important for our task as many studies show networks can amplify shocks in non-linear ways.[1]

We find the main drivers of SR vary with the size of the initial shock, as well as the dimension of the risk – i.e., whether the risk refers to the potential loss which may be caused by or imputed to the financial institution (FI). Due to the remarkable differences between banks and credit unions, we perform our analysis separately for each type of FI. Our results also indicate the main determinants of SR are different for banks and credit unions.

In financial markets, SR and contagion are two intertwined concepts. A concise definition of SR can be found in Schwarcz (2008): "The risk that (i) an economic shock such as market or institutional failure triggers (through a panic or otherwise) either the failure of a chain of markets or institutions or a chain of significant losses to financial institutions, (ii) resulting in increases in the cost of capital or decreases in its availability, often evidenced by substantial financial-market price volatility" (p. 204). Therefore, contagion is one of the key ingredients

[1] Indeed, in traditional econometric models, based on linear regression, these non-linear linkages are often neglected. These non-linear relationships can be important in the study of the determinants of complex phenomena in a network approach.

of systemic risk. This is the mechanism through which an idiosyncratic event limited to an individual component could propagate throughout the whole system, developing into a system-wide impact.[2] Moreover, contagion unveils the two quantitative dimensions of SR, *impact diffusion* and *impact susceptibility* (Silva, Souza and Tabak (2017)). Impact diffusion measures the potential harm that one institution could cause to the economy, while the impact susceptibility measures the likelihood that random negative events end up causing losses to an institution. Therefore, they capture different aspects of SR and hence complement each other.

Identifying systemically relevant FIs – both in terms of impact diffusion and susceptibility perspectives – is crucial not only methodologically, but also from the financial regulation viewpoint. Policy instruments aiming at addressing systemic risk have been headed towards systemically important FIs. Their purpose is to minimize the probability and the costs of a financial crisis. The Dodd-Frank Act is concerned about the regulation of systemically relevant firms and sectors (Richardson (2012)). The new Basel III agreement requires an additional capital surcharge on domestic and global systemically important banks, as defined by the Financial Stability Board (FSB) and the Basel Committee on Banking Supervision (BCBS) (BCBS (2012a), BCBS (2012b)). For this reason, the proper detection of systemically important institutions and their determinants is a key concern to ensuring financial stability.

The driving factors of SR depend on how it is measured. There are two approaches aiming at computing SR: the market-based approach and the network-based approach. The market-based approach is underpinned on the premise that banks are strongly disciplined by the market (Gropp, Vesala and Vulpes (2006)). Hence, there is a strong relationship between SR and market values. The main shortfall of this approach is that it neglects interconnections between FIs, which are taken into consideration within the network-based approach. These interconnections proved to be an important driver of SR in the 2007-2008 financial crisis. The network-based approach assesses how an initial shock propagates throughout a network of FIs interconnected through some kind of vulnerability link (debt obligations, common asset exposures, etc.), resulting in some kind of aggregate fragility (such as credit risk and liquidity risk).

Within the market-based approach, both the triggering event and its impact are evaluated in terms of some market value, such as stock prices or credit default swaps (CDS) spreads. For instance, the *marginal expected shortfall*, or MES (Acharya *et al.* (2017)), is defined as the expected net equity return of a bank when the market is at its 5% worst performance level in a year. Other examples of market-based measures of SR include the ΔCoVaR (Adrian and Brunnermeier (2016)), the *distress insurance premium* – DIP (Huang, Zhou and Zhu (2009)), the

[2] Contagion may take place through several transmission mechanisms, sometimes with two or more operating at the same time. Some examples are: i) losses engendered by fire sales in face of common asset exposures (Gangi, Lillo and Pirino (2018)), bank runs due to confidence crisis (Diamond and Dybvig (1983)), and default cascade among banks connected through debt obligations (Nier *et al.* (2007)). For a thorough review, see Glasserman and Young (2016).

Lehar's indicator (Lehar (2005)), and the SRISK (Acharya, Engle and Richardson (2012)).[3]

Studies relying on market-based measures (e.g., Jonghe (2010), Weiβ, Bostandzic and Neumann (2014), Laeven, Ratnovski and Tong (2016), Black *et al.* (2016), Kleinow, Horsch and Garcia-Molina (2017), Varotto and Zhao (2018), Brunnermeier, Dong and Palia (2020)) frequently pose banks' asset size as positively related to SR. Alternatively, banks' equity (or equity-to-assets ratio) is pointed as a mitigating factor of systemic relevance. Other elements with a positive effect on banks' SR include engagement in non-traditional banking activities, higher leverage, lower liquidity, higher non-performing loans ratio, and more government support. However, Weiβ, Bostandzic and Neumann (2014) claim the bank-specific determinants of SR are often unique to each crisis and depend on the characteristics of the regulatory regime.

The network-based approach has emerged as an important ally for the analysis of SR. It allows for the estimation of SR as the result of an initial shock in a given component propagating through a network of interlinked components. The initial shock is usually represented by a depletion in the agent's economic value (e.g., equity). In network models, there are two approaches of shock propagation: i) the Eisenberg and Noe (E-N) approach (Eisenberg and Noe (2001)), in which contagion is triggered by a complete depletion of the agent's resources, and ii) the *distress* approach, in which contagion is triggered by a partial loss of economic value (Battiston *et al.* (2012c), Battiston *et al.* (2012b), Bardoscia *et al.* (2015)).

The E-N approach is useful in the modeling of catastrophic events, such as the bankruptcy of big banks. A key limitation of this approach is that, under this contagion trigger, a shock engenders a significant SR only when combined with other conditions. The E-N approach is unable to reproduce crises driven by the transmission of small shocks among highly interconnected FIs, as in the 2007-2008 financial crisis. The *distress* methodology overcomes this problem. It holds two differences regarding the previous approach: i) first, it considers potential rather than real losses; ii) second, the contagion trigger may be a partial (not necessarily a complete) depletion of the agent's resources. When these two mechanisms are activated, interconnectedness gains a much more prominent role in propagating shocks throughout financial networks.

In financial network models, the links can be represented by debt obligations (Allen and Gale (2000)), common asset exposures (Acharya (2009)), ownership relationships (Vitali, Glattfelder and Battiston (2011)), derivative contracts (D'Errico *et al.* (2018)), liquidity risk (Silva, Alexandre and Tabak (2017), Silva, Alexandre and Tabak (2018)), among others. A fruitful literature has employed the network approach in the assessment of SR mainly in the interbank market (e.g., Allen and Gale (2000), Nier *et al.* (2007), Upper (2011), Battiston *et al.* (2012c)). However, it was also successfully applied to other contexts, such as payment systems (Bech and Garratt (2012)), production networks (Battiston *et al.* (2007), Gatti *et al.* (2010)), multilayer financial networks (Silva, Alexandre and Tabak (2017), Silva, Alexandre and Tabak (2018)), and bipartite bank-credit networks (Lux (2016)).

[3] For a comprehensive review on market-based measures of SR, see Bisias *et al.* (2012).

The main advantage of the network approach is that it allows to understand how the topological features of the underlying financial network contribute as amplifying or attenuating drivers of SR. Among financial regulators, expressions as "too-interconnected-to-fail" and "too-systemic-to-fail" have been used in parallel to the term "too-big-to-fail". It reflects the general consensus that the most systemically important FIs are not necessarily the biggest ones. Assessing data from U.S. institutions from August 2007 to June 2010, Battiston *et al.* (2012c) have shown the correlation between *DebtRank* and asset size is lower than 0.4. Moreover, this correlation decreases towards the peak of the crisis. Interconnectedness, other than size, should be taken into account when assessing systemic relevance.[4] The complex networks literature has a large body of research devoted to designing measures that capture local to global topological patterns within the network. This paper employs these measures to understand how the network structure drives SR.

Interconnectedness is related to how important and influential an FI is in the whole financial network. It can be naturally captured by the concept of *centrality* according to the complex network literature. There are at least three classical measures of centrality: the degree (the number of direct neighbors of a given node), the betweenness centrality (the fraction of shortest paths[5] going through a given node), and the closeness centrality (the average of the shortest path length from a given node to every other node in the network). Other measures of centrality include, for instance, the eigenvector centrality (Bonacich (1972)), the subgraph centrality (Estrada and Rodríguez-Velázquez (2005)), the PageRank centrality (Gleich (2015)), and the communicability centrality (Estrada and Hatano (2008)).

Centrality measures have been successfully applied to the identification of systemically important banks. Assessing two Mexican financial networks, Martinez-Jaramillo *et al.* (2014) have found the contagion ranking and the centrality ranking are highly correlated in the top 15 positions in both networks (the interbank market and the payment systems network). In the study of Kuzubas, Omercikoglu and Saltoglu (2014), the centrality measures (degree, betweenness, closeness, and Bonacich centrality) performed very well in identifying systemically relevant institutions in the Turkish interbank market. In a simulation exercise, Ghanbari, Jalili and Yu (2018) have found the cascade depth – the number of failed nodes as a consequence of single failure in one of the nodes – is negatively correlated with node degree, but positively correlated with betweenness centrality and local rank. Our paper contributes to this literature by bringing supervised ML algorithms to understand the main drivers of systemic risk.

[4] A study commissioned by the International Monetary Fund, the Bank for International Settlements, the Financial Stability Board and the G20 (IMF, BIS and FSB (2009)) has found interconnectedness is the second most important factor in the determination of the systemic importance of FIs. Although size is the most important factor, it is not the only dimension that prevails when establishing the systemic importance of FIs.

[5] The shortest path between two nodes is the one in which the sum of the weights of the constituent edges is minimized. There are some excellent textbooks the reader unfamiliar with the complex networks concepts may refer to, as Estrada (2012), Silva and Zhao (2016) and Barabási (2016).

The aim of this paper is to assess the role of both topological and non-topological features as drivers of SR. We compute the systemic relevance of institutions in the Brazilian interbank market through the *differential DebtRank* methodology (Bardoscia *et al.* (2015)). The triggering event, or initial shock, is represented by an equity loss of individual institutions in a given fraction. We simulate different initial losses and analyze the importance of topological and non-topological features in explaining the contagion losses arising from the triggering events. We analyze both from the perspective of inflicting losses (systemic impact) and the likelihood of being recipient of losses initiated by any other institution in the network (systemic vulnerability). To analyze the importance of topological and non-topological features in shaping SR, we employ two ML techniques: XGBoost and random forest. Moreover, we perform this task separately for banks and credit unions since they have very different business models.[6] Finally, further insights were brought about by computing the Shapley values. This provides information not only on the size, but also on the direction of the effect of a given feature.

Among the potential explanatory variables, there are financial and topological variables. The topological features assessed in our study are the following centrality measures: degree, clustering coefficient, closeness centrality, betweenness centrality, k-core, and PageRank. As for the financial variables, we use all relevant financial information available in our data set: total assets, equity, return on equity, interbank assets-to-equity ratio, and interbank liabilities-to-equity ratio.

Our results can be summarized as follows: the importance of a given feature in driving SR varies with i) the level of the initial shock, ii) the type of FI, and iii) the dimension of the risk (impact or vulnerability) which is being assessed. Systemic impact is mainly driven by topological features for both types of FIs. However, while the importance of topological features to the prediction of systemic impact of banks increases with the level of the initial shock, it decreases for credit unions. Concerning systemic vulnerability, this is mainly determined by financial features, whose importance increases with the initial shock level for both types of FIs.

The PageRank is the most important driver of the systemic impact of banks. Moreover, this importance increases with the level of the initial shock. This measure reflects not only the in-degree (number of lenders) of the node, but also that of its direct and indirect connections. Hence, a shock in an FI with a high PageRank will spam through a large number of FIs, causing a large impact in the whole system. On the other hand, the systemic impact of credit unions is driven by a combination of topological (closeness centrality and PageRank) and financial (interbank liabilities-to-equity ratio and total assets) variables. The higher the level of the initial shock, the higher the relevance of these two financial features. Interbank assets-to-equity ratio is the main driver of systemic vulnerability for both banks and credit unions, especially for higher levels of the initial shock. Thus, while the impact of an FI is mainly driven by its centrality, its

[6] The main differences of credit unions from banks are: i) credit unions are not profit-oriented and ii) they conduct their business activities solely with their members. To more details, see, e.g., McKillop and Wilson (2011).

vulnerability depends on how much it is exposed to other FIs in the financial network.

Our contribution to the literature is threefold. First, we address SR considering different levels of initial shock. As discussed in Bartesaghi *et al.* (2020), traditional centrality measures assess networks from a static point of view. A bank which is very central – that is, systemically relevant – in a financial network at a high level of external risk (which, in our framework, is represented by the initial fraction of equity loss) will not necessarily be central at a lower level of external risk, and vice versa. Therefore, a change in the external level of risk can make an FI more or less systemically relevant. It is worth investigating whether not only the systemic relevance of individual institutions, but also its determinants, are affected by the level of external risk. This result is also related to the study of Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), that assessed the importance of the shock size as determinant of the relationship between interconnectedness and SR. The authors showed a more (less) interconnected financial network brings a higher stability to the financial system under sufficiently small (large) negative shocks. We go one step further by showing that the role of financial and other topological features, other than interconnectedness, in driving SR changes with the shock size.

Second, to our best knowledge, the application of ML methods to the identification of systemically important financial institutions is a novelty. The relationship between SR and its determinants can be expressed by the equation $Y_i = f(\mathbf{X}_i) + \varepsilon$. Our interest is in the optimal prediction of Y_i instead of the interpretability of f, which is often the case of microeconometric models that use linear models such as OLS or panel fixed effects. We believe networks encode complex financial relationships among FIs. In this way, non-linear models could largely improve the model's estimation quality. Hence, we employ ML methods for this task.

Third, we clearly disentangle the two dimensions of SR. Most measures consider the SR posed by an institution as positively correlated to its loss given a distress in the system (Varotto and Zhao (2018)). However, this statement is not true in many situations. For instance, suppose there is an institution acting mainly as a borrower in the interbank market. Its default would cause great distress in the system: a great number of institutions would not receive their debt obligations. Nonetheless, it would not be so impacted by the default of other institutions, as it has few borrowers.

Besides the literature on bank-specific determinants of SR, our research is also related to studies tackling which network properties are more relevant to the dynamics of the system (e.g., Arenas *et al.* (2008), Pastor-Satorras *et al.* (2015), Arruda, Rodrigues and Moreno (2018), Rodrigues *et al.* (2019)). For instance, in studies devoted to the dynamics of disease spreading (Arruda, Rodrigues and Moreno (2018), Pastor-Satorras *et al.* (2015)), the purpose is to predict the stationary value of Y_i, the share of infected nodes when the disease is seeded at node i. They concluded the degree distribution is crucial for the existence of a vanishing threshold. Studies on other dynamical processes, as synchronization phenomena (Arenas *et al.* (2008)) and rumor spreading (Kitsak *et al.* (2010)), reached similar conclusions. Even though the financial network is exogenous, the spreading of an initial shock can be considered a dynamical process. By counting each time a shock propagates from one node to its neighbors as one time step, this process spans for a certain number of periods T. After this time, the outcome of this process – in our case, the aggregate loss of economic value – reaches a stationary value.

This paper proceeds as follows. Methodological issues and the data set are discussed in Section 3.2. Section 3.3 brings the results. Finally, conclusions take Section 3.4.

3.2 Methodology and data set

3.2.1 The data set

Our data set comprises quarterly information from March 2012 through December 2015 on the institutions participating in the Brazilian interbank market. We considered financial conglomerates or individual FIs belonging to the Brazilian banking sector (classified from "b1" through "b4" according to the Central Bank of Brazil's classification system). Institutions with negative net worth were excluded. The number of institutions in our sample on each date varies from 839 to 950.

Next, we build the network formed by the net exposures of these institutions in the interbank market. In this network, we consider all types of unsecured financial instruments registered in the Central Bank of Brazil. The main types of financial instruments are credit, capital, foreign exchange operations, and money markets. These operations are registered and controlled by different custodian institutions: Cetip[7] (private securities), the Central Bank of Brazil's Credit Risk Bureau System (SCR)[8] (credit-based operations), and the BM&FBOVESPA[9]

[7] Cetip is a depositary of mainly private fixed income, state and city public securities, and other securities. As a central securities depositary, Cetip processes the issue, redemption, and custody of securities, as well as, when applicable, the payment of interest and other events related to them. The institutions eligible to participate in Cetip include commercial banks, multiple banks, savings banks, investment banks, development banks, brokerage companies, securities distribution companies, goods and future contracts brokerage companies, leasing companies, institutional investors, non-financial companies (including investment funds and private pension companies) and foreign investors.

[8] SCR is a very thorough data set that records every single credit operation within the Brazilian financial system worth 200BRL or above. Up to June 30th, 2016, this lower limit was 1,000BRL. Therefore, all the data we are assessing have been retrieved under this rule. SCR details, among other things, the identification of the bank, the client, the loan's time to maturity and the parcel that is overdue, modality of loan, credit origin (earmarked or non-earmarked), interest rate, and risk classification of the operation and the client.

[9] BM&FBOVESPA is a privately-owned company that was created in 2008 through the integration of the Sao Paulo Stock Exchange (Bolsa de Valores de São Paulo) and the Brazilian Mercantile & Futures Exchange (Bolsa de Mercadorias e Futuros). As Brazil's main intermediary for capital market transactions the company develops, implements and provides systems for trading equities, equity derivatives, fixed income securities, federal government bonds, financial derivatives, spot FX, and agricultural commodities. On March 30th, 2017, BM&FBOVESPA and Cetip merged into a new company named B3.

(swaps and options operations).

We calculate the following node centrality measures on our interbank network: degree (K), clustering coefficient (C), closeness centrality (CC), betweenness centrality (B), PageRank (PR), and k-core (KC). Our network is directed. Thus, two centrality measures (K and CC) are computed for both incoming and outgoing edges, being differentiated by the suffixes "in" and "out". The incoming (outgoing) edges refer to the relationships an institution takes part as a borrower (lender) in the interbank market.

In addition to these centrality measures, we collected some financial information on the institutions in our sample: total assets, net worth, and return on equity.[10] We also computed the interbank assets/liabilities-to-equity ratio. The set of variables that will be explored as potential determinants of SR are presented in Table 7, and the correlation among them is depicted in Figure 13. We can observe there are expressive correlations between topological variables (e.g., Kin and PR), financial variables (e.g., NW and TAS), and between different types of variables (e.g., Kout and TAS).

Type	Variable	Acronym
Financial	Total assets	TAS
	Net worth	NW
	Return on equity	ROE
	Interbank assets-to-equity ratio	IBA
	Interbank liabilities-to-equity ratio	IBL
Topological	Degree	Kin/Kout
	Clustering coefficient	C
	Closeness centrality	CCin/CCout
	Betweenness centrality	B
	PageRank	PR
	k-core	KC

***Table 3** – Potential determinants assessed in the study.*

[10] This information was retrieved from <https://www3.bcb.gov.br/ifdata>.

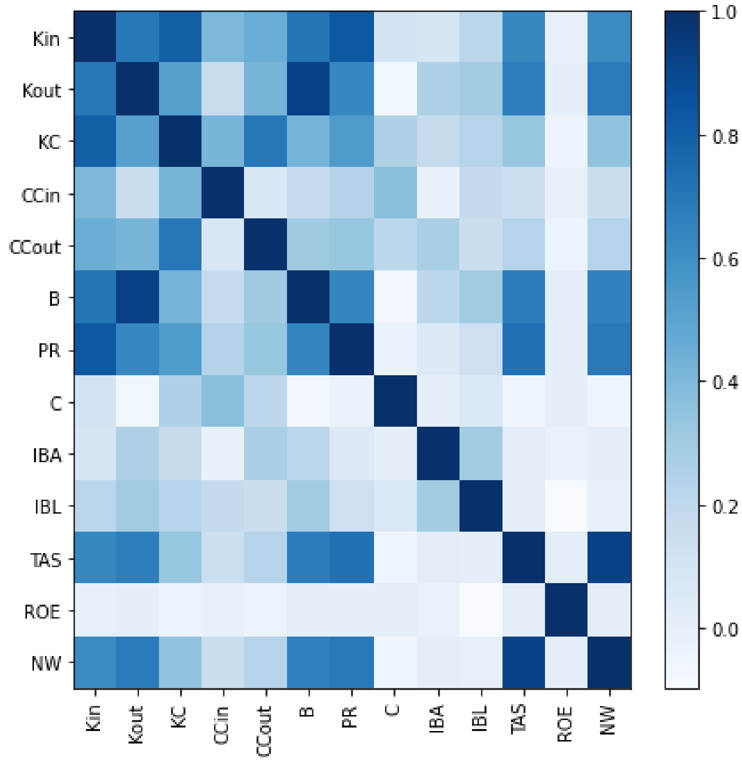


Figure 13 – *Correlation between the potential determinants.*

3.2.2 Systemic impact and vulnerability

We compute our metrics of SR following the *differential DebtRank* methodology (Bardoscia *et al.* (2015)). The exposure network of the interbank market is represented by $\mathbf{A} \in N \times N$, where N is the number of banks and A_{ij} is the asset invested by i at j. At period 0, we impose an exogenous shock on FI j, reducing its equity by a fraction of ζ. It will cause a subsequent loss $L_{ij}(1)$ to its creditors, indexed by i, equal to $\mathbf{A}_{ij}\zeta$. At period 2, j's creditors will propagate this loss to their creditors in a similar fashion, and so on. Formally, we have

$$L_{ij}(t) = min\left(A_{ij}, L_{ij}(t-1) + \mathbf{A}_{ij}\frac{[L_j(t-1) - L_j(t-2)]}{E_j}\right), \tag{3.1}$$

$$L_i(t) = min\left(E_i, L_i(t-1) + \sum_j \mathbf{A}_{ij}\frac{[L_j(t-1) - L_j(t-2)]}{E_j}\right), \tag{3.2}$$

in which $t \geq 0$ and E_j is FI j's equity. Thus, when an FI j suffers an additional loss equal to fraction ζ of its equity, it will impose a loss to its creditors that corresponds to ζ times their exposures towards j. Observe that equity positions as well as the exposure network are time-invariant, i.e., they are taken as exogenous. The propagation considers stress differentials rather than stress absolute values (hence the methodology's name) to avoid double-counting. Two more restrictions apply:

- L_{ij} cannot be greater than A_{ij}, i.e., j cannot impose to i a loss greater than i's exposures towards j. When $L_{ij} = A_{ij}$, j stops imposing losses on i;
- L_i cannot be greater than E_i, i.e., i's losses cannot be greater than its equity. When $L_i = E_i$, i stops propagating losses to other FIs.

The system converges after a sufficiently large number of periods $T \gg 1$. Then we have the final matrix of losses $\mathbf{L}^{j,\zeta} \in N \times 1$, where $L_i^{j,\zeta}$ is the total loss suffered by agent i after an initial shock of size ζ at agent j.

We repeat this process for the other FIs. Finally, we compute our two measures of SR. We define the *systemic impact* (SI) of bank i as

$$SI_{i\zeta} = \frac{\sum_j \left[L_j^{i,\zeta} - L_j^{i,\zeta}(0) \right]}{\sum_j E_j}, \tag{3.3}$$

where $L_j^{i,\zeta}(0) = \zeta E_j$ if $j = i$ and 0 otherwise. Our second measure, the *systemic vulnerability* (SV), is represented by the following equation:

$$SV_{i\zeta} = \frac{1}{N} \sum_j \frac{L_i^{j,\zeta} - L_i^{j,\zeta}(0)}{E_i}. \tag{3.4}$$

Therefore, $SI_{i\zeta}$ measures the fraction of the aggregate FIs' equity which is lost as a consequence of an initial shock of size ζ at FI i's equity. On the other hand, $SV_{i\zeta}$ refers to the average i's equity loss when the other FIs are reduced by ζ. Observe the following:

- We remove the initial shock from the computation of the SR measures, as we are interested only in the losses caused by the contagion;
- We also compute $SI_{i\zeta}$ for the FI that suffered the initial shock. Due to network cyclicality, a shock propagated by a given FI can hit it back. For the same reason, we include the loss imposed by an FI on itself in the calculation of $SV_{i\zeta}$.

3.2.3 Random forest and XGBoost

After the computation of the systemic risk measures, we employ two machine learning techniques – XGBoost (Friedman, Hastie and Tibshirani (2000)) and random forest (Breiman (2001)) – to assess their determinants. Both are ensemble learning methods that can be used for both classification and regression. In this case, they are employed for regression tasks.

Random forest (RF) operates by constructing several decision trees.[11] It returns the average prediction of the individual decision trees. XGBoost (XB) is an optimization algorithm

[11] On decision trees, see, e.g., Breiman *et al.* (1984)

that works with an ensemble of weak predictors (usually, decision trees) and creates a more efficient predictor model. At each boosting stage, the XB algorithm attempts to increase the performance of the predecessor model by including a new estimator.

The purpose is to estimate a predicted output $\hat{y}_i$ from an observed output y_i and a vector of explanatory variables X_i. In this paper, the output to be predicted are the systemic risk measures $SI_{i\zeta}$ and $SV_{i\zeta}$, and the explanatory variables are those listed in Table 7. Both models are trained and validated through a process known as *repeated k-fold cross-validation*. The data set (the observed output and the explanatory variables) is split into k different parts (folds). $k-1$ folds are used in the development of the model. Then, the model is trained on the remaining fold: the predicted output $\hat{y}_i$ and the observed output y_i of the remaining fold are used to compute score measures, such as the root mean squared error (RMSE). Each fold is used as the testing data set. In this paper, we applied a repeated k-fold cross-validation with $k = 5$ and 10 repetitions. Hence, a total of 50 regressions are run.

The RMSE is used to tune the number of estimators of both methods. In the RF, the number of estimators is the number of decision trees in each forest. In the XB, this is the number of boosting stages to be performed. The number of estimators varies within a grid of ascending values. For each of these values, the regressions are run and the average score is computed. The number of estimators is chosen so that increasing it does not improve the performance of the method. We performed the tuning within the grid [30, 50, 70, 100, 300, 500]. After this procedure, we set the value of both parameters as 50.

3.3 Results

We computed $SI_{i\zeta}$ and $SV_{i\zeta}$ varying the value of ζ in the interval (0.1,1] with step 0.1. Hence, there are 20 dependent variables for each observation. We excluded 76 outliers out of 14,467 observations, with $SV_{i\zeta} > 10$. These are small FIs, most of them credit unions, highly leveraged as lenders in the interbank market between March 2012 and September 2013.

We applied the two ML techniques – RF and XB – to predict $SV_{i\zeta}$ only using the observations with positive assets in the interbank market. The reason is that, if an FI did not grant loans, it is not vulnerable to other FI's defaults. Hence, its vulnerability is zero by definition. Similarly, we performed the ML analysis to predict $SI_{i\zeta}$ only using the observations with positive liabilities. We also performed the analysis separately for banks (FIs classified as b1, b2, or b4) and credit unions (FIs classified as b3C or b3S). Credit unions have many differences from banks. Unlike most FIs, credit unions are not profit-oriented. Their business activities (receive deposits or shares and grant loans) are conducted solely with their members, which are also their owners. Managers of credit unions do not receive bonuses and any surplus is distributed among their members-owners (McKillop and Wilson (2011)). Due to these distinctive characteristics, credit unions are also expected to have specific SR drivers.

The differences between banks and credit unions are also evidenced in our sample. Credit unions are much more numerous than banks, but are smaller in terms of assets and equity. Banks are much more interconnected and leveraged (both in terms of assets and liabilities) in the interbank market. However, while banks act mainly as lenders in the interbank market (the out-degree is greater than the in-degree), credit unions act mainly as borrowers. All this implies that banks are more vulnerable to shocks in other FIs and shocks in banks cause a higher impact in the whole system.

	Bank	Credit union
Number per period	128.75	775.44
Kin	11.39	1.59
Kout	16.04	0.73
IBA	1.43	0.32
IBL	1.81	0.99
NW*	3.82	0.03
TAS*	50.30	0.15
V = 0.1	0.19	0.07
V = 1	0.57	0.26
S = 0.1	0.48	0.18
S = 1	1.88	0.28

*: in BRL billions.

Table 4 – *Average value of some variables by type of FI.*

3.3.1 Systemic impact

The systemic impact of the banks is mainly driven by the PageRank (Figure 14). PageRank is a centrality measure specially designed for directed graphs and it is computed recursively. The PageRank of an FI is positively impacted by its in-degree (number of lenders), but also by the in-degree of its direct and indirect neighbors, weighted by a dumping factor (the further away the neighbor, the smaller its impact on the FI's PageRank). Therefore, a shock in an FI with a high PageRank is expected to propagate through a high number of other FIs.

Both methods provide similar outcomes. After PageRank, total assets appears as the second most important feature for small values of the initial shock. As ζ increases, so the relevance of the PageRank and total assets become less important. Considering the aggregate relevance of financial and topological variables (Figure 15), we can observe that the latter become more important drivers of the systemic impact of banks as ζ increases.

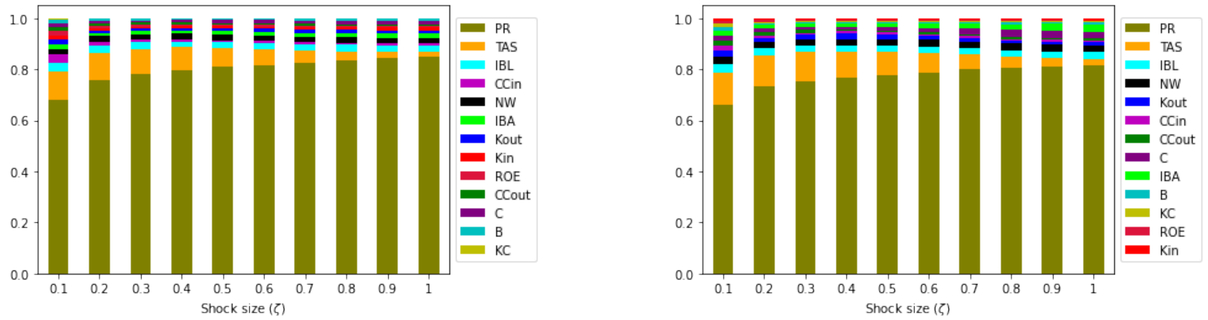


Figure 14 – *Importance of the features to the prediction of the systemic impact of the banks obtained through RF (left) and XB (right).*

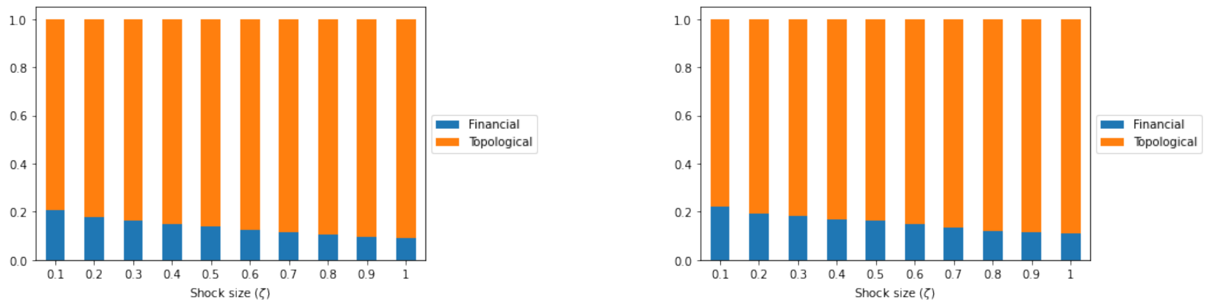


Figure 15 – *Aggregate importance of financial and topological features to the prediction of the systemic impact of the banks obtained through RF (left) and XB (right).*

As expected, the systemic impact of credit unions is driven by features different from those of banks. Closeness centrality and PageRank appear as the main topological features driving the systemic impact of credit unions. Closeness centrality is related to physical proximity. Nodes with high closeness centrality have the shortest average distance (as measured by the shortest path) to all other nodes in the network. Both methods attach a higher importance to two financial features – interbank liabilities-to-equity ratio and total assets – as far as ζ increases. Unlike the case of banks, the aggregate importance of the financial variables increases with ζ, although the topological variables are the main drivers of systemic impact for credit unions for any value of the initial shock. All these considerations can be seen in Figures 16 and 17.

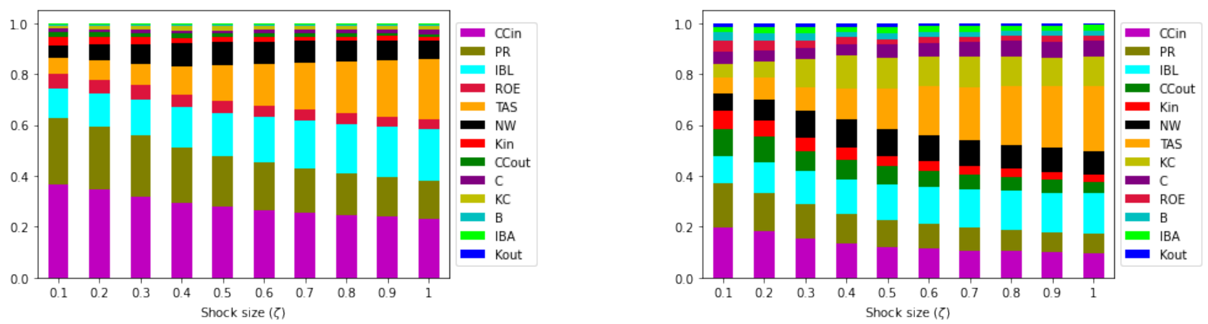


Figure 16 – *Importance of the features to the prediction of the systemic impact of the credit unions obtained through RF (left) and XB (right).*

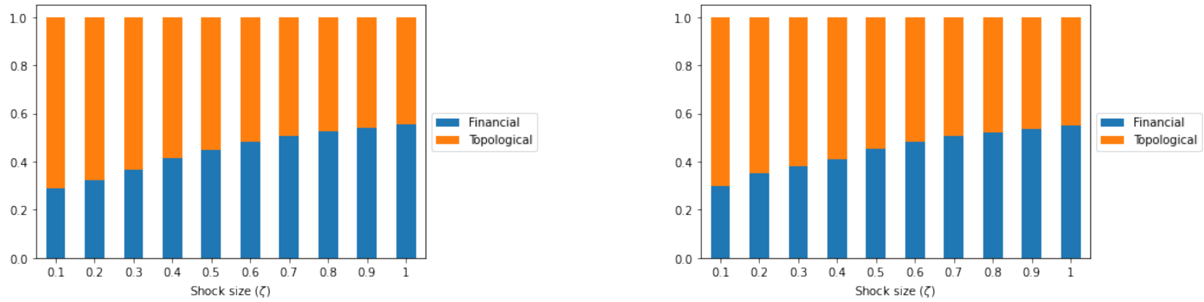


Figure 17 – *Aggregate importance of financial and topological features to the prediction of the systemic impact of the credit unions obtained through RF (left) and XB (right).*

3.3.2 Systemic vulnerability

Unlike the case of systemic impact, the vulnerability of FIs is mainly driven by financial variables, in particular by the interbank assets-to-equity ratio. Thus, an FI's systemic vulnerability essentially depends on its exposure in the interbank market. However, this feature alone is not enough to predict the FIs' systemic vulnerability, mainly for smaller values of ζ. The aggregate impact of the other financial and topological features is non-negligible. XB attaches a smaller importance to interbank assets (and to financial features in general) than RF. Moreover, financial variables appear to be more important for credit unions than for banks. These considerations are depicted in Figures 18-21.

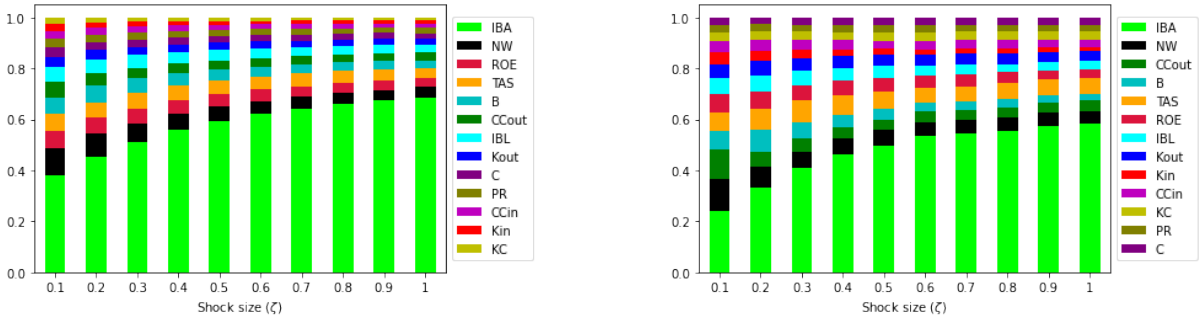


Figure 18 – *Importance of the features to the prediction of the systemic vulnerability of the banks obtained through RF (left) and XB (right).*

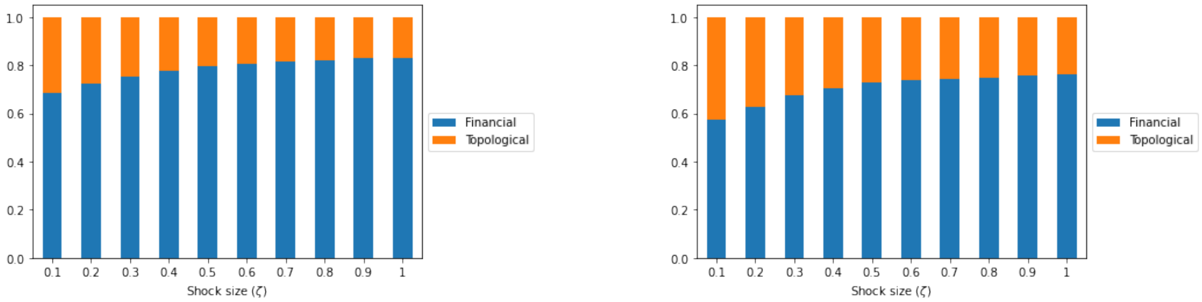


Figure 19 – *Aggregate importance of financial and topological features to the prediction of the systemic vulnerability of the banks obtained through RF (left) and XB (right).*

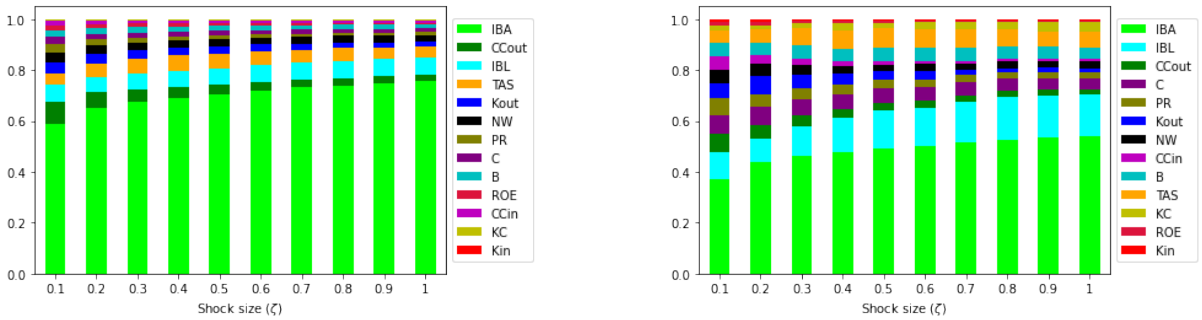


Figure 20 – *Importance of the features to the prediction of the systemic vulnerability of the credit unions obtained through RF (left) and XB (right).*

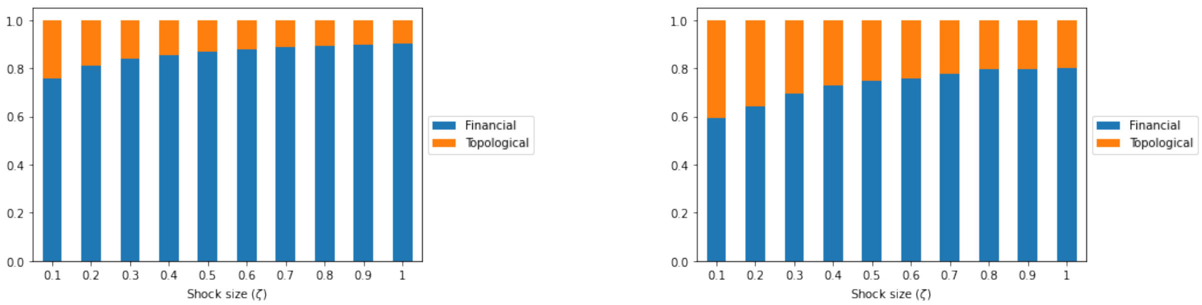


Figure 21 – *Aggregate importance of financial and topological features to the prediction of the systemic vulnerability of the credit unions obtained through RF (left) and XB (right).*

Comparing Figures 15 and 19, we can observe an important asymmetry. The aggregate importance of topological features in driving the systemic impact of banks varies between 0.8 and 0.9. Notwithstanding, the aggregate importance of financial features in driving systemic vulnerability is smaller, in the range 0.6-0.8 (depending on ζ and the method used). We observe a similar asymmetry in the case of credit unions, namely, the importance of financial variables driving systemic vulnerability is higher than the importance of topological variables driving systemic impact (Figures 17 and 21).

3.3.3 Shapley values

In order to go further on the interpretability of our results, we resort to the computation of Shapley values. This approach is originated from the coalition games theory (Shapley (1953), Shoham and Leyton-Brown (2008)). Besides providing additional evidence on features' importance, Shapley values can also inform whether a given feature is positively or negatively correlated to the systemic risk measure. We compute Shapley values through the SHAP (SHapley Additive exPlanation) framework proposed by Lundberg and Lee (2017). The authors propose an explainer model g aiming at predicting an output using a set of M features as inputs. The predicted value for a given data-instance is given by

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z'_i, \tag{3.5}$$

where z' is a binary variable indicating whether feature i was included in the model or not. Therefore, the SHAP value ϕ_i indicates in which extent the feature i shifts the predicted value up or down from a given mean output ϕ_0. Lundberg and Lee (2017) showed that, under certain properties (local accuracy, missingness, and consistency), ϕ_i corresponds to the Shapley value of the game theory. The SHAP value of feature i is given by

$$\phi_i = \sum_{S \subseteq M \setminus i} \frac{|S|!(|M|-|S|-1)!}{M!} [F(S \cup \{i\}) - F(S)]. \tag{3.6}$$

Therefore, the SHAP value of feature i for a given data-instance computes the difference between the predicted value of the instance using all features in S plus feature i, $F(S \cup \{i\})$, and the prediction excluding feature i, $F(S)$. This is weighted and summed over all possible feature vector combinations of all possible subsets S.[12] We then proceed as follows:

- Compute the SHAP value according to the explainer models (RF and XB), considering our systemic risk measures as the output to be predicted;

[12] For details on the calculation of SHAP values, see, e.g., Lundberg and Lee (2017) and Kalair and Connaughton (2021).

- Compute the average absolute SHAP value over all data-instances. This will inform the size of the feature importance in driving the output;
- Multiply the average absolute SHAP value by the sign of the correlation between the feature value and the SHAP value. This will show whether the feature is positively or negatively correlated to the output.

As in the previous section, for both models (RF and XB), we implement a k-fold cross-validation with $k = 5$ and 10 repetitions. The results are presented in Figures 22-25 and roughly corroborate those of the previous subsection. The systemic impact of banks is mainly (positively) determined by the PageRank. However, this effect is nonlinear regarding the size of the initial shock. The maximum impact of PageRank on banks' systemic impact is observed at a shock size $\zeta_{max} < 1$. The importance of the interbank liabilities-to-equity ratio, net worth, and interbank assets-to-equity ratio increases monotonically with ζ. As expected, while the first two variables have a positive impact on banks' systemic impact, the last one impacts it negatively.

The relative importance of total assets, interbank liabilities-to-equity ratio, and net worth in driving the systemic impact of credit unions increases monotonically with ζ. The most important topological variables in determining the systemic impact of credit unions are the closeness centrality (in) and PageRank. The impact of the former is positive, whereas the latter has a negative impact in most cases (according to the RF model, the PageRank has a negative effect on the systemic impact of credit unions for small values of ζ).

The vulnerability of both banks and credit unions, according to both methods, is mainly driven by the interbank assets-to-equity ratio. Its impact is positive. However, there is an important difference between banks and credit unions. While the effect of the feature increases monotonically with the initial shock size in the former case, it has a maximum at a level of ζ below 1 in the latter one.

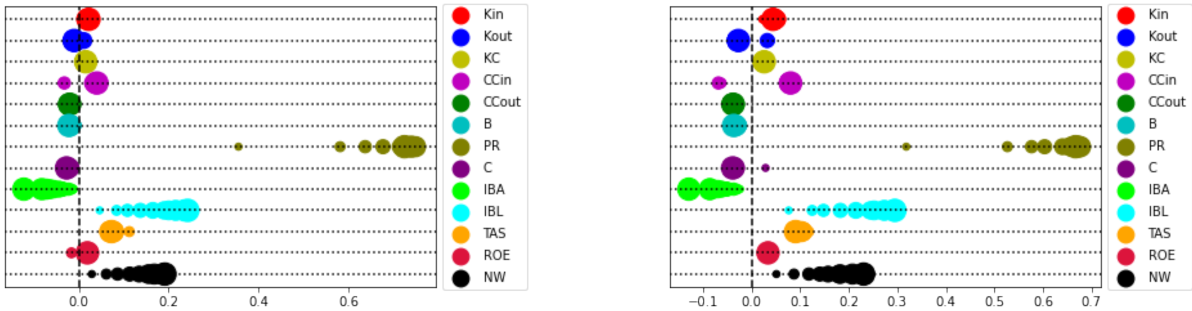


Figure 22 – *Average absolute SHAP values multiplied by the sign of the correlation between SHAP values and the feature values. The predicted output is the systemic impact of the banks obtained through RF (left) and XB (right). Dots size is proportional to the size of the initial shock (ζ).*

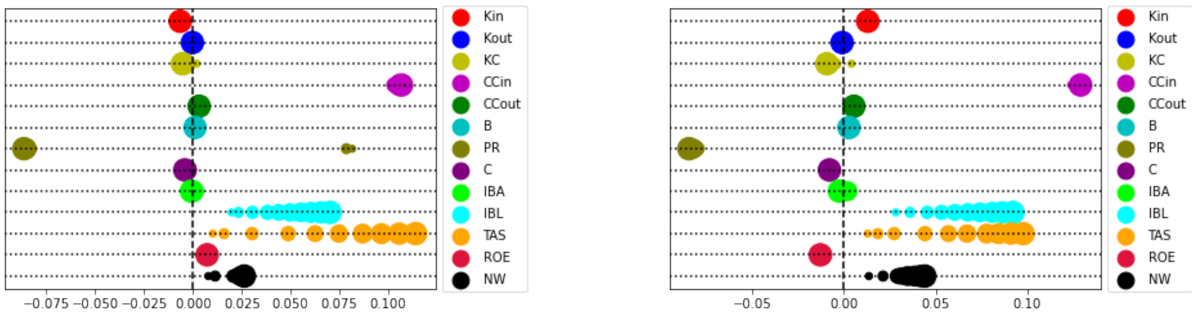


Figure 23 – *Average absolute SHAP values multiplied by the sign of the correlation between SHAP values and the feature values. The predicted output is the systemic impact of the credit unions obtained through RF (left) and XB (right). Dots size is proportional to the size of the initial shock (ζ).*

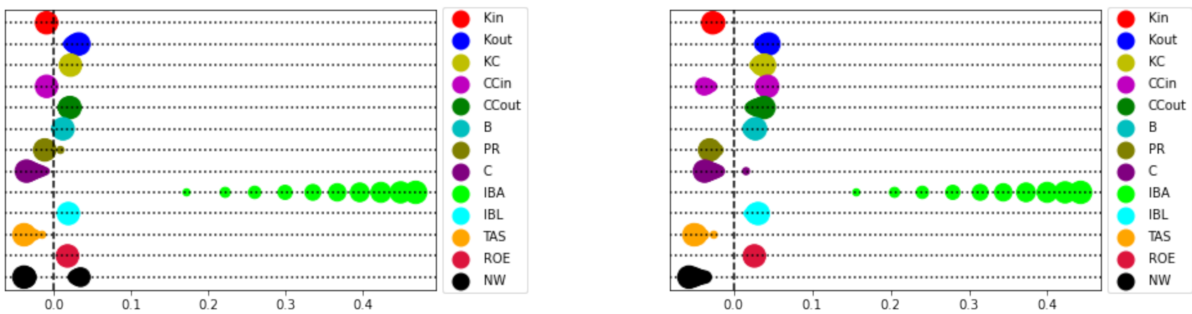


Figure 24 – *Average absolute SHAP values multiplied by the sign of the correlation between SHAP values and the feature values. The predicted output is the systemic vulnerability of the banks obtained through RF (left) and XB (right). Dots size is proportional to the size of the initial shock (ζ).*

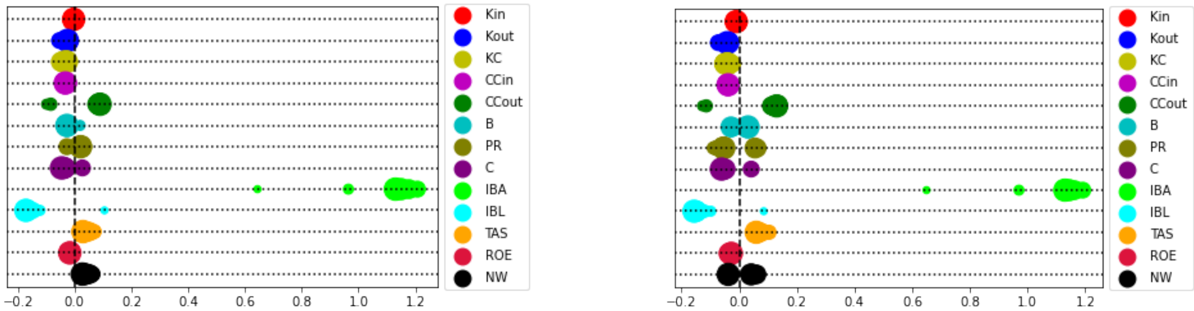


Figure 25 – *Average absolute SHAP values multiplied by the sign of the correlation between SHAP values and the feature values. The predicted output is the systemic vulnerability of the credit unions obtained through RF (left) and XB (right). Dots size is proportional to the size of the initial shock (ζ).*

3.4 Concluding remarks

In this study, we assessed the role of financial and topological features as drivers of SR. Our data set comprises quarterly information on FIs in the Brazilian interbank market between March 2012 and December 2015. We computed the SR in its both dimensions – systemic impact and systemic vulnerability – for different levels of the initial shock. We performed this task using the *differential DebtRank* methodology. To assess the relevance of each feature, we used two machine learning techniques: random forest and XGBoost. As banks and credit unions have different characteristics, we carried out this last step separately for each type of FI. We also computed the Shapley values employing these two techniques as explainer models. Shapley values inform not only on the size of the effect of a given feature on the SR, but also on the direction of this effect – that is, whether the feature is positively or negatively correlated to the SR measure.

We have found that the drivers of SR depend on the dimension of the risk that is being assessed. Topological features are the most important drivers of the systemic impact. PageRank appears as the main determinant of systemic impact for banks. In the case of credit unions, the most important topological features are closeness centrality, and PageRank. On the other hand, financial variables are the main determinants of systemic vulnerability. Interbank assets-to-equity ratio figures as the most important driver of systemic vulnerability for both types of FIs, although the role of other variables cannot be neglected mainly for small levels of initial shock.

Another interesting finding is that the importance of a given feature in driving SR varies with the level of the initial shock. In general terms, the importance of topological features on the prediction of systemic impact of the banks increases for higher levels of the initial shock. For credit unions, the opposite happens. Financial variables become more relevant, although topological variables play a more important role for any value of initial shock. Moreover, the importance of financial features as drivers of systemic vulnerability increases with the initial shock level for both types of FIs.

Finally, our results show that different types of FIs have different key drivers of SR.

Interbank assets-to-equity ratio is the main driver of systemic vulnerability for both banks and credit unions. However, while the systemic impact of banks is mainly determined by the PageRank, the systemic impact of credit unions is driven by a combination of topological and financial variables.

This study brings an important contribution to the literature on the determinants of systemic risk. We show that the drivers of systemic risk depend on at least three aspects: the dimension of the risk – the loss *suffered* or *caused* by the FI -, the size of the initial shock on the system, and the type of the FI. It also provides insights to policymakers aiming at targeting systemically important FIs. Finally, it sheds some light on the dynamical process concerning the spread of shock in financial networks.

CHAPTER

4

DOES DEFAULT PECKING ORDER IMPACT SYSTEMIC RISK?

4.1 Introduction

The aim of this paper is to shed some light on the following question: does the default pecking order – that is, a criterion for deciding which creditors to default on first – have some effect on the systemic risk? Network models have been extensively applied to the assessment of systemic risk in financial systems (Eisenberg and Noe (2001), Nier *et al.* (2007), Gai and Kapadia (2010), Upper (2011), Caccioli, Catanach and Farmer (2012), Battiston *et al.* (2012c), Battiston *et al.* (2012b), Hałaj and Kok (2013), Roukny *et al.* (2013), Acemoglu, Ozdaglar and Tahbaz-Salehi (2015)). Here, we build on network models in which agents are interconnected through contractual debt obligations (e.g., an interbank market or a bank-firm credit network). Agents are endowed with an economic value – equity. An outgoing link from agent i to agent j means that the former is the latter's creditor (or, alternatively, that the latter is the former's debtor). The weight of each link represents the value of the claim. The sum of the weights of the agent's outgoing (incoming) links corresponds to its assets (liabilities). Consider the stylized interbank market depicted in Figure 26. For instance, node C received loans from nodes B and G (of values 2 and 3, respectively), and extended loans to nodes E and F (both of value 3).

Negative shocks (which may be idiosyncratic or endogenous to the model) are at least partially absorbed by the agent's equity. However, part of this loss may be borne by their creditors, as this shock may lead the agent to not fully honor its debt obligations with its counterparties. Systemic risk is measured as the fraction of aggregate equity lost as a result of a shock spread throughout the network.

How shocks on a given agent affects its creditors varies according to the approach. In network models, there are two approaches of shock propagation. In the Eisenberg and Noe (2001) (E-N) approach, contagion is triggered by the default of the agent – i.e., by the complete depletion

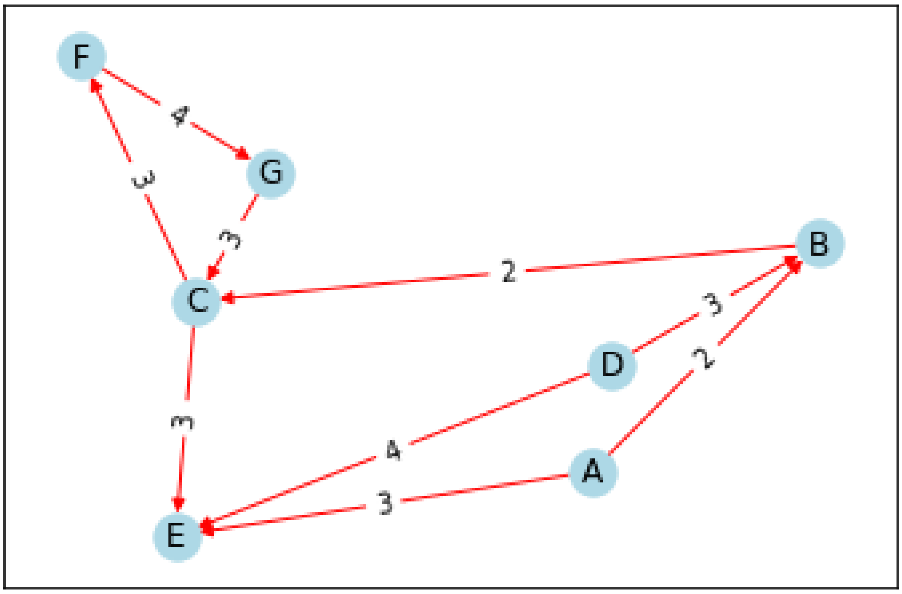


Figure 26 – *Stylized representation of an interbank market.*

of its resources. The *DebtRank* (Battiston *et al.* (2012c), Battiston *et al.* (2012b), Bardoscia *et al.* (2015)) approach holds two main differences with respect to the E-N approach: the losses which trigger contagion are i) potential rather than real, and ii) may be partial rather than necessarily complete.

One strand of studies within the E-N approach considers that a negative shock is first absorbed by the agent's equity. Only the residual between the shock and the equity (if any) is transmitted to the agent's creditors. In the classical model developed by Eisenberg and Noe (2001), the residual loss is transmitted to creditors in proportion to their nominal claims on the assets of the debtor. Consider again the example depicted in Figure 26. Suppose node E has an equity e_E of 80. It is hit by a negative shock of size $s_E = 85$. Three other nodes (A, C, and D) have extended loans to E of amounts $l_{AE} = 3$, $l_{CE} = 3$, and $l_{DE} = 4$, adding up to $l_E = 10$. Only the residual loss $r_E = s_E - e_E = 5$ will be transmitted to its creditors proportionally to their claims on E. Therefore, D will bear 40% (l_{DE}/l_E) of the residual loss (2). Similarly, A and C will bear 30% (1.5) each. This mechanism of loss transmission is present in other studies. Elsinger, Lehar and Summer (2006) assumed that e_i is a random variable and that interbank loans are junior to other assets. Nier *et al.* (2007) developed a theoretical framework to assess the role of the parameters of the financial system (as the level of banks' capitalization and the banks' degree) on systemic risk and knock-on defaults.

Another strand of the literature relying on the E-N mechanism of shock propagation considers that the default of a given agent will imply that their creditors will lose a fraction – the *loss given default* (LGD) – of their exposures to the defaulted agent. The main drawback of this approach comes from the lack of an appropriate criterion to define the LGD value. Empirical evidence shows LGD has a bi-modal distribution (either relatively high or low) and is higher in recessions (Asarnow and Edwards (1995), Hurt and Felsovalyi (1998), Schuermann (2003), Dermine and Carvalho (2006)). Moreover, the computation of LGD depends on some information, such as the availability of collateral or the seniority of the claims, which is usually not accessible. The seminal theoretical paper of Gai and Kapadia (2010) sets for simplicity an LGD of 100%. Empirical papers (e.g., Blavarg and Nimander (2001), Upper and Worms (2004), Lelyveld and Liedorp (2006), Degryse and Nguyen (2007)) compute systemic risk for a broad range of values of LGD, which is assumed to be exogenous and constant across creditors. Upper and Worms (2004), for instance, use the following values of LGD: 0.05, 0.1, 0.25, 0.4, 0.5, and 0.75.

The *DebtRank* methodology poses that losses in the assets extended to a given debtor are proportional to the fraction of equity lost by the debtor – the *distress*. In the original *DebtRank* formulation (Battiston *et al.* (2012c), Battiston *et al.* (2012b)), if a debtor i has lost a fraction $h_i(t) \leq 1$ of its equity, its creditor j will suffer a loss equal to $A_{ji}h_i(t)$, where A_{ji} is the exposure of j towards i. In order to ensure the systemic risk estimate will converge, each node propagates only the first shock it receives. However, due to the cyclicality of the network of exposures, the same node can be hit more than once. Hence, by ignoring these further shocks, the original *DebtRank* leads to an underestimation of the systemic risk. Bardoscia *et al.* (2015) solve both problems – non-convergence and underestimation of the systemic risk – by incorporating cyclical propagation of additional (rather than accumulated) losses. In their approach, the *differential DebtRank*, the formula above is updated to $A_{ji}[h_i(t) - h_i(t-1)] = A_{ji}\Delta h_i(t)$.

In spite of the differences among them, all models reviewed above share a common characteristic: a debtor affected by a negative shock distributes the loss among its creditors following a pro-rata fashion. The loss suffered by the creditor as a percentage of its exposure on the debtor hit by the shock is fixed. The LGD is assumed to be exogenous and constant across creditors, even when a range of LGD values is tested. In the residual loss approach, the LGD can be implicitly computed as the residual loss over the debtor's total liabilities. In the example discussed above, $20/100 = 0.2$. In the *DebtRank* approach, the loss transmitted by the stressed debtor as a fraction of their creditors' claims is $h_i(t)$ (or $\Delta h_i(t)$ in the updated formulation). That is, it is equal to the loss suffered by the debtor as a fraction of its equity.

However, the assumption that losses are imposed on creditors proportionally to the loan extended to the debtor under distress is unrealistic. It is more plausible to assume that debtors will choose to default on certain creditors first, before transmitting the residual loss to other creditors. Agents can be better off by setting a *default pecking order* (DPO) rather than adopting a pro-rata mechanism for loss distribution. Default implies the impairment of the relationship with the creditor. For instance, creditors will grant less loans to borrowers who have defaulted on them in the past. Therefore, agents will be more likely to default on weaker creditors due to the smaller expected value of continuing this relationship (Schiantarelli, Stacchini and Strahan (2020)). In the model developed by Bertschinger, Hoefer and Schmand (2019), agents maximize the resources that propagate through the network and return as additional internal assets. Under this criterion, the pro-rata mechanism is not always optimal. Thus, in a more realistic framework, each creditor would lose a fraction of its loans equal to $\beta_j = f(\mathbf{X})$, where $\mathbf{X}$ is a set of creditor's attributes used by debtors to set the DPO.

In this study, we compute the systemic risk assuming a heterogeneous distribution of losses by distressed debtors. In our framework, contagion is triggered by stress – i.e., a partial loss of equity – as in the *differential DebtRank* approach (Bardoscia *et al.* (2015)). The aggregate loss imposed by a given debtor on its counterparties is equal to the fraction of equity lost by the debtor times its liabilities. Although this mechanism resembles that of the *differential DebtRank* approach, there is a key difference between that framework and ours. In the *differential DebtRank* approach, losses are due to a mark-to-market adjustment made by the creditors of their exposures on the stressed debtor. On the other hand, we assume distressed debtors will perform a *strategic default*. This term was coined by bankers to define a default situation in which there is the ability, but not the willingness, to pay (Das and Meadows (2013)). This is not an uncommon phenomenon. For instance, assessing the U.S. housing mortgage market, Guiso, Sapienza and Zingales (2013) found out 26.4% (35.1%) of defaults appear to be strategic in March 2009 (September 2010).The few empirical studies addressing the determinants of strategic default on corporate loans (Asimakopoulos *et al.* (2016), Karthik *et al.* (2018)) bring evidences that a decrease in the debtor's profitability – i.e., a worsening in its financial health – increases its probability of a strategic default. This is coherent with our hypothesis that distressed debtors will perform a strategic default.

The debtor will choose a heuristic in order to rank their creditors, setting a DPO for the loss distribution. We will set heuristics based on the evidences brought by the literature. The first evidence is that creditor's weakness affects negatively its probability of default. Results presented by Schiantarelli, Stacchini and Strahan (2020) show, everything else constant, debtors are more likely to default on weaker creditors. The expected value of continuing a relationship with a weaker creditor is smaller, as it has a smaller ability in fulfilling the debtor's needs (e.g., its demand for credit). An agent's strength can be proxied by its size. Some studies on the creditor-specific determinants of loan default (Salas and Saurina (2002), Rajan and Dhal (2003), Hu, Yang and Yung-Ho (2004)) mention size as negatively correlated to non-performing loans. This can be explained by the fact that large banks are more involved in risk diversification (Salas and Saurina (2002), Rajan and Dhal (2003)) and have higher capabilities for loan evaluation (Hu, Yang and Yung-Ho (2004)). However, another possible explanation is that debtors are more likely to default on loans extended by weaker creditors first for the reasons discussed above.[1]

[1] There are counterbalancing effects of creditors' size on its non-performing loans. The "too-big-to-fail" channel can lead large banks to engage in riskier activities, as they expect to be protected by the government in case of failure (Stern and Feldman (2004)). Hence, the overall effect of creditor's size on its non-performing loans is ambiguous. At any rate, it does not invalidate our hypothesis, as we are discussing to which creditors the debtor will transmit its losses *given that it has already decided to*

The second evidence is that there are peer effects on debtor's default decisions. This is discussed in some theoretical frameworks using global games (Bond and Rai (2009), Carrasco and Salgado (2014), Drozd and Serrano-Padial (2018)). Moreover, there is evidence of peer effects on default decisions brought by empirical studies (Breza (2012), Li, Yanyan and Deininger (2009), Li, Liu and Deininger (2013)). Similar results were provided by the experimental study of Trautmann and Vlahu (2013). Default peer effects work through many channels. An increase in the number of defaulting borrowers may, for instance, i) threaten the creditor's future lending ability (Bond and Rai (2009)), ii) increase the lender's verification cost (Carrasco and Salgado (2014)), iii) convey information about the probability of being sued (Guiso, Sapienza and Zingales (2013)), and iv) reduce the lender's enforcement ability (Vlahu (2008), Drozd and Serrano-Padial (2018)). All these channels provide an incentive for other borrowers to default as well. We assume default incentives are driven by the creditor's out-degree (i.e., its number of debtors) relying on these default peer effects. As discussed above, the probability of a given borrower defaulting on a given creditor is negatively related to some attributes of the creditor (e.g., its future viability as a lender or its ability to enforce defaulting loans). Moreover, borrowers default negatively affects these attributes. Suppose the borrower will decide to default if these attributes fall below a given threshold. These attributes would not be threatened by few defaults if the creditor has a high out-degree. On the other hand, a debtor would be more likely to default on a creditor with a small out-degree, as in this case, a few defaults could be enough to reduce the attributes to a level below the threshold.

Based on these evidences, we set three heuristics. In the first heuristic, the distressed debtor ranks its creditors in ascending order according to their equity. The debtor's loss will be transmitted to the first creditor of the list, at the limit of the loan extended by this creditor to the debtor. The residual loss, if any, will be transmitted to the next creditor in the list, and so on, until all the debtor's loss has been transmitted to its creditors. In the second heuristic, the process is the same, but the creditors will be ranked in ascending order according to their out-degree. We also consider a heuristic in which debtors rank their creditors according to the loan granted by them. As the default leads to the impairment of the relationship with the creditor, it is reasonable to assume that debtors will be willing to default first on those creditors that granted them smaller loans. Finally, it is important to verify whether the impact on the systemic risk – if any – is due to the heterogeneous distribution of losses *per se* or to the heterogeneity in the loss distribution according to the heuristics we set. To address this point, we set a heuristic according to which creditors are randomly ranked by distressed debtors.

We apply this framework to a data set comprising quarterly information (from March 2012 through December 2015) on two Brazilian credit networks: the bank-bank (interbank) network and the firm-bank bipartite network. On the combination of these two layers, we compute the systemic risk for different levels of the initial shock. The shock is represented by an equity

default.

loss suffered by institution i in a given fraction ζ. The fraction of the overall system equity lost due to the propagation of this shock throughout the network is the systemic risk $s_{i,\zeta}$. The systemic risk is computed according to three rules of loss distribution: i) homogeneous distribution (the standard one), ii) heterogeneous distribution according to each of the three heuristics (equity, out-degree, and loans extended), and iii) heterogeneous distribution following a random sorting of the creditors.

Our results show the adoption of a DPO considerably increases the systemic risk *vis-à-vis* the standard approach. For an initial shock of 0.1, the random sorting entails a systemic risk 7.4 (15.5) times greater than the homogeneous distribution of losses in the case of banks (firms). The sorting according to the heuristics (equity, out-degree, and loan extended) entails even greater increase of systemic risk: 11.4, 14, and 27.5 times, respectively, for the banks; 32.2, 36.8, and 94.8 for the firms. It shows the heuristic also plays an important role in the increase of the systemic risk. When loss is transmitted preferentially to more fragile agents rather than randomly, the average systemic risk is higher. Moreover, the proportional increase in the systemic risk is higher for smaller values of the initial shock. For an initial shock of 0.5, in the case of banks, the ratio between the systemic risk entailed by the heterogeneous distribution of losses (random sorting, equity, out-degree, and loan extended) and that entailed by the standard approach is, respectively, 3, 3.7, 4.6, and 7.3. If the initial shock is equal to 1 (i.e., complete default), these ratios are even smaller: 2.4, 2.5, 3.2, and 4.6. A similar pattern can be observed for the firms. Finally, we also find the rise in the systemic risk brought by the heterogeneous distribution over the homogeneous case is higher when the shock is on small-sized agents.

Our findings corroborate those of Tran, Vuong and Zeckhauser (2016). In a stylized banking network, the authors show that sequential losses entail a smaller total loss to the system than a single larger loss of the same cumulative magnitude. In our study, we show that when the loss is concentrated in a few creditors, instead of being shared equally among all creditors, the systemic risk is greater.

Our results are also related to the dual role played by financial networks in its *robust-yet-fragile* nature (Chinazzi and Fagiolo (2015)). They are a channel for risk-sharing, but also propagate shocks. When a proportional distribution of losses is adopted, as in the standard approach, the risk-sharing is maximized. On the other hand, if loss is mainly transmitted to more fragile creditors, shock propagation prevails over risk-sharing and the systemic risk is higher.

We test this hypothesis by assessing the determinants of systemic risk. Among the potential explanatory variables, we include the interconnectedness, as measured by the density of the financial network. We perform this task employing machine learning techniques (random forest and XGBoost) and Shapley values analysis. The results corroborate this hypothesis. Under the homogeneous loss distribution, which maximizes risk-sharing, the impact of interconnectedness on systemic risk is meagre. However, when this assumption is abandoned, the density has a positive impact on the systemic risk. It suggests that, in the first case, the two financial network effects (risk-sharing and shock propagation) counterbalance. In the second case, the shock propagation effect gains relative importance over the risk-sharing effect. Under the DPO, weakest nodes bear a fraction of the loss greater than their share of the loan extended to distressed debtors. Thus, more interconnections would result in a heavier penalty on them and lead to a higher systemic risk.

Our contribution to the literature is twofold. First, we show the unrealistic assumption of homogeneous loss distribution leads to a non-negligible underestimation of the systemic risk. Therefore, by incorporating our methodology, systemic risk models can provide a more accurate measure of the systemic risk. Second, we shed some light on the role played by interconnectedness in driving systemic risk. We show this depends on the assumptions concerning the loss distribution by distressed debtors. Essentially, when losses are mainly transmitted to weaker creditors, a more interconnected network leads to a higher systemic risk.

This paper proceeds as follows. The data set and methodological issues are discussed in Sections 4.2 and 4.3, respectively. Section 4.4 brings the results. Finally, final considerations are presented in Section 4.5.

4.2 The Data Set

Our data set comprises several unique Brazilian databases with supervisory and accounting data. We extract quarterly information from March 2012 through December 2015 (16 periods) and build two networks: the bank-bank (interbank) network and bank-firm bipartite network.

In the interbank network, we consider all types of unsecured financial instruments registered in the Central Bank of Brazil. The main types of financial instruments are credit, capital, foreign exchange operations, and money markets. These operations are registered and controlled by different custodian institutions: Cetip[2] (private securities), the Central Bank of Brazil's Credit Risk Bureau System (SCR)[3] (credit-based operations), and the BM&FBOVESPA[4]

[2] Cetip is a depositary of mainly private fixed income, state and city public securities, and other securities. As a central securities depositary, Cetip processes the issue, redemption, and custody of securities, as well as, when applicable, the payment of interest and other events related to them. The institutions eligible to participate in Cetip include commercial banks, multiple banks, savings banks, investment banks, development banks, brokerage companies, securities distribution companies, goods and future contracts brokerage companies, leasing companies, institutional investors, non-financial companies (including investment funds and private pension companies) and foreign investors.

[3] SCR is a very thorough data set that records every single credit operation within the Brazilian financial system worth 200BRL or above. Up to June 30th, 2016, this lower limit was 1,000BRL. Therefore, all the data we are assessing have been retrieved under this rule. SCR details, among other things, the identification of the bank, the client, the loan's time to maturity and the parcel that is overdue, modality of loan, credit origin (earmarked or non-earmarked), interest rate, and risk classification of the operation and the client.

[4] BM&FBOVESPA is a privately-owned company that was created in 2008 through the integration of the Sao Paulo Stock Exchange (Bolsa de Valores de Sao Paulo) and the Brazilian Mercantile & Futures Exchange (Bolsa de Mercadorias e Futuros). As Brazil's main intermediary for capital market

(swaps and options operations). On March 30th, 2017, BM&FBOVESPA and Cetip merged into a new company named B3.

We consider net financial exposures among different financial conglomerates or individual financial institutions that do not belong to conglomerates (classified as "b1", "b2", or "b4" in the Central Bank of Brazil's classification system), removing intra-conglomerate exposures. Institutions with negative equity were excluded. Financial institutions' equity was retrieved from <https://www3.bcb.gov.br/ifdata>.

In the bank-firm network, we considered accounting and supervisory data from non-financial firms listed on the Brazilian stock exchange (BM&FBOVESPA). Information on firms' equity was retrieved from the *Economatica* database. For each of these firms, we identified the loans granted by financial institutions using the SCR information. The criteria to include a financial institution in the bank-firm network are the same of the interbank network – that is, financial institutions with positive equity and classified as "b1", "b2", or "b4".

Table 5 brings some statistics of the financial networks. They present some characteristics reported by other empirical studies on financial networks, such as disassortative behavior (e.g., Bottazzi, Sanctis and Vanni (2020)), sparseness (e.g., Souza *et al.* (2016)), and a distribution of banks' degrees wider than that of firms in the bank-firm network (e.g., Luu and Lux (2019)). In each period t, we combine both networks to create the overall matrix of exposures $\mathbf{A}_t \in NB_t \times (NB_t + NF_t))$, where NB_t is the number of banks at t, NF_t is the number of firms at t, and A_{ijt} is the net exposure of i towards j at t. Recalling that creditors can be only banks, and debtors can be either firms or banks.

Variable	Interbank network	Bank-firm credit network
Number of banks	128.75	128.75
Number of firms	–	313.50
Banks' in/out-degree – average	10.17	22.23
Banks' in-degree – minimum	0	-
Banks' in-degree – maximum	49.81	-
Banks' out-degree – minimum	0	1
Banks' out-degree – maximum	80.38	233.94
Firms' in-degree – average	–	4.99
Firms' in-degree – minimum	–	1
Firms' in-degree – maximum	–	27.19
Assortativity	-0.3652	-0.3649
Density	0.0793	0.0581

Table 5 *– Topological features of the financial networks – average over periods.*

transactions the company develops, implements and provides systems for trading equities, equity derivatives, fixed income securities, federal government bonds, financial derivatives, spot FX, and agricultural commodities.

4.3 Methodology

4.3.1 Systemic Risk Computation

We compute the systemic risk on the exposure network $\mathbf{A}$ following the *differential DebtRank* (Bardoscia *et al.* (2015)) methodology. The aggregate loan extended to j is A_j. At period 0, we impose an exogenous shock on agent j, reducing its equity by a fraction of ζ.[5] It will cause a subsequent loss on their creditors, indexed by i, whose aggregate value is equal to $\mathbf{A}_j\zeta$. At period 2, j's creditors will propagate this loss to their creditors in a similar fashion, and so on. We define $L_{ij}(t)$ as the accumulated loss transmitted by j to i up to period t. Moreover, $\Delta L_{ij}(t) = L_{ij}(t) - L_{ij}(t-1)$ is the new flow of loss transmitted by j to i and $L_i(t) = \sum_j L_{ij}(t)$ is the total loss transmitted to i by their debtors up to t. Finally, $\Delta L_i(t) = L_i(t) - L_i(t-1)$ is the variation in the total loss transmitted to i by their debtors up to t.

There are two mechanisms of loss distribution. In the first mechanism, which corresponds to the standard approach of systemic risk computation in network models, the loss distribution is homogeneous, proportional to the loan extended by each creditor to the distressed debtor. In the second mechanism, the distribution is heterogeneous. Creditors are ranked according to a given heuristic. The distressed debtor defaults first on the top creditor of the rank, transmitting only the residual loss to the remaining creditors. The rest of this section discusses each mechanism more formally.

Homogeneous loss distribution: In the homogeneous case, the dynamics of loss propagation are represented by the following equations:

$$\Delta L_{ij}(t) = min\left(A_{ij} - L_{ij}(t-1), \mathbf{A}_{ij}\frac{[L_j(t-1) - L_j(t-2)]}{E_j}\right), \tag{4.1}$$

$$\Delta L_i(t) = min\left(E_i - L_i(t-1), \sum_j \Delta L_{ij}(t)\right), \tag{4.2}$$

in which $t \geq 0$ and E_j is agent j's equity. Thus, when an agent j suffers an additional loss equal to a fraction ζ of its equity, it will impose a loss to its creditors that corresponds to ζ times their exposures towards j. Observe that equity positions as well as the exposure network are time-invariant, i.e., they are taken as exogenous. The propagation considers stress differentials rather than stress absolute values (hence the methodology's name) to avoid double-counting.

Observe that, from Equation 4.1, L_{ij} cannot be greater than A_{ij}, i.e., j cannot impose to i a loss greater than i's exposures towards j. When $L_{ij} = A_{ij}$, j stops imposing losses on i. Moreover, as can be observed from Equation 4.2, L_i – the loss imposed on agent i – cannot be greater than

[5] In this paper, there are two period notations. The subscript notation t – present in the previous section and omitted in this subsection for simplicity – refers to the date (month-year). The notation between parenthesis refers to the number of iterations after the shock, where 0 refers to the period in which the shock is imposed.

E_i. That is, i's losses cannot be greater than its equity. When $L_i = E_i$, i stops propagating losses to other agents.

Heterogeneous loss distribution: In the second approach, the distressed debtor prefers to default on certain creditors first. Agent j will rank their creditors as $i = 1, 2, ..., J$, where J is j's number of creditors. It prefers to default on creditor 1 first, then on creditor 2, and so on. Debtor j transmits all the loss to creditor 1 at the limit of the loan extended by the creditor 1 to j. Only will the residual loss, if any, be transmitted to creditor 2. The process continues until j has transmitted the entire loss to their creditors. Therefore, Equation 4.1 is replaced by

$$\Delta L_{ij}(t) = min\left(A_{ij} - L_{ij}(t-1), \mathbf{A}_j\zeta - \sum_{k<i} \Delta L_{kj}(t)\right), \tag{4.3}$$

where $\zeta = \frac{L_j(t-1)-L_j(t-2)}{E_j}$. Therefore, the loss propagated to a certain creditor i is equal to the aggregate loss agent j will transmit to its creditors, $A_j\zeta$, minus the loss already transmitted to the other agents j prefers to default on rather than i. Equation 4.2 also holds in this case.

Figure 27 illustrates the differences between the two approaches. Suppose a distressed debtor has four creditors. They are ranked according to the debtor's default preference, meaning the debtor prefers to default on creditor 1 (C1) first. The loss the debtor will transmit to their creditors corresponds to 20% of its entire debt. In the figure on the left, which corresponds to the homogeneous loss distribution case, the debtor transmits to each creditor a loss which corresponds to 20% of the loan granted by the creditor. In the heterogeneous case (figure on the right), the debtor transmits the maximum loss it can to C1 (in this case, all loans granted by C1) and only the residual loss to C2.

Systemic risk: After the initial shock on j, following one of the loss distribution mechanisms, the system converges after a sufficiently large number of periods $T \gg 1$. Then we have the final matrix of losses $\mathbf{L}^{j,\zeta} \in N \times 1$, where $L_i^{j,\zeta}$ is the total loss suffered by agent i after an initial shock of size ζ at agent j.

We repeat this process for the other agents. We define the systemic risk of agent i as

$$s_{i,\zeta} = 100 \times \frac{\sum_j [L_j^{i,\zeta} - L_j^{i,\zeta}(0)]}{\sum_j E_j}, \tag{4.4}$$

where $L_j^{i,\zeta}(0) = \zeta E_j$ if $j = i$ and 0 otherwise. Therefore, $s_{i,\zeta}$ measures the percentage of the aggregate agents' equity which is lost as a consequence of an initial shock of size ζ to agent i's equity. Note that we remove the initial shock to the agent i ($L_i^{i,\zeta}(0)$) from the computation of the systemic risk, as we are interested only in the losses caused by the contagion. Moreover, we compute $s_{i,\zeta}$ also for the agent that suffered the initial shock. Due to network cyclicality, a shock propagated by a given agent can hit it back.

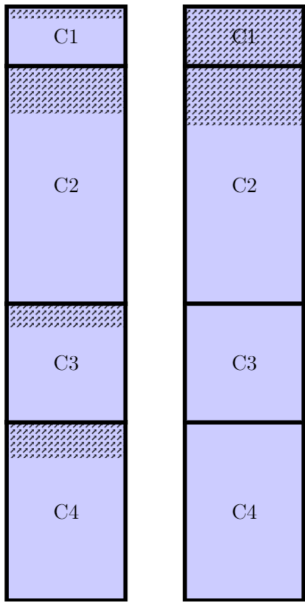


Figure 27 – *Homogeneous (left) and heterogeneous (right) loss distribution. The loan extended by each creditor is proportional to the heights of the rectangles. The hatched area corresponds to the loss. In the homogeneous case, the fraction of the hatched area (0.2) is the same in all rectangles. The sum of the hatched area (i.e., the aggregate loss) is the same in both figures.*

4.3.2 Machine Learning Techniques

After computing the systemic risk for our data instances using the methodology presented in Section 4.3.1, we will employ two machine learning techniques – random forest (RF) and XGBoost (XB) – to assess the determinants of the systemic risk (Section 4.4.2). Shapley values will be used to give a better interpretability to our results. These techniques will be discussed briefly in this subsection.

Random forest and XGBoost: RF (Breiman (2001)) and XB (Friedman, Hastie and Tibshirani (2000)) are ensemble learning methods that can be used for both classification and regression. RF operates by constructing several decision trees.[6] For regression tasks, which is the case in this paper, it returns the average prediction of the individual decision trees. XB is an optimization algorithm that works with an ensemble of weak predictors (usually, decision trees) and creates a more efficient predictor model. At each boosting stage, the XB algorithm attempts to increase the performance of the predecessor model by including a new estimator. In both cases, the purpose is to estimate a predicted output $\hat{y}_i$ from an observed output y_i and a vector of explanatory variables X_i.

The models are trained and validated through a process known as *repeated k-fold cross-validation*. The data set, comprised of the output to be predicted and a set of potential explanatory variables, is split into k different parts (folds). $k-1$ folds are used in the development of the model. Then, the model is trained on the remaining fold: the predicted output $\hat{y}_i$ and the observed output y_i of the remaining fold are used to compute score measures, such as the root mean

[6] On decision trees, see, e.g., Breiman *et al.* (1984)

squared error (RMSE) and the R^2. Each fold is used as the testing data set. Hence, for instance, in a repeated k-fold cross-validation with $k = 5$ and 10 repetitions, a total of 50 regressions are run.

These score measures are used to tune the number of estimators of both methods. In the RF, the number of estimators is the number of decision trees in each forest. In the XB, this is the number of boosting stages to be performed. The number of estimators varies within a grid of ascending values. For each of these values, the regressions are run, and the average score is computed. The number of estimators is chosen so that increasing it does not improve the performance of the method.

Shapley values: We go further on the interpretability of our results by resorting to the computation of Shapley values. This approach, originated from the coalition games theory (Shapley (1953), Shoham and Leyton-Brown (2008)), provides evidence on features' importance. Moreover, Shapley values can also inform whether a given feature is positively or negatively correlated to the output. We compute Shapley values through the SHAP (SHapley Additive exPlanation) framework proposed by Lundberg and Lee (2017). The authors propose an explainer model g aiming at predicting an output using a set of M features as inputs. The predicted value for a given data-instance is given by

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z'_i, \tag{4.5}$$

where z' is a binary variable indicating whether feature i was included in the model or not. Therefore, the SHAP value ϕ_i indicates to what extent the feature i shifts the predicted value up or down from a given mean output ϕ_0. Lundberg and Lee (2017) showed, under certain properties (local accuracy, missingness, and consistency), ϕ_i corresponds to the Shapley value of the game theory. The SHAP value of feature i is given by

$$\phi_i = \sum_{S \subseteq M \setminus i} \frac{|S|!(|M| - |S| - 1)!}{M!} [F(S \cup \{i\}) - F(S)]. \tag{4.6}$$

Therefore, the SHAP value of feature i for a given data-instance computes the difference between the predicted value of the instance using all features in S plus feature i, $F(S \cup \{i\})$, and the prediction excluding feature i, $F(S)$. This is weighted and summed over all possible feature vector combinations of all possible subsets S.[7]

[7] For details on the calculation of SHAP values, see, e.g., Lundberg and Lee (2017) and Kalair and Connaughton (2021).

4.4 Results

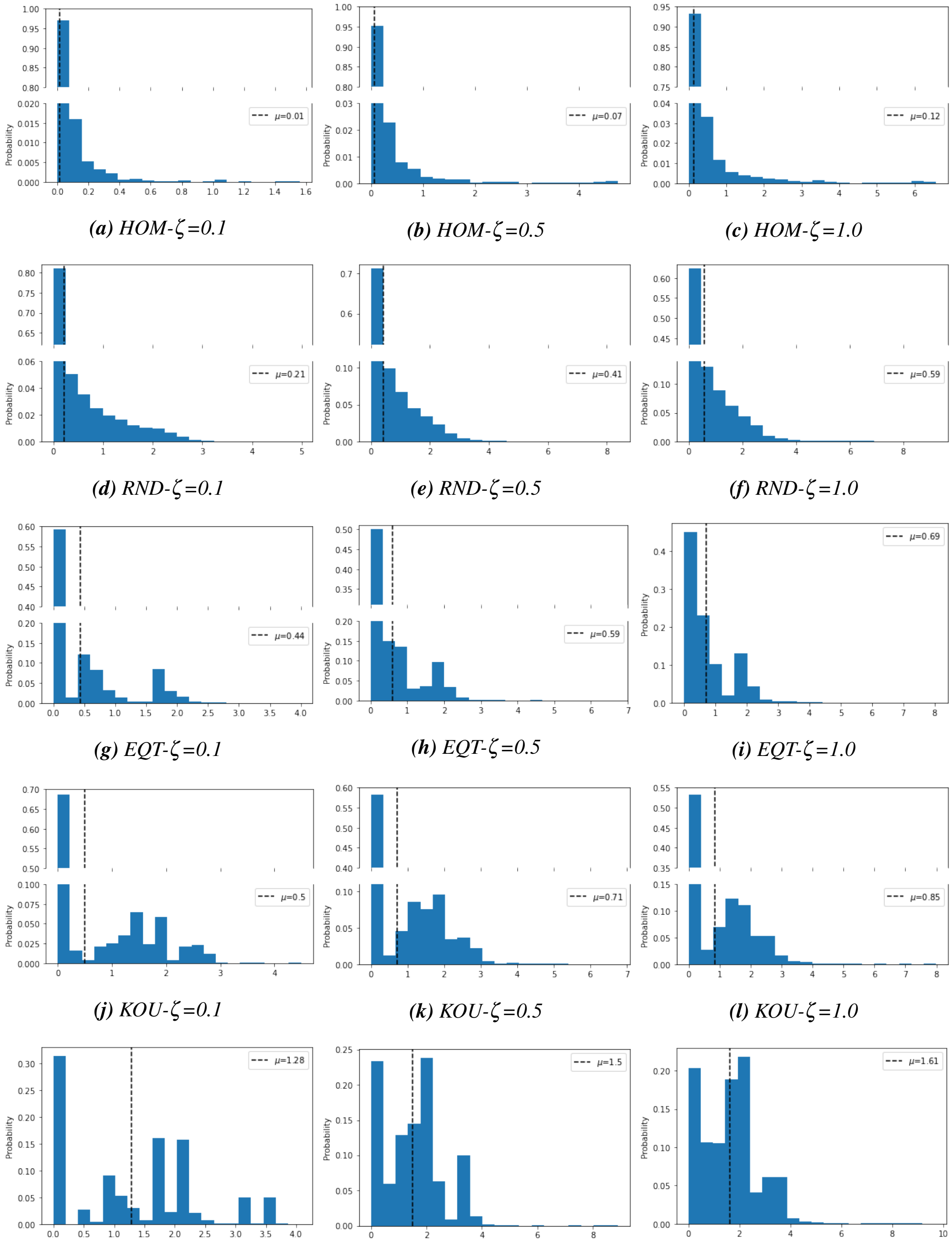
4.4.1 General Results

We compute the systemic risk (Equation 4.4) considering three values of ζ (0.1, 0.5, and 1.0) for 7,076 observations (2,060 date-bank data-instances and 5,016 date-firm data-instances). We consider five loss distribution mechanisms:

- The homogeneous loss distribution mechanism.
- The heterogeneous distribution mechanism according to the three heuristics discussed in Section 4.1: equity, out-degree, and loan extended. For instance, according to the equity heuristic, the distressed debtor ranks their creditors in ascending order by their equities, preferring to default on those with smaller equity first. The other heuristics follow the same reasoning (i.e., creditors are ranked in ascending order according to their out-degree or their loan extended).
- The heterogeneous distribution mechanism in which the creditors are randomly sorted. This is to check whether the differences regarding the homogeneous case (if any) are due to the heterogeneous distribution *per se* or also due to the heuristic adopted. We run 10 different realizations considering this loss distribution mechanism.

The results are presented in Figures 28 and 29. It can be seen the systemic risk increases when a heterogeneous loss distribution is adopted. Moreover, the systemic risk of firms is smaller than that of banks. This is because firms are only debtors in the network. They cannot be hit back by shocks to themselves. By contrast, banks can be both debtors and creditors. Thus, shocks to banks are amplified by the cyclicality of the network.

The heuristic also plays an important role in the increase of the systemic risk. When loss is transmitted preferentially to more fragile agents rather than randomly, the average systemic risk is higher. The loan granted heuristic entails the highest average systemic risk. Moreover, the rise in the systemic risk brought by the heterogeneous distribution over the homogeneous case decreases with the level of the initial shock. For an initial shock of 0.1, the ratio between the systemic risk entailed by the heterogeneous distribution of losses (random sorting, equity, out-degree, and loans granted) and that entailed by the standard approach is, respectively, 7.4, 11.4, 14.0, and 27.5 for the banks. If the initial shock is 0.5, these ratios decrease to 3.0, 3.7, 4.6, and 7.3. For an initial shock of 1.0 (complete default), these values are even smaller: 2.4, 2.5, 3.2, and 4.6. A similar decreasing pattern can be observed for firms. Finally, the heuristics also change the distribution of the systemic risk. The distribution of the systemic risk entailed by the homogeneous distribution and the random sorting heterogeneous distribution of losses is right-skewed. When some heuristic is introduced, the distribution of the systemic risk becomes multimodal.



(a) HOM-ζ=0.1 *(b) HOM-ζ=0.5* *(c) HOM-ζ=1.0*

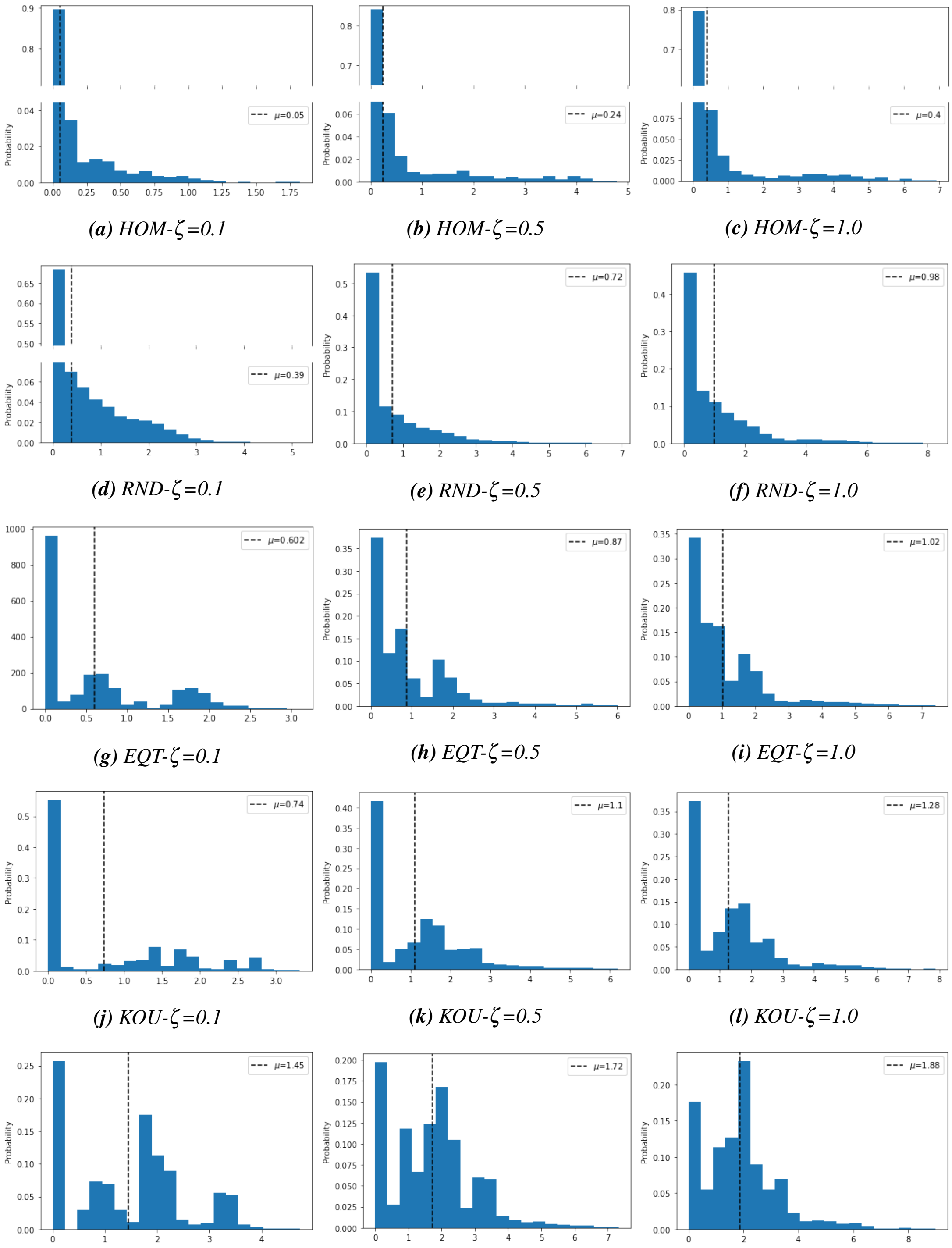
(d) RND-ζ=0.1 *(e) RND-ζ=0.5* *(f) RND-ζ=1.0*

(g) EQT-ζ=0.1 *(h) EQT-ζ=0.5* *(i) EQT-ζ=1.0*

(j) KOU-ζ=0.1 *(k) KOU-ζ=0.5* *(l) KOU-ζ=1.0*

(m) LOA-ζ=0.1 *(n) LOA-ζ=0.5* *(o) LOA-ζ=1.0*

Figure 28 – *Density probability of the systemic risk – firms. Legend: HOM: homogeneous loss distribution; RND: random sorting; EQT: equity heuristic; KOU: out-degree heuristic; LOA: loan granted heuristic. The vertical lines indicate the average systemic risk.*



(a) HOM-ζ=0.1 *(b) HOM-ζ=0.5* *(c) HOM-ζ=1.0*

(d) RND-ζ=0.1 *(e) RND-ζ=0.5* *(f) RND-ζ=1.0*

(g) EQT-ζ=0.1 *(h) EQT-ζ=0.5* *(i) EQT-ζ=1.0*

(j) KOU-ζ=0.1 *(k) KOU-ζ=0.5* *(l) KOU-ζ=1.0*

(m) LOA-ζ=0.1 *(n) LOA-ζ=0.5* *(o) LOA-ζ=1.0*

Figure 29 – *Density probability of the systemic risk – banks. Legend: HOM: homogeneous loss distribution; RND: random sorting; EQT: equity heuristic; KOU: out-degree heuristic; LOA: loan granted heuristic. The vertical lines indicate the average systemic risk.*

Table 6 presents the weighted average systemic risk $\sum_i w_{it} s_{i\zeta t}$, where w_{it} is the agent i's participation in total equity at period t. Thus, this is the loss caused by a shock in the agents weighted by their equities. In this case the differences between the systemic risk entailed by the different approaches are less remarkable. This suggests the increase in the systemic risk brought by the heterogeneous loss distribution depends on the agents' equity. We then investigate the relationship between the systemic risk entailed by the heterogeneous distributions of losses and that entailed by the homogeneous distribution HET/HOM at the agent level. Results are presented in Figures 30 and 31. For the sake of better visualization this ratio is presented on a natural logarithmic scale. The highest differences between the systemic risk entailed by the heterogeneous loss distributions and that entailed by the homogeneous approach are observed in the small-sized agents. In a few cases, this ratio is smaller than one.

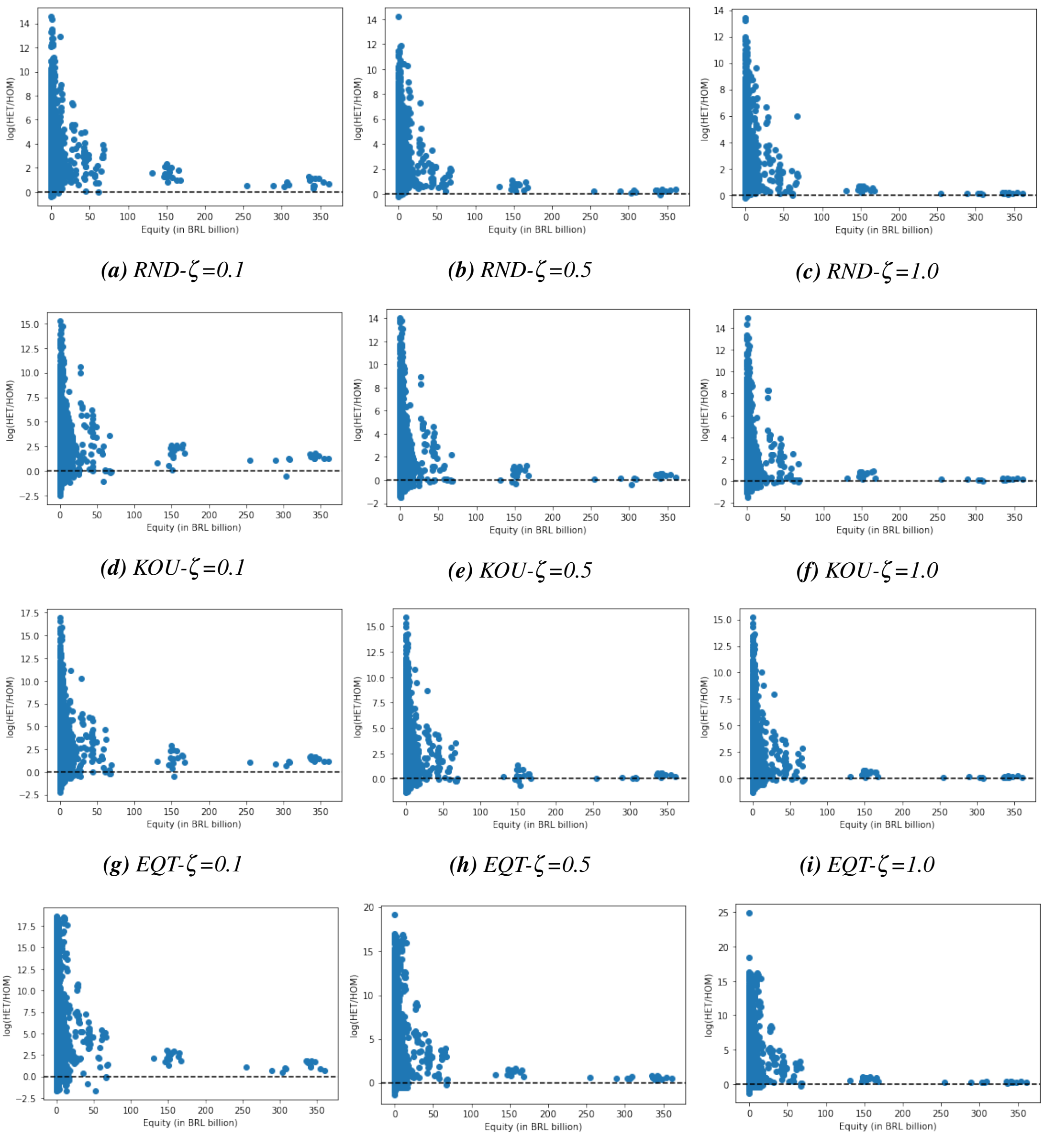
Type	Method	ζ=0.1	ζ=0.5	ζ=1.0
Firms	HOM	0.20	0.87	1.43
	RND*	0.59	1.34	2.00
	EQT	0.89	1.42	2.01
	KOU	1.03	1.55	2.16
	LOA	1.38	2.36	2.73
Banks	HOM	0.14	0.58	0.86
	RND*	0.42	0.80	1.11
	EQT	0.42	0.85	1.06
	KOU	0.47	0.94	1.15
	LOA	0.73	1.13	1.30

*: Average of 10 realizations.

Table 6 *– Average systemic risk for different levels of ζ, weighted by the agent's equity. Legend: HOM: homogeneous loss distribution; RND: random sorting; EQT: equity heuristic; KOU: out-degree heuristic; LOA: loan granted heuristic.*

4.4.2 Risk-sharing versus Shock Propagation

Our results can be interpreted in the light of the dual role of financial networks. They can work as a channel for risk-sharing, but also for shock propagation (Chinazzi and Fagiolo (2015)). The role played by interconnectedness in the systemic risk depends on which effect prevails over the other. If the risk-sharing effect prevails over the shock propagation effect, a more interconnected network will be more robust. Hence, the systemic risk is smaller. Otherwise, more interconnections will increase the level of systemic risk. When the distribution of losses follows a pro-rata fashion, risk-sharing is maximized. On the other hand, when the loss is mostly transmitted to the more fragile creditors, the financial network acts mainly as a shock propagator. The shock propagation effect of the financial network gains relevance, while the risk-sharing effect is curtailed. This explains the increase in the systemic risk when the homogeneous loss distribution is abandoned.



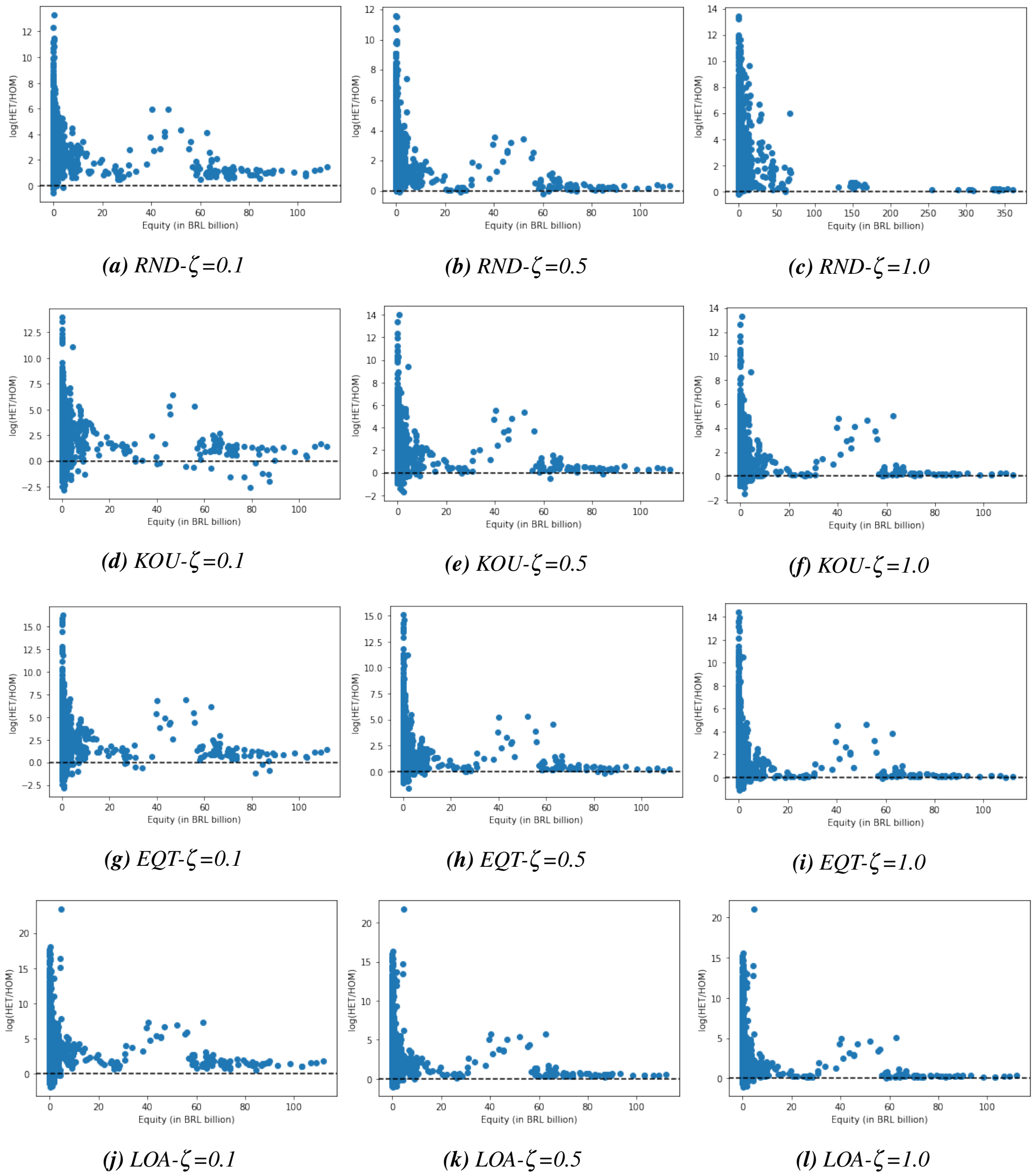
(a) RND-ζ=0.1 *(b) RND-ζ=0.5* *(c) RND-ζ=1.0*

(d) KOU-ζ=0.1 *(e) KOU-ζ=0.5* *(f) KOU-ζ=1.0*

(g) EQT-ζ=0.1 *(h) EQT-ζ=0.5* *(i) EQT-ζ=1.0*

(j) LOA-ζ=0.1 *(k) LOA-ζ=0.5* *(l) LOA-ζ=1.0*

Figure 30 – *Systemic risk entailed by the heterogeneous loss distribution-to-systemic risk entailed by the homogeneous loss distribution ratio – firms. Legend: RND: random sorting; EQT: equity heuristic; KOU: out-degree heuristic; LOA: loan granted heuristic.*



(a) *RND-ζ=0.1* ***(b)*** *RND-ζ=0.5* ***(c)*** *RND-ζ=1.0*

(d) *KOU-ζ=0.1* ***(e)*** *KOU-ζ=0.5* ***(f)*** *KOU-ζ=1.0*

(g) *EQT-ζ=0.1* ***(h)*** *EQT-ζ=0.5* ***(i)*** *EQT-ζ=1.0*

(j) *LOA-ζ=0.1* ***(k)*** *LOA-ζ=0.5* ***(l)*** *LOA-ζ=1.0*

Figure 31 – *Systemic risk entailed by the heterogeneous loss distribution-to-systemic risk entailed by the homogeneous loss distribution ratio – banks. Legend: RND: random sorting; EQT: equity heuristic; KOU: out-degree heuristic; LOA: loan granted heuristic.*

We go further on this hypothesis by assessing the effect of interconnectedness on our measures of systemic risk. We employed two machine learning techniques – RF and XB – to predict the agents' systemic risk. Besides individual level variables (equity, total borrowing-to-equity ratio, PageRank, in-degree, and a dummy variable for firms), we use the density of the financial network as a potential explanatory variable. The potential explanatory variables are described in Table 7. For a given date, we calculate the density of the financial network as follows:

$$dens_t = \frac{k_t}{NB_t \times (NB_t + NF_t - 1)}, \tag{4.7}$$

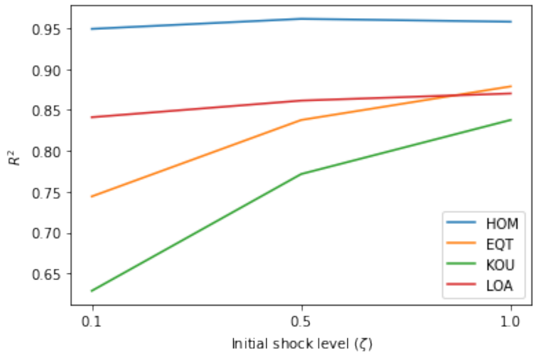
where k_t is the total number of links of the network at period t, NB_t is the total number of different banks in the network at t, and NF_t is the total number of different firms. The denominator represents the maximum number of links, as only banks can be lenders (except for themselves), but both banks and firms can be borrowers. Thus, the density is the number of links over the number of possible links.

Variable	Acronym
Equity (net worth)	NW
Total borrowing-to-equity ratio	CA
PageRank	PR
In-degree	Kin
Dummy variable for type of agent (firm: 1)	Type
Density of the financial network	dens

Table 7 *– Potential determinants assessed in the study.*

We implemented a repeated k-folds cross-validation with k = 5 folds and 10 repetitions. After tuning the number of estimators of both methods using the root mean squared error (RMSE) as the score measure within the grid [30, 50, 70, 100, 300, 500], we set the value of both parameters as 50. Finally, we apply both techniques to predict the systemic risk. The outputs to be predicted are the four measures of systemic risk, each one engendered by a different methodology of loss distribution (homogeneous, equity heuristic, out-degree heuristic, and loan granted heuristic). The potential explanatory variables are those presented in Table 7. Both methods have a similar performance in terms of the average R^2 (Figure 32), which generally increases with ζ.

We assess the importance of each feature in driving the systemic risk by computing Shapley values through the SHAP (SHapley Additive exPlanation) framework (Lundberg and Lee (2017)). Once the two machine learning techniques are employed as explainer models for our systemic risk measures, we compute the SHAP values. Then we compute, for each feature presented in Table 7, the average absolute SHAP value over all data-instances. Finally,



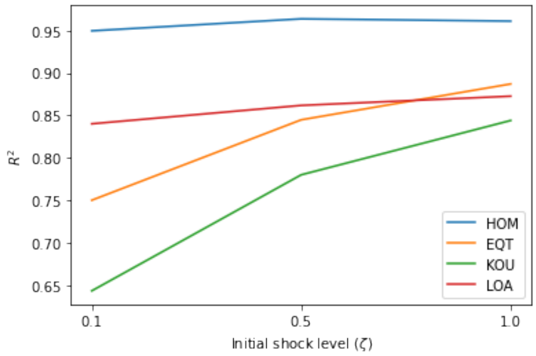


***Figure 32** – Average R^2 of the regressions performed by RF (left) and XB (right). Legend: HOM: homogeneous loss distribution; RND: random sorting; EQT: equity heuristic; KOU: out-degree heuristic; LOA: loan granted heuristic.*

we multiply this value by the sign of the correlation between the feature value and the SHAP value. The final value gives us two pieces of information. Its absolute value shows the feature importance in driving the output. Its sign informs whether the feature is positively or negatively correlated to the output.

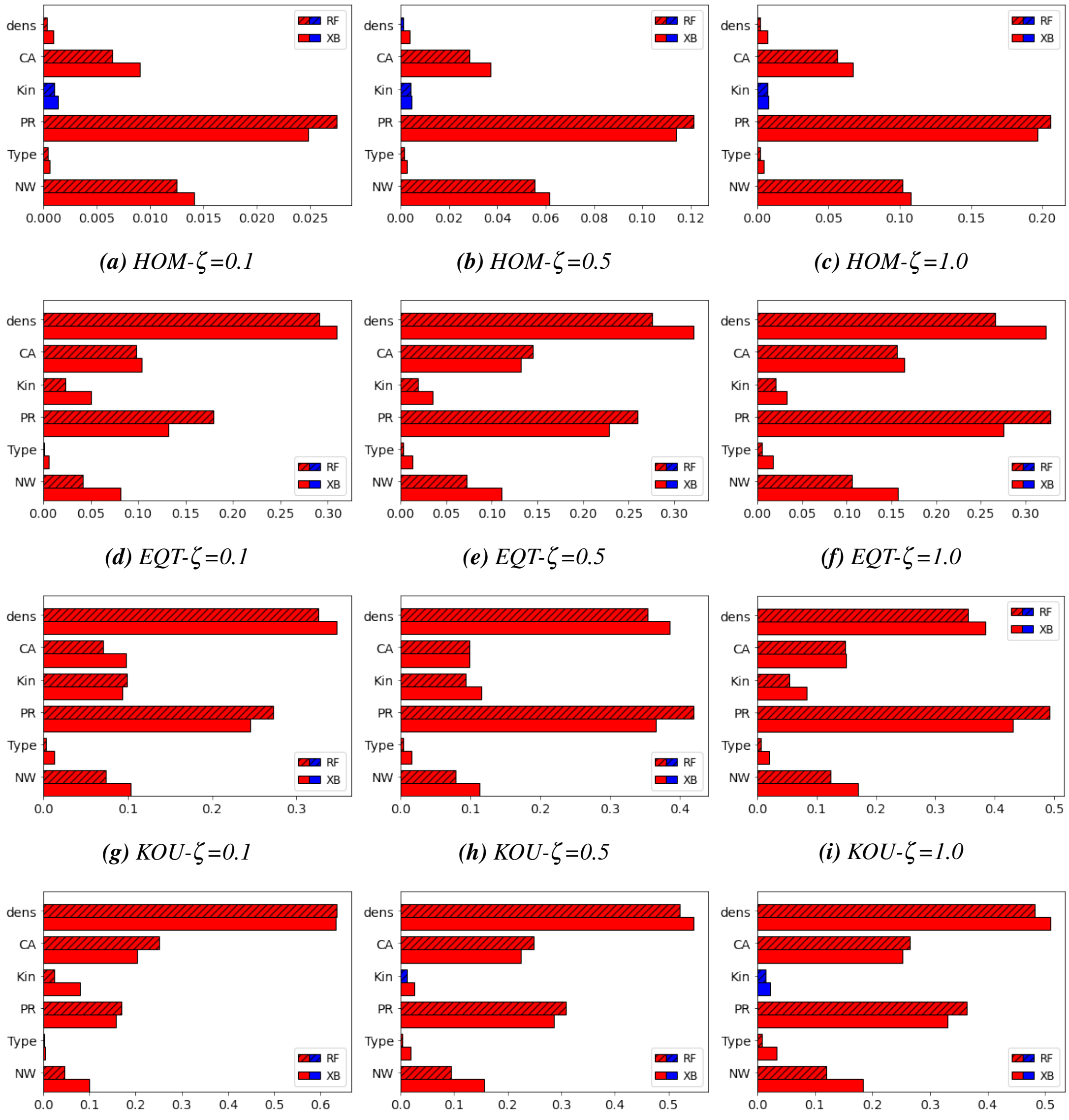
The results are presented in Figure 33. Density has a meagre effect in driving systemic risk under the homogeneous loss distribution rule. However, this is an important systemic risk driver when the heterogeneous distribution of loss is adopted, rivaling in importance with PageRank. Its impact is positive, which means that a more interconnected network leads to a higher systemic risk when losses are mainly transmitted to fragile creditors.

These results corroborate our hypothesis. When risk-sharing is maximized through the adoption of the homogeneous distribution of loss, interconnectedness (as measured by the network's density) has no significant impact on systemic risk. This suggests both effects (risk-sharing and shock propagation) almost counterbalance. However, when losses are transmitted mostly to fragile creditors, the shock propagation effect gains relative importance over the risk-sharing effect. In this case, interconnectedness is positively correlated to systemic risk, as the financial network now is acting mainly as a channel for shock propagation rather than for risk sharing.

4.5 Concluding Remarks

In this paper, we computed the systemic risk relaxing the assumption of pro-rata distribution of losses by distressed debtors among their creditors. This assumption is adopted by traditional network models of systemic risk. However, this assumption is not realistic. Empirical studies show debtors are more likely to default on fragile creditors. Default implies the impairment of the debtor-creditor relationship. For this reason, debtors prefer to default first on those creditors whose relationships are less valuable to them in the future.

For a Brazilian multilayer credit network (interbank credit network and bank-firm credit



(a) HOM-ζ=0.1 *(b) HOM-ζ=0.5* *(c) HOM-ζ=1.0*

(d) EQT-ζ=0.1 *(e) EQT-ζ=0.5* *(f) EQT-ζ=1.0*

(g) KOU-ζ=0.1 *(h) KOU-ζ=0.5* *(i) KOU-ζ=1.0*

(j) LOA-ζ=0.1 *(k) LOA-ζ=0.5* *(l) LOA-ζ=1.0*

Figure 33 – *Average absolute SHAP values. Legend: HOM: homogeneous loss distribution; EQT: equity heuristic; KOU: out-degree heuristic; LOA: loan granted heuristic. Bars in red (blue) indicates the corresponding feature is positively (negatively) correlated to the SHAP value.*

network), we compared the systemic risk computed under the homogeneous and heterogeneous rule of loss distribution. In the homogeneous rule, distressed debtors transmit the loss to its creditors proportionally to the loan extended by these creditors. In the heterogeneous rule, creditors are ranked in ascending order according to some criterion (equity, out-degree, loan extended, or randomly). Once distressed debtors compute the aggregate loss to be transmitted to their creditors, they default on their creditors following this default pecking order. Therefore, under the heterogeneous rule (except in the random sorting case), losses are mostly transmitted to the more fragile creditors.

Our results show systemic risk increases substantially when the heterogeneous loss distribution is adopted. The rise in the systemic risk brought by the heterogeneous distribution over the homogeneous case decreases with the level of the initial shock and is higher for small-sized agents. These results are related to the dual role of financial networks. They can be a channel for both risk-sharing and shock transmission. Risk-sharing is maximized under the homogeneous loss distribution. Creditors experience a loss which is proportional to the loan they extended to the distressed debtor. When this assumption is relaxed, the shock transmission effect of the financial network gains relative importance over the risk-sharing effect, leading to an increase in the systemic risk.

We tested this hypothesis by assessing the determinants of systemic risk under different rules of loss distribution. Among the potential explanatory variables, we included the density of the financial network. We performed this task employing two machine learning techniques (random forest and XGBoost) and Shapely values to give more interpretability to our results. The results corroborated this hypothesis. Under the homogeneous rule (i.e., when risk-sharing is maximized), the two effects of the financial network (risk-sharing and shock transmission) counterbalance and the density has a meagre impact on systemic risk. On the other hand, when losses are mostly transmitted to more fragile creditors, the density has a positive impact on systemic risk, suggesting in this case the financial network acts mainly as a shock transmission channel.

Our study contributes to the literature on systemic risk by showing the magnitude of the systemic risk depends on the strategy of loss distribution adopted by the debtors. The unrealistic assumption that losses are evenly distributed among creditors leads to an underestimation of the systemic risk. Moreover, we shed a new light on the role played by interconnectedness on systemic risk. When the assumption of homogeneous loss distribution is relaxed, the shock transmission channel of the financial network becomes relatively more important *vis-à-vis* the risk-sharing channel. In this case, interconnectedness has a positive impact on systemic risk, as the financial network is working mainly as a shock transmission channel.

CHAPTER

5

THE FINANCIAL NETWORK CHANNEL OF MONETARY POLICY TRANSMISSION: AN AGENT-BASED MODEL

5.1 Introduction

The intrinsically ‘robust-yet-fragile’ nature of a financial network (FN) has been long recognized as a key feature requiring due and careful consideration when analyzing the dynamic stability of the economy. In fact, complex market interconnections among heterogeneous and uncoordinated agents acting in a decentralized way, by their very nature, inevitably perform as both shock-absorbers and shock-amplifiers (Chinazzi and Fagiolo (2015)). Throughout this paper, by the notion of financial interconnection we mean the existence of direct contractual financial obligations between agents, such as loans extended by banks to firms and debt obligations in the interbank market. Our focus, in this paper, is on the impact of shocks to the base interest rate that propagate through direct and indirect network linkages between economic agents – here, firms and banks.[1]

In an influential paper, Allen and Gale (2000) argue that the benefits of risk diversification generated by a more interconnected FN more than offset the perils of risk propagation. However, this view has been subject to various criticisms (e.g., Freixas, Parigi and Rochet (2000), Brusco and Castiglionesi (2007)). The *coup de grâce*, so to speak, came with the 2007-2008 financial crisis, which has clearly (and costly) shown that a localized shock may spread to a large part of the

[1] There are other types of indirect interconnections that give rise to the operation of other mechanisms of shock propagation but are not our object of study here. For instance, when agents are interconnected through common asset exposures, shock propagation is engendered by fire sales (Acharya (2009)). We neglect these mechanisms for simplicity, in order to keep the model clearly understandable. Our choice can be justified by the fact that most of the existing literature even neglects bank-firm linkages, being restricted to the interbank market (Battiston, Caldarelli and D’Errico (2016)). For a thorough review on financial contagion mechanisms, see Riccetti (2019).

economy through complex financial linkages. As a result, policymakers and academic researchers have become considerably more aware that the role played by network interconnectedness in the propagation of a localized shock should not be neglected. Nevertheless, the ways in (and more precisely yet the mechanisms through) which network interconnectedness affect the 'resilience-cum-fragility' of the economy as a complex adaptive system is understandably still an open issue.

Direct interconnections in a FN can lead to shock propagation through two main risk channels. The first one – the so-called *counterparty risk* – refers to the risk of creditors not recovering at least part of their investment in agents affected by a negative shock. This channel is present in many network-based models of financial contagion (e.g., Gatti *et al.* (2010), Upper (2011), Battiston *et al.* (2012c), Bech and Garratt (2012)). The second one is the so-called *funding risk*. This channel affects debtors and can operate in two ways when agents hit by, say, a negative shock either refuse to roll-over short-term sources of funding, such as loans and repo lending (e.g., López-Espinosa *et al.* (2012)), or anticipate the liquidation of assets (e.g., Allen and Gale (2000)). Notice the inherent asymmetry involved in the operation of these channels: in the case of the counterparty risk, a creditor will not recover more than what was specified in the respective financial contract if the agent she had invested in is hit by a same-size but now positive shock; in the case of the funding risk, a debtor hit by a same-size but instead positive shock will not necessarily be willing or capable to either roll-over (or contract new) short-term sources of funding or anticipate the acquisition of assets.

An important question raised by many studies is what topological features of the financial network are mostly related to its resilience to shock propagation and how such a relation works. Interconnectedness is often pointed as playing the most important role in determining the financial network resilience. However, there is a relative consensus on some points about this relationship: i) there are some topological features which are important predictors of the financial network resilience, such as the degree distribution and the assortativity, ii) it is not linear (e.g., it seems that shock transmission rather than shock absorption dominates at low levels of connectivity), and iii) it depends on other elements, as the size of the shock (Acemoglu, Ozdaglar and Tahbaz-Salehi (2015)) (more on this in Section 5.4.1).

Network models have been largely used both in the measurement of systemic risk and the assessment of supervision and regulation policies intended to mitigate it. In effect, macroprudential policy tools have been usually employed for such purpose. Although monetary policy is primarily concerned with achieving and maintaining macroeconomic stability, its impact on financial stability has been extensively studied, especially after the 2007-2008 crisis (e.g., Stein (2012), Alexandre and Lima (2020a), Riccetti, Russo and Gallegati (2013)). But only a few financial network models have incorporated monetary policy issues to their analytical framework. In Georg (2013) and Bluhm, Faia and Krahnen (2014), for instance, the central bank provides liquidity in the interbank market. Meanwhile, Silva *et al.* (2020) estimate both direct and indirect impacts of monetary policy shocks (as measured by changes in the policy interest rate) on the economy by applying a multi-layer network model to a unique Brazilian data set.

Yet policy-oriented network models of financial contagion typically assume that shocks propagate through an exogenously given network. In effect, little is known about how shock propagation affects the topology of a FN, although there is robust evidence that the topology of a FN is sensitive to economic or regulation policy. Hałaj and Kok (2015) calibrated a model for a sample of eighty European banks and showed that the topology of the interbank network generated by the model can be affected by different types of regulation. For instance, when high exposure limits are lowered as a regulation policy, banks reduce the size of their exposure and increase the number of connections in the interbank market. Bluhm, Faia and Krahnen (2014) found that liquidity provision increases banks' resilience to shocks, although it is detrimental to financial stability through two different but considerably interrelated channels: it encourages risk-taking behavior and increases interconnectedness, thus facilitating the propagation of shocks. Given that the topology of a FN plays a key role in the propagation of shocks through the financial and the real sides of the economy, which are themselves interrelated in a complex way, a proper assessment of how the manipulation of a policy instrument such as the interest rate impacts on systemic risk requires that the intermediating effects operating by means of topological features of the FN are duly considered. These intermediating effects constitute what we dub here the *financial network channel of monetary policy transmission*. Using an analogy with the Lucas critique (Lucas (1976)) originally applied to stabilization policy, it seems reasonable to conjecture that the topology of a FN, by virtue of it being to a great extent affected in a complex manner by the decentralized and uncoordinated decisions and actions of its heterogeneous participants, is highly unlikely, to be invariant to monetary policy shocks.

The purpose of this paper is in contributing to a further understanding of the working of the financial network channel of monetary policy. To this aim, we develop an agent-based model (ABM) in which banks extend loans to consumption-good firms. The bank-firm credit network is endogenously time-varying as determined by plausible and realistic behavioral assumptions, with both firms and banks being always willing (but not always able) to close a credit deal with the network partner perceived to be less risky. We will then assess how exogenous shocks to the policy interest rate affect some key topological measures of the bank-firm credit network (density, assortativity, size of largest component, and degree distribution). In particular, we will focus our simulation analyses on the timely issue of how positive and negative shocks of different signs, magnitudes, and durations to the base interest rate operate through the financial network channel of monetary policy to affect the above-mentioned topological features of the bank-firm credit network.

Our main results can be summarized as follows: i) a positive (negative) interest rate shock decreases (increases) the density of the network. Therefore, when the flow of credit between banks and firms increases as a result of a negative interest rate shock, there is the creation of new links rather than a more intense flow through the existing ones. On the other hand, a decrease in the flow of credit leads to the destruction of links. That is, the flow of credit increases/decreases mainly along the extensive margin (i.e., creation/destruction of links) rather than the intensive one (i.e., more/less intense flow in the existing links); ii) negative shocks make the financial network more disassortative, as the links created in this case are mostly between highly-connected agents and poorly-connected agents of the oppositive type. Similarly, the impact of positive shocks to the base interest rate is mostly to destroy the links between highly-connected agents and those with less connections of the opposite type, decreasing the disassortativity of the financial network; and iii) interest rate shocks have a long-term impact in the kurtosis of the degree distribution of both banks and firms. Temporary shocks lead to a decrease (in most of the cases) in the kurtosis of the degree distribution, suggesting an asymmetry in the impact of negative and positive shocks. On the other hand, permanent negative (positive) shocks decrease (increase) the kurtosis of banks' degree distribution. In the case of the firms, this relationship is the opposite. A possible explanation for these results is that a higher supply of credit, caused by a negative interest rate shock, takes the form of more banks supplying credit to the more credit-demanding firms.

Besides this introduction, the paper is organized as follows. Section 5.2 presents the structure of the model, while Section 5.3 reports and discusses several simulation results. In particular, this section shows that our model is able to reproduce some key stylized facts of the financial network studied in this paper. After discussing the relationship between network topology and resilience, Section 5.4 shows the impact of monetary policy shocks in key topological features of the bank-firm credit network. Finally, Section 5.5 offers concluding remarks.

5.2 Structure of the model

5.2.1 *Firms: technology, wage costs and demand for bank credit*

Many firms, indexed by $i = 1, \ldots, N^F$, the number of which remains constant, produce a homogenous consumption good using homogeneous labor as the only physical input. The production function faced by all firms is given by $y = \eta L$, where L is hired labor and $\eta > 0$ is the labor productivity parameter, which for simplicity is assumed to be exogenously given and constant due to the focus of this paper on the financial network channel of monetary policy instead of technological change. The supply of labor is perfectly elastic so that firms can hire as much available labor as they need and want by paying the current nominal wage w_t, which is uniform across firms. However, the nominal wage varies endogenously over time according to the following expression:

$$w_t = \begin{cases} w_{t-1} & \text{if } g_{t-2} \leq 0 \\ w_{t-1}(1 + adjwg_{t-1}) & \text{if } g_{t-2} > 0 \end{cases}, \tag{5.1}$$

where $g_{t-2} = (Y_{t-1}/Y_{t-3})^{0.5} - 1$, with $Y = \sum_i y$, denotes the average growth rate of the aggregate real output in the last two periods, and $adjw \sim U(\psi_w^{min}, \psi_w^{max})$, with ψ_w^{min} and ψ_w^{max} being exogenously given and constant. Therefore, when the growth rate of the real output is positive, the nominal wage increases by a random percentage of that growth rate. Yet the growth of rate the nominal wage is limited to 2% in each period. Meanwhile, the formal specification in equation 5.1 implies that the nominal wage is rigid downward.

The flow of demand for bank credit of each firm is represented by the following expression:

$$B^*_{i,t} = max(0, l^*_{i,t} NW_{i,t} - B^S_{i,t-1}), \tag{5.2}$$

where $B^S_{i,t-1}$ is the stock of debt of firm i in the previous period; firms set a target leverage (debt-to-net worth ratio) $l^*_{i,t}$, which is defined by the following equation:

$$l^*_{i,t} = \begin{cases} l^*_{i,t-1}(1 + adjl) & \text{if } \pi_{i,t-1} > 0 \\ l^*_{i,t-1}(1 - adjl) & \text{if } \pi_{i,t-1} \leq 0 \end{cases}, \tag{5.3}$$

where $adjl \sim U(0, \psi_l^{max})$, with ψ_l^{max} being exogenously given and constant, and $\pi_{i,t}$ is the nominal profit of firm i at period t. The target leverage of each firm will never be greater than l^{max} or smaller than l^{min}, which are exogenously given and remain constant.

5.2.2 The bank-firm matching process

Once the demand for bank credit of each firm is determined, the matching process between firms and banks, where the latter are indexed by $j = 1, \ldots, N^B$, takes place. It is plausibly assumed that banks, the number of which remains constant, are more prone to lend to less leveraged firms and that firms in turn prefer to borrow from less leveraged banks. This occurs because leverage is negatively correlated to financial soundness: less leveraged firms have a lower perceived probability of bankruptcy, whereas less leveraged banks can charge a lower interest rate.[2]

In addition to setting the base interest rate in its role as monetary policymaker, the central bank also acts as a regulation authority by exogenously setting the maximum leverage ratio κ applicable to all banks, where $0 < \kappa < 1$. Additionally, each bank sets a capital buffer that is a function of $bda_{j,t-1}$, the non-performing loans-to-net worth ratio of the previous period (the concept of non-performing loans is properly explained in Section 5.2.4). Therefore, the amount of credit supplied by each bank cannot be greater than $NW_{j,t}/[\kappa(1 + \alpha bda_{j,t-1})]$, where $NW_{j,t}$

[2] A firm does not strategically and deliberately demand credit from a highly leveraged bank betting on the prospect that the bank is likely or about to go bankrupt, so that the respective debt will not have to be paid back in full. The reason is that the government is openly and credibly committed to bail out a bank if its net worth becomes negative, as described later.

is the net worth of bank j at period t and $\alpha > 0$ is an exogenously given and constant parameter. The maximum flow of credit of bank j at period t is set by:

$$B_{j,t}^{MAX} = max[NW_{j,t}/\kappa(1+\alpha bda_{j,t-1}) - B_{j,t-1}^{S}, 0]. \tag{5.4}$$

Thus, the flow in equation 5.4 is equal to the maximum credit supply minus the previous stock of loans $B_{j,t-1}^{S}$. Debt lasts for t_D periods, the value of which is exogenously given and constant, and is paid in periodic installments. Suppose a debt of value X is originated at period t. An amount equal to X/t_D should be paid back by the firm to the bank between $t+1$ and $t+t_D$. The interest to be paid at each period is computed on the residual amount.

As incumbent firms are deemed as less risky than the newly entrant ones, bank credit is granted only to the former. The incumbent firms with a positive demand for bank credit and the banks which are capable of supplying credit are sorted in ascending order according to their leverage. In this pattern of interaction, the less leveraged firm is prone to approach the less leveraged bank. However, with a small probability λ, which is exogenously and constant, it will choose a bank at random. The deal is closed only if the bank can supply at least a fraction equal to f^{min} of the bank credit demanded by the firm. This fraction f^{min} is an exogenously given constant. The value of the loan is the minimum between $B_{i,t}^{*}$ and $B_{j,t}^{MAX}$. Moreover, in order to ensure risk diversification, the bank never grants to a single firm a loan that is worth more than 25% of its net worth, as set by the Basel Committee on Banking Supervision (BCBS (2014)). If a bank is approached, it is removed from the list, even if a deal has not been closed. Thus, at each time step, a firm does not approach the same bank more than once. If this firm is still willing to borrow more funds, it approaches the next bank of the list with probability $1-\lambda$ and a random bank with probability λ. This process is repeated until the fulfillment of all demand for bank credit placed by firms or the exhaustion of the banks' available supply of credit.

The flow of funds lent by bank j to firm i at period t is represented by $B_{i,j,t}^{F}$. The stock of debt of firm i at period t, $B_{i,t}^{S}$, evolves according to the flow of loans and the debt payments made by the firm (interest plus periodic installments). The total loan of bank j, $B_{j,t}^{S}$, is updated in a similar fashion. The nominal interest rate charged by bank j on firm i, $i_{i,j,t}$, is set by applying a variable markup, $h_{i,j,t}$, on the base interest rate, $i^{B}(1+h_{i,j,t})$, where the base interest rate i^{B} is set exogenously by the central bank in its institutional role as monetary policymaker. Following Gatti *et al.* (2010), the banking markup is given by:

$$h_{i,j,t} = \beta[(l_{j,t})^{\gamma} + (l_{i,t})^{\gamma}]. \tag{5.5}$$

In the expression above, $l_{j,t}$ is bank j's leverage, $l_{i,t}$ is firm i's leverage, β is a parameter between 0 and 1, and γ is a positive risk premium parameter ranging from 0 to 1. These two parameters are exogenously given and constant. The relationship between the variable banking markup and the leverage as formally expressed in equation 5.5 implies that more leveraged firms and banks are perceived as less financially robust and hence riskier financial partners with whom to close a credit deal, as discussed earlier.

5.2.3 Firms: investment, production, profits, and net worth dynamics

At the beginning of each period, households invest in the firms the resources they saved for this purpose in the previous period. The total amount of the financial investment is I_t[3], and how this amount is determined is explained below. The fraction of the financial investment received by each firm is represented by:

$$I_{i,t} = I_t[(1 - f_{RI})z_{i,t-1} + f_{RI}RI_{i,t-1}], \tag{5.6}$$

where $0 < f_{RI} < 1$ is an exogenously given and constant parameter and $RI_{i,t}$ is a random number, with $\sum_i RI_i = 1$. The variable $z_{i,t}$ is equal to $v_{i,t}/(\sum_i v_{i,t})$, where $v_{i,t} = 1/[1 + exp(-\varepsilon op_{i,t})]$, with $\varepsilon \geq 1$ being an exogenously given and constant parameter. Therefore, a fraction f_{RI} of the total investment is shared randomly among firms. The remaining fraction is reasonably invested in each firm according to an increasing function of its operating profitability $op_{i,t} = (\pi_{i,t} + D_{i,t})/(NW_{i,t} + B^S_{i,t})$, which in turn is equal to the nominal profit without excluding the debt service $(\pi_{i,t} + D_{i,t})$ over total assets – net worth plus loans (see equation 5.13). The debt service $D_{i,t} = \sum_j \sum_t i_{i,j,t} B^F_{i,j,t}$ denotes the total amount of interest paid on the outstanding debt commitment of firm i.

After the interaction with banks in the credit market, as described in the preceding subsection, each firm will have its total capital, composed by its net worth plus loans. Recalling that the production function faced by all firms is given by $y = \eta L$, the real output production of an individual firm i at period t will be equal to:

$$y_{i,t} = (\eta/w_t)(NW_{i,t} + B^S_{i,t}). \tag{5.7}$$

Therefore, firms will spend their funds – net worth and debt – to hire labor and produce the consumption good according to a linear production function. The amount of labor hired by an individual firm i at period t is given by $L_{i,t} = (NW_{i,t} + B^S_{i,t})/w_t$.

The individual price of the consumption good $p_{i,t}$ is set by a firm i at period t by applying a variable markup, $\mu_{i,t}$, on the unit cost $\omega_{i,t}$, which is the sum of labor and debt service costs per unit of real output:

$$\omega_{i,t} = \frac{w_t L_{i,t} + D_{i,t}}{y_{i,t}}. \tag{5.8}$$

[3] We use the term "financial investment" to stress the difference with respect to the most common use of I as real investment. However, despite being a financial variable, this amount is used for real investment and production.

The variable markup applied by an individual firm follows a behavioral rule adapted from Dosi *et al.* (2013):

$$\mu_{i,t} = \mu_{i,t-1}\left(1+\phi\frac{s_{i,t-1}-s_{i,t-2}}{s_{i,t-2}}\right), \tag{5.9}$$

where $0<\phi<1$ is an exogenously given and constant parameter and $s_{i,t}$ is firm i's market share at period t. The specification in equation 5.9 implies that firms that lost market share try to recover at least part of it through a reduction of their markup (as specified in equation 5.14 below).

The nominal aggregate demand, C_t, is represented by the following equation:

$$C_t = \rho_t(R^H_{t-1}+w_tL_t) - NWF_{t-1} + E_t. \tag{5.10}$$

The expression above represents the total resources that can be spent by the agents (households and government). The nominal aggregate demand includes two positive components: i) household consumption, which is equal to the household cash in hand, R^H_{t-1}, not spent in and hence accumulated from the previous period, plus the aggregate wage bill paid by the population of firms, w_tL_t, where $L_t = \sum_i L_{i,t}$, multiplied by the uniform propensity to consume ρ_t, which is endogenously time-varying, and ii) the government spending E_t. The amount given by $(1-\rho_t)(R^H_{t-1}+w_tL_t)$ is saved by households to be invested in the firms in the next period, as described earlier, thus corresponding to I_{t+1}. The uniform propensity to consume evolves over time according to the following expression:

$$\rho_{i,t} = \begin{cases} 0.95 - U(0,\psi_\rho) & \text{if } g_{t-2} > 0 \\ 0.95 + U(0,\psi_\rho) & \text{if } g_{t-2} \leq 0 \end{cases}, \tag{5.11}$$

where $0<\psi_\rho<0.05$ is an exogenously given and constant parameter. In our model, households are assumed to be "hand-to-mouth" (HtM) consumers, which explains their high marginal propensity to consume.[4] A positive output growth rate impacts positively on expected profits, so that households will be willing to consume less and invest more to receive more dividends, which add to their cash in hand. An opposite effect operates when the output growth rate is negative.

In equation 5.10, any positive net worth of new firms created in the previous period (NWF_{t-1}), up to the limit of 50% of households' previous funds ($R^H_{t-1}+w_tL_t$), will be subtracted

[4] HtM consumers allocate almost all, if not all, their current income to consumption due to unsophisticated behavior (of the non-optimizing or rule-of-thumb variety) or inability to trade in asset markets because of high transaction costs (Weil (1992)). There is robust empirical evidence that HtM consumers correspond to a large fraction of households in developed countries and have a high marginal propensity to consume even out of temporary income shocks (Kaplan, Violante and Weidner (2014), Attanasio, Kovacs and Moran (2020)). Another feature of our model that further validates the assumption that households behave as HtM consumers, and which is in keeping with the evidence offered in Kaplan and Violante (2010), is that households do not have access to consumer credit.

from the nominal aggregate demand, in order to guarantee the stock-flow consistency of the model. Any possible amount of money still needed to finance the new entrants is included in the government spending (more on this in subsection 5.2.5). The nominal aggregate output can be equal to, smaller than or greater than C. In the latter case, as the consumption good is fully perishable, the amount of unsold output will not be accumulated as inventory by the respective firm(s) for the next period.

An exogenously given and constant fraction f_{RD} of the nominal aggregate demand is uniformly distributed among firms. This is mostly due to imperfect information on the part of households, as they do not know precisely which firm is charging the smallest price. The remaining nominal aggregate demand is distributed according to each firm's market share $s_{i,t}$, which is proportional to the firm's price competitiveness (as specified in equation 5.14 below). Therefore, the potential nominal revenue of an individual firm i is equal to:

$$S_{i,t} = C_t[(1-f_{RD})s_{i,t} + f_{RD}u_{i,t}], \tag{5.12}$$

where $u_{i,t} = p_{i,t}y_{i,t}/\sum p_{i,t}y_{i,t}$. The nominal profit of an individual firm i is given by:

$$\pi_{i,t} = min(p_{i,t}y_{i,t}, S_{i,t}) - w_t L_{i,t} - D_{i,t}. \tag{5.13}$$

Firms' nominal revenue cannot be greater than their nominal output. Their expenses include the wage bill and the debt service. The initial market share of an individual firm i is set as proportional to its net worth and evolves according to the following expression:

$$s_{i,t} = s_{i,t-1}\left(1+\theta\frac{p^M_{t-1}-p_{i,t-1}}{p^M_{t-1}}\right), \tag{5.14}$$

where $0 < \theta \leq 1$ is an exogenously given and constant parameter and p^M_t is the average price at period t. The individual market share has an upper bound equal to s^{max}, which is exogenously given and constant. Thus, firms setting a price below (above) the average price will increase (reduce) their market share.

Firms pay taxes and dividends on positive profits. Consequently, the net worth of an individual firm i evolves according to $NW_{i,t+1} = NW_{i,t} + (1-\delta-\tau)\pi_{i,t}$ if $\pi_{i,t} > 0$, or $NW_{i,t+1} = NW_{i,t} + \pi_{i,t}$ otherwise. The exogenously given and constant parameters δ and τ are strictly between 0 and 1 and correspond to the dividends rate and the tax rate, respectively.

In any given period, firms with a negative net worth go bankrupt and are expelled from the model. For simplicity, the number of firms is kept constant. The sum of the market share of bankrupt firms is randomly distributed among entrant firms, whose number is equal to that of bankrupted firms. The target leverage of entrant firms is set according to the uniform distribution $U(1.5,2)$. The net worth and markup of entrant firms are set according to the uniform distribution $U(0.9,1)M^I$, where M^I is the average value of the respective attribute of incumbent firms.

5.2.4 The banking system

The nominal profit of an individual bank j is given by:

$$\pi_{j,t} = D_{j,t} - NPL_{j,t}. \tag{5.15}$$

In the expression above, $D_{j,t} = \sum_i \sum_t i_{i,j,t} B^F_{i,j,t}$ is the receivable interest on the nominal stock of granted bank credit. The non-performing loans $NPL_{j,t}$ corresponds to the concept of bad debt presented in Gatti *et al.* (2007): $\sum_{i \in H} \chi_{j,i,t}(-NW_{i,t})$, where $\chi_{j,i,t} = B^S_{i,j,t}/B^S_{i,t}$ is the proportional credit granted by bank j to firm i at period t, and H corresponds to the set of expelled firms with negative net worth. Thus, if a firm fails due to it having a negative net worth, the correspondent loss $(-NW_{i,t})$ is distributed among the firm's creditors (the banks), proportionally to the loan granted by each bank to the firm.

Meanwhile, the net worth of an individual bank j evolves according to $NW_{j,t+1} = NW_{j,t} + (1-\tau)\pi_{j,t}$ if $\pi_{j,t} > 0$, or $NW_{j,t+1} = NW_{j,t} + \pi_{j,t}$ otherwise. In order to sharpen our focus on the impact of shocks to the base interest rate on the topology of the bank-firm network, we abstract from the possibility that banks on the brink of or already in bankruptcy can rely on an interbank market. However, also in keeping with the main focus of this paper, we assume that the government bails out the banks in trouble, covering any difference between the bank's net worth and its minimum level.[5]

5.2.5 The government

The fiscal balance of the government evolves according to:

$$\Gamma_{t+1} = \Gamma_t + \tau\left(\sum_{\pi>0} \pi_{i,t} + \sum_{\pi>0} \pi_{j,t}\right) - E_t - \sum_j BO_{j,t}. \tag{5.16}$$

The variable Γ_t represents the stock of resources (or debt, if negative) of the government in a given period. Government revenues are made up of the taxes collected from firms and banks with positive profits. In addition to disbursements with the bailing out of banks (see equation 5.15), government spending E_t has two components:

$$E_t = max\left[0, NWF_{t-1} - 0.5\left(R^H_{t-1} + W_t Lt\right)\right] + \zeta_t \sum p_{i,t} y_{i,t}. \tag{5.17}$$

Following Riccetti, Russo and Gallegati (2015), the government plays a role in financing the new entrants. The net worth of new firms will be subtracted from households' funds (see equation 5.10), up to the limit of 50% of these funds. Any amount of money still needed to

[5] This minimum level is equal to the maximum between i) the net worth necessary to meet the maximum leverage ratio: $BO_{j,t} = max(0, \kappa B^S_{j,t} - NPL_{j,t})$, and ii) 5% of the firms' average net worth.

finance the new entrants will correspond to the first component of the government spending. Moreover, the government spends a value that is equal to a fraction ζ_t of the total nominal output, defined according to the following equation:

$$\zeta_t = \begin{cases} \zeta_{t-1}[1 - U(0, \psi_\zeta)] & \text{if } g_{t-2} > g^* \\ \zeta_{t-1}[1 + U(0, \psi_\zeta)] & \text{if } g_{t-2} \leq g^* \end{cases}, \tag{5.18}$$

where $g^* \geq 0$ is the growth rate target and $0 < \psi_\zeta < 1$ is an exogenously given and constant parameter. Therefore, the government adopts an anticyclical fiscal policy, spending a fraction of the total nominal output greater (smaller) than that of the previous period when the growth rate of aggregate output is below (above) its target. This fraction is never smaller than ζ^{min}, which is exogenously given and constant.

5.3 Simulations

In this section, we run 50 simulations of 3,000 periods of the baseline model. The time interval composed by the first 1000 periods is disregarded as the transient interval. The parameters and initial conditions specified for running the simulations are reported in the Appendix 5.5.

5.3.1 Time series

Table 8 provides statistics of the main series considering the 50 simulations of 3,000 periods. One can observe that the variables oscillate considerably around a long-run mean, and take values which are comparable to real time series and to those generated by other agent-based models (e.g., Riccetti, Russo and Gallegati (2021)). The output growth rate, the inflation rate, and the non-performing loans oscillate more (with the coefficient of variation given by the standard deviation-to-mean ratio being above 0.25), and the other variables, less (with a coefficient of variation below 0.1). This oscillation seems to be mainly explained by the two countercyclical mechanisms at work in the system: the fiscal policy and the households' financial investment in firms. Regarding the operation of the fiscal policy, the government increases (decreases) its expenditures when the growth rate of the economy is below (above) its target, pushing up (down) aggregate demand. Concerning the second mechanism, the households increase their financial investment in firms when the growth rate of the economy is positive. However, this comes at the expense of a lower demand for consumption goods in the next period (equation 5.11). Thus, this causes a subsequent decrease in aggregate demand, pushing the economy down in the following periods. In the boom period, higher profits lead firms to revise upward their target leverage. The resulting growth of output and aggregate demand sustains the firms' satisfactory profitability. The non-performing loans are kept at a low level, enhancing the supply of credit by the banks. In the descending phase, firms reduce their markup in order to compete for market share. Firms' target leverage is brought down. Aggregate demand decreases, causing the non-performing loans to increase. As a consequence, banks reduce the supply of credit, thus accentuating the descending phase of the cycle.

	Average	Standard dev. (simulations)[1]	Standard dev. (periods)[2]
Output growth rate	0.0299	0.0088	0.0088
Price variation	0.0239	0.0067	0.0067
Firms' leverage	0.9990	0.0344	0.0365
Banks' leverage	4.1420	0.2814	0.2934
Nominal credit[3]	0.4415	0.0079	0.0081
NPL[4]	1.7919	0.4527	0.4548
Public debt[3]	0.5424	0.0077	0.0080
Density	0.1629	0.0157	0.0157

1: Average over 50 standard deviation values computed for each simulation.

2: Average over 2,000 standard deviation values computed for each time period.

3: As a proportion of nominal output.

4: As % of total credit.

Table 8 – *Statistics of some variables considering 50 simulations.*

We applied the Hodrick-Prescott (HP) filter to two of our artificial series – real output and real consumption – in order to isolate the cyclical component. Figure 34 depicts the autocorrelation function (ACF) of the cyclical component of these variables. These results bear some similarities with those generated by other agent-based models (e.g., Assenza, Gatti and Grazzini (2015), Alexandre and Lima (2020a)), as well as with real time series – e.g., the shape of the ACF and a high, positive first lag autocorrelation (e.g., Collard (1998)).

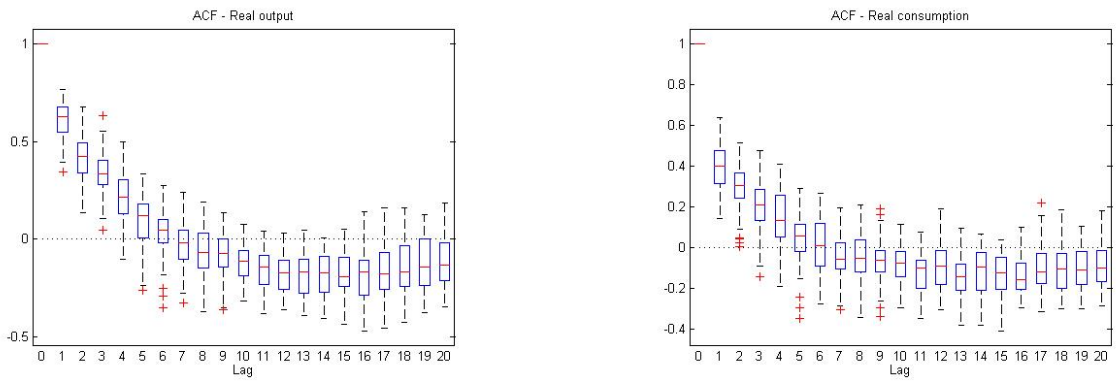


Figure 34 – *ACF of the real output (left) and real consumption (right).*

5.3.2 Stylized facts of the bipartite bank-firm credit network

In this section, we show that the model is also able to reproduce a handful of key stylized facts of bipartite bank-firm credit networks reported in the related literature (Masi *et al.* (2011), Masi and Gallegati (2012), Bottazzi, Sanctis and Vanni (2020), Luu and Lux (2019)):

- The degree distributions are fat-tailed.

- The bipartite bank-firm credit network is characterized by a disassortative behavior.
- The correlation between the size of the node and its degree is positive.

Figure 35 presents the empirical counter-cumulative distribution function (CCDF) of the degrees. In the top panel, we report the absolute number of links. In the bottom panel, we consider the sum of the weights of the links. This corresponds to the concept of strength presented in Masi *et al.* (2011). For firms (banks), this is equal to the total amount borrowed (lent). One can clearly observe that the distributions are right-skewed, approximately fitted by a power law. Similar results have been reported in Masi *et al.* (2011) using Japanese data, Masi and Gallegati (2012) using Italian data, Miranda and Tabak (2013) using Brazilian data, Luu and Lux (2019) using Spanish data, and Bottazzi, Sanctis and Vanni (2020) using data from an international financial network. This finding implies that a few firms and banks have many connections, receiving (supplying) most of the credit, while most of them have few partners and negotiate a small proportion of the total credit.

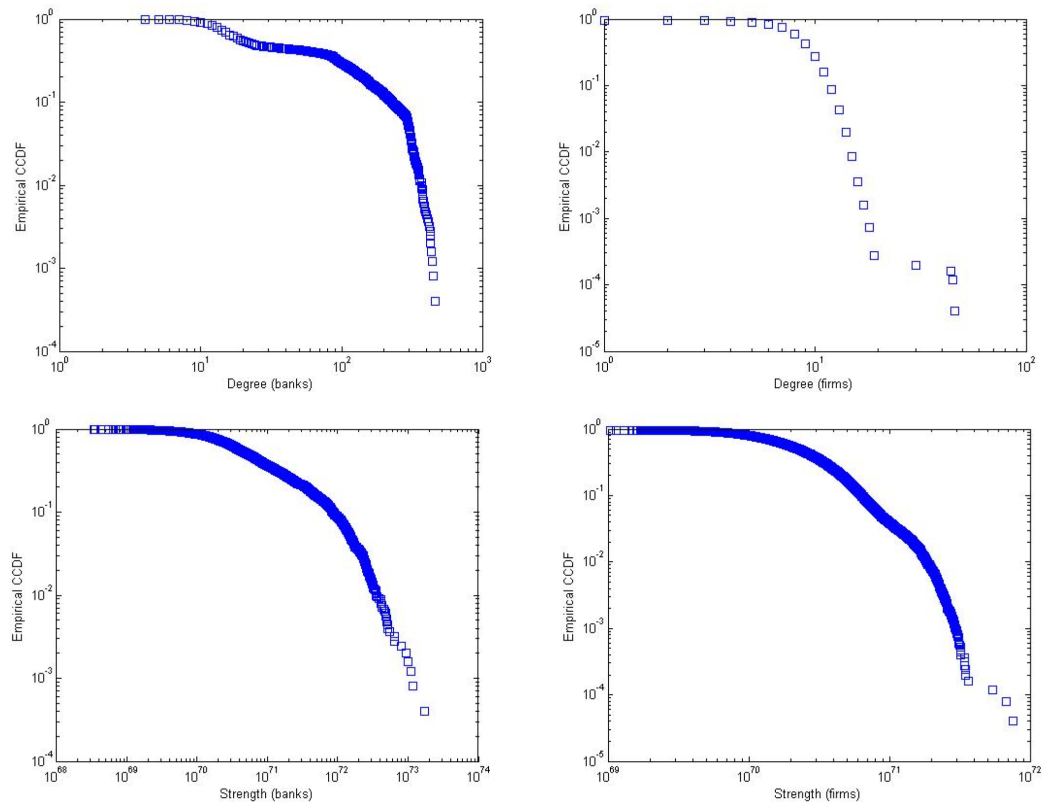


***Figure 35** – Empirical CCDF of the degree (top) and node strength (bottom) in log-log scale. We considered the result of 50 simulations at period t=3,000 (25,000 firms and 2,500 banks).*

The disassortative behavior of the simulated bank-firm credit network is shown in Figure 36. Assortativity is the correlation between the node degree and the average degree of its direct neighbors. Despite oscillating considerably over time and across simulations, the assortativity is negative in most of the cases. This means that highly-connected nodes are more likely to connect with nodes of the opposite type (firm or bank) that have few connections. Empirical evidence on negative assortativity has been reported in Bottazzi, Sanctis and Vanni (2020).

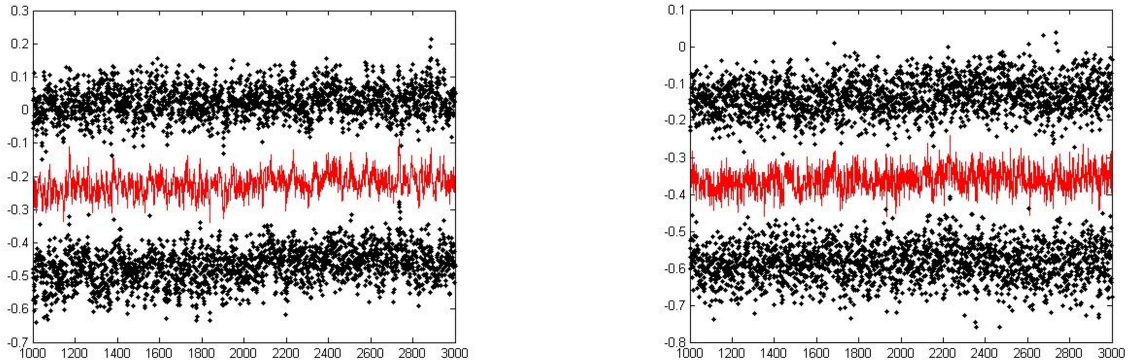


Figure 36 – *Assortativity for banks (left) and firms (right). Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

The correlation between the size of the node (represented by its net worth) and its degree is positive (Figure 37 – top). The node size is also positively correlated to its strength (Figure 37 – bottom). Thus, large nodes tend to have more connections, as well as to lend (borrow) more resources in the case of banks (firms). This is in accordance with the empirical evidence provided in Bottazzi, Sanctis and Vanni (2020). Miranda and Tabak (2013) and Masi and Gallegati (2012) reported a positive correlation between the size of the banks and their degree. However, the latter authors did not find a well-defined relationship between the firms' size and their degree.

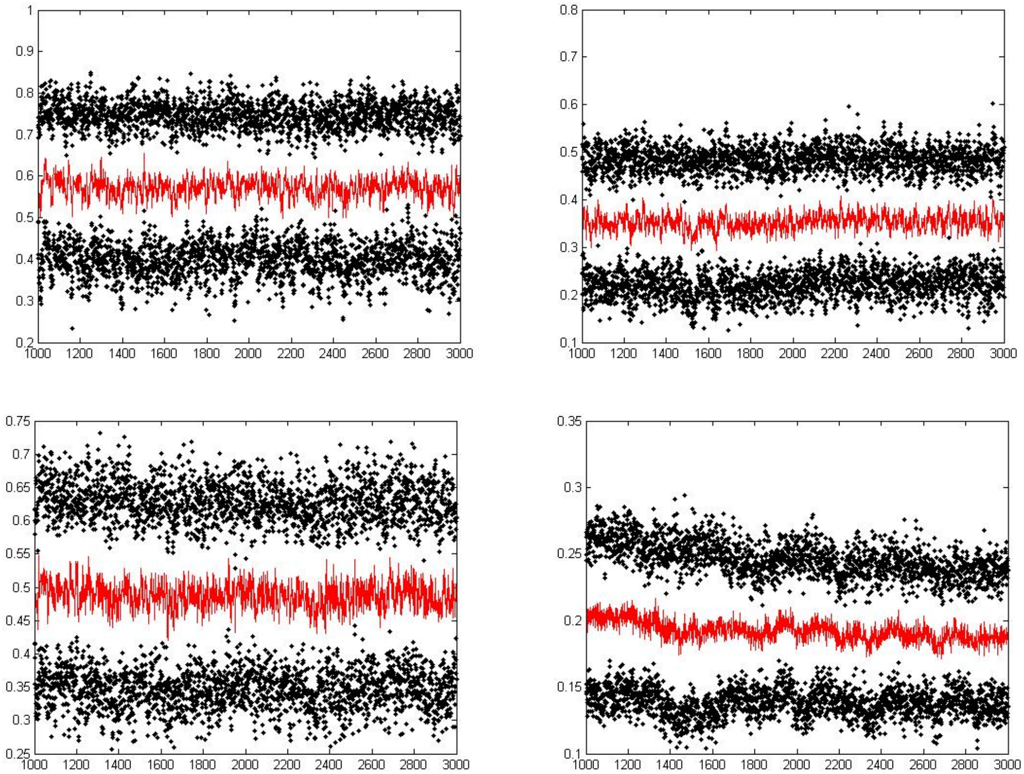


Figure 37 – *Net worth-degree correlation (top) and net worth-strength correlation (bottom) of banks (left) and firms (right). Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

The degree also correlates positively with the strength, mainly in the case of the banks (Figure 38). As expected, nodes with more connections borrow/lend a larger amount of resources. Our simulations also nicely reproduce two empirical findings with respect to the degree-strength correlation reported in Masi *et al.* (2011): i) it is positive, and ii) it is higher for banks than for firms. The largest component of the bank-firm credit network includes almost all nodes (Figure 39). This means that there are few isolated components in the network.

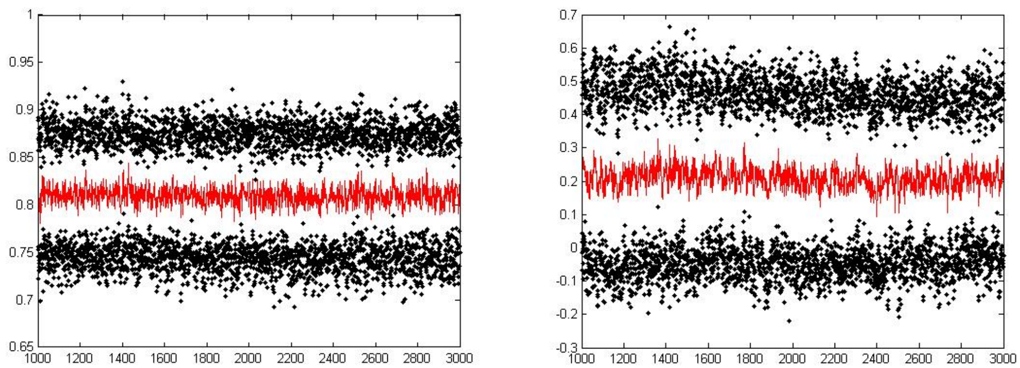


Figure 38 – *Degree-strength correlation for banks (left) and firms (right). Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

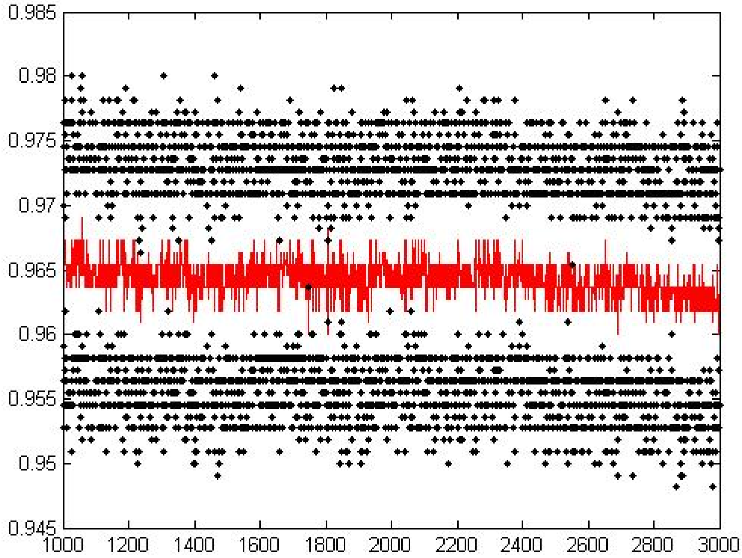


Figure 39 – *Fraction of nodes in the largest component of the financial network. Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

5.4 The impact of shocks to the base interest rate on the financial network topology

In this section, we assess how interest rate shocks impact on the topology of the financial network. After carefully assessing which topological features of the financial network are important drivers of its resilience (Section 5.4.1), we investigate the effect of shocks to the base interest rate on these features (Section 5.4.2).

5.4.1 Network topology and resilience

Some features of a financial network are related to its resilience to shocks. Several studies have carefully investigated the relationship between network interconnectedness and systemic risk – that is, the potential damage to or even collapse of a non-negligible part of a system caused by a shock (even if a small one) in some of its components. It is relatively consensual in the related literature that this relationship, by its very nature, is non-linear in the degree of interconnectedness. Some studies (e.g., Nier *et al.* (2007), Gai and Kapadia (2010), Haldane and May (2011)) point out that shock transmission dominates at low connectivity levels. However, once a certain threshold is crossed, shock absorption dominates, and higher interconnectedness is beneficial for the resilience of a highly networked system like the economy. Working on two different dimensions of network interconnectedness, Elliott, Golub and Jackson (2014) argue that higher integration (greater dependence on counterparties) decreases the probability of an initial failure but leads to a higher probability of contagion once this initial failure has occurred. Meanwhile, increasing diversification (more counterparties per organization) initially promotes contagion, but when a certain threshold is crossed, it protects organizations against each other's failures.

Another point largely accepted in the literature is that network interconnectedness alone is intuitively a poor predictor of systemic risk. In effect, the nature and magnitude of the impact of interconnections on shock propagation, shock absorption, and systemic risk does depend on other topological features of a financial network. It is intuitive that interconnectedness itself is highly connected in complex ways to other salient topological features of a financial network. Several empirical studies focus on degree heterogeneity. For instance, Amini, Cont and Minca (2016) found through numerical simulations that heterogeneity in degree distribution negatively affects the resilience of a network, which explains why scale-free networks tend to be more fragile than random networks. Caccioli, Catanach and Farmer (2012) point out that contagion is less likely in scale-free networks when attacks are random, but that such type of network is more fragile when attacks are targeted to high-degree banks. Roukny *et al.* (2013) argue that the optimal network structure depends on the underlying market conditions. For instance, scale-free networks are the most fragile when markets are illiquid. Georg (2013) finds that, while in normal times different network topologies have a similar performance regarding systemic risk, the network topology becomes quite important in times of crisis. In these circumstances, contagion seems to be stronger in random networks, whereas scale-free networks are more resilient.

Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) assessed three types of networks: a complete graph, a cycle graph (ring), and a γ-convex combination of the two (the highest the value of parameter γ, the closest is the graph to the cycle network). They concluded the following: (i) for small shocks, the cycle (complete) graph is the least (most) resilient; moreover, the system becomes less stable as γ increases; and (ii) for large shocks, the effect is non-linear: the cycle and complete graphs are the least stable structures, while the system is more resilient for intermediate values of γ.

Meanwhile, Loepfe, Cabrales and Sánchez (2013) explored the impact of topological features other than degree heterogeneity on the resilience of a FN. In a thorough study combining both analytical models and empirical data, the authors assessed the role of the topology of the FN in affecting systemic risk. They found a transition from safe to risky regimes, with the critical range of which being located at a low level of link density and high levels of modularity and size heterogeneity. These authors also showed that degree heterogeneity increases vulnerability only when shocks are targeted to high-connected firms. Besides, the removal of links with the highest centrality betweenness can significantly increase the stability of the system.

Assortativity is also pointed as strongly related to the financial network resilience. Computational simulations performed by D'Agostino *et al.* (2012) show that assortativity has an ambiguous effect on network resilience. On the one hand, distress propagates more easily in assortative (i.e., with positive assortativity) networks. However, assortativity was found to enhance the effectiveness of a targeted immunization policy. Hurd, Gleeson and Melnik

(2017) developed a measure which is a combination of edge- and node-assortativity, the *graph-assortativity*. This measure proved to be a better predictor of systemic vulnerability than the usual edge-assortativity measure. The study of Ramadiah *et al.* (2019) points out that, in an assortative structure, the network is more resilient when different blocks are scarcely connected. However, a disassortative network is more resilient when the structure moves away from a pure bipartite one. Assessing data taken from the Italian electronic broker market e-MID, Krause *et al.* (2021) did not find a correlation between assortativity and systemic risk. However, the authors found that the scalar assortativity measure with respect to the interbank leverage is positively correlated to the systemic risk level. That is, the systemic risk is intuitively higher when risky (i.e., highly leveraged) banks interacts mostly with other risky banks.

5.4.2 The impact of base interest rate shocks on the topological features of the financial network

As discussed in the preceding subsection, some of the topological features mostly related to shock propagation in financial networks are interconnectedness, assortativity, and degree distribution. In network models of systemic risk, the topology of the financial network is assumed to be exogenous. However, an interesting question is the following: what if the occurrence of the shock and its propagation impact on the topology of the financial network? In other words, is it possible that the topology of the financial network and the shock propagation mutually influence and affect each other? In this subsection, we investigate this issue by assessing how shocks to the base interest rate impact on the aforementioned topological features. As the largest component is a proxy for the financial network resilience, we include this measure among the variables to be assessed.[6]

We proceed as follows: at period $t = 1500$, we impose a shock of magnitude s on the base interest rate. This shock will last for D periods. Thus, during periods from 1501 to 1500+D, the base interest rate will be equal to $i^B(1+s)$. We considered two values of s (0.1 and 0.2) of both signs (positive and negative), and four values of D (50, 100, 200, and 1500). Note that in the latter case the considered shock can be interpreted as becoming permanent as far as the length of time of the model is concerned, in that it lasts for all the remaining periods of the whole set of 3,000 simulated periods.

A positive shock on the base interest rate increases the dispersion of the loan interest rates – as measured by the coefficient of variation – charged by the banks, while a negative shock engenders the opposite effect. This impact is observed when both all stock of loans (Figure 40 – left panel) and only new loans (Figure 40 – right panel) are considered. This result goes in hand

[6] In general, the resilience or robustness of a network is related to the ability of its nodes to communicate being unaffected even by unrealistically high failure rates. In our case, it refers to the ability of firms (banks) to borrow from (extend loans to) banks (firms). In fragmented networks, in which the fraction of nodes belonging to the largest cluster is small, the removal of a link will create isolated nodes with a higher probability. For more details, see, for instance, Albert, Jeong and Barabási (2000).

with the literature on the interest rate pass-through (e.g., Cottarelli and Kourelis (1994), Bondt (2002), Hofmann and Mizen (2004)). It is important to notice that, in the case of the interest rate pass-through when all the stock of loans is considered, a shock of any sign increases for a few periods the variation of the loan interest rates.

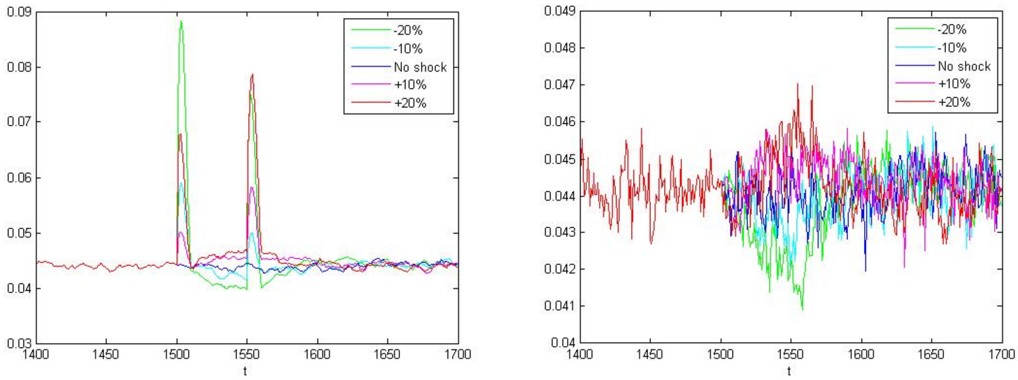


Figure 40 – *Impact of the interest rate shock on the coefficient of variation of the loan interest rates considering all loans (left) and only new loans (right). The computation considers 2,500 values (50 banks times 50 simulations) in each period. Shocks last for 50 periods.*

Figure 41 displays the impact of the base interest rate shocks on the density. A positive interest rate shock decreases the density of the network, while a negative shock has the opposite effect. In the case of a permanent shock, this initial impact dissipates slowly, mainly for negative shocks. As expected, an increase (decrease) in the base interest rate decrease (increase) the leverage of both firms and banks (Figure 42). Hence, an increase in the flow of credit between banks and firms resulting from a fall in the base interest rate results in the creation of new links. Alternatively, a decrease in the flow of credit results in the destruction of links.

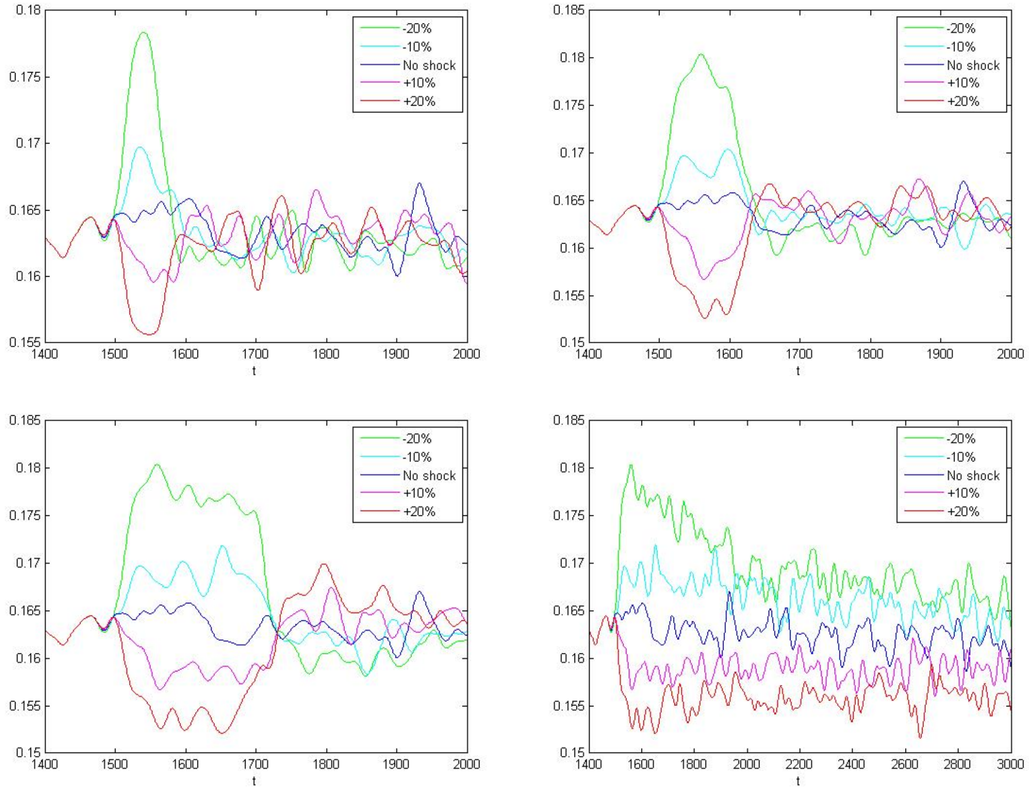


Figure 41 – *Impact of the interest rate shock on the financial network density. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

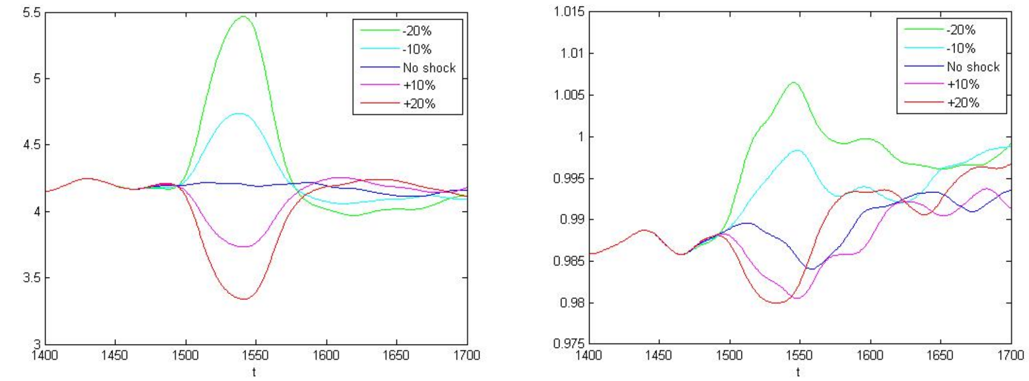


Figure 42 – *Impact of the interest rate shock on the leverage of banks (left) and firms (right). Average of 50 simulations. Shocks start at period t=1500 and last for 50 periods. For the sake of a better visualization of the trend component, the series were smoothed applying the HP filter.*

Another interesting effect that can be observed is overshooting, mainly in the case of shocks of higher magnitude. For instance, a positive shock of 20% with duration equal to 200 periods causes a decrease in the density. When the shock ceases – that is, when the base interest rate comes back to its original value – at period 1700, the density starts to increase again. However, before returning to a value close to that of the no shock case, it reaches a value well above this one (approximately at period 1800) and then begins to move down again.

In order to further understand the relationship between the density of the network and the leverage measure, we decomposed the average leverage $l_{F,B}^{M}$ (where F and B stands, respectively, for firms and banks) into two components: the average degree $k_{F,B}^{M}$ – i.e., the average number of partners of the opposite type – multiplied by $(l_{F,B}^{M})/(k_{F,B}^{M})$, the average flow of credit (as a fraction of the net worth) granted to (in the case of banks) or received by (in the case of firms) each partner. Then, we evaluated how shocks on the base interest rate affect each element of that decomposition.

The results are presented in Figures 43 and 44. A positive (negative) interest rate shock decreases (increases) both the average degree (Figure 43, left) and the average leverage-to-degree ratio (Figure 44, left) for the set of banks. Thus, the resulting changes along the extensive margin (measured by the average degree) and along the intensive margin (measured by the average flow of credit) occur in the same direction. However, for the firms, a positive interest rate shock decreases the average degree (Figure 43, right), but increases the average leverage-to-degree ratio (Figure 44, right). Therefore, the reduction in the average number of partners (that is, the reduction along the extensive margin) is accompanied by an increase in the average flow of credit across the remaining partners (that is, an increase along the intensive margin). Meanwhile, with a negative interest rate shock the average degree increases but the average leverage-to-degree ratio decreases, so that the rise in the average number of partners is accompanied by a decrease in the average flow of credit across the remaining partners.

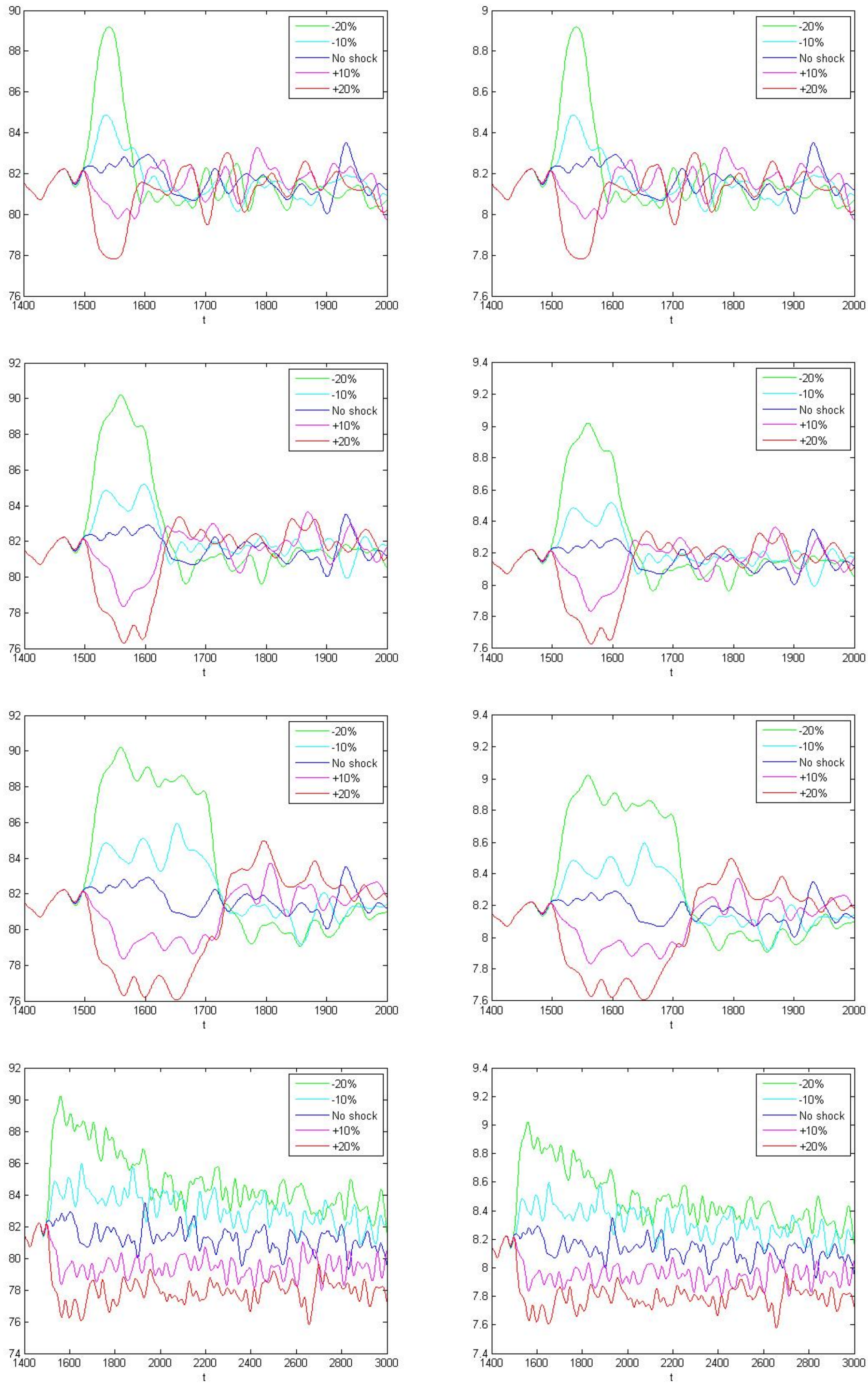


Figure 43 – *Impact of the interest rate shock on the average degree of banks (left) and firms (right). Average of 50 simulations. Shocks last for 50 (top), 100 (2^{nd} row), 200 (3^{rd} row), and 1,500 (bottom) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

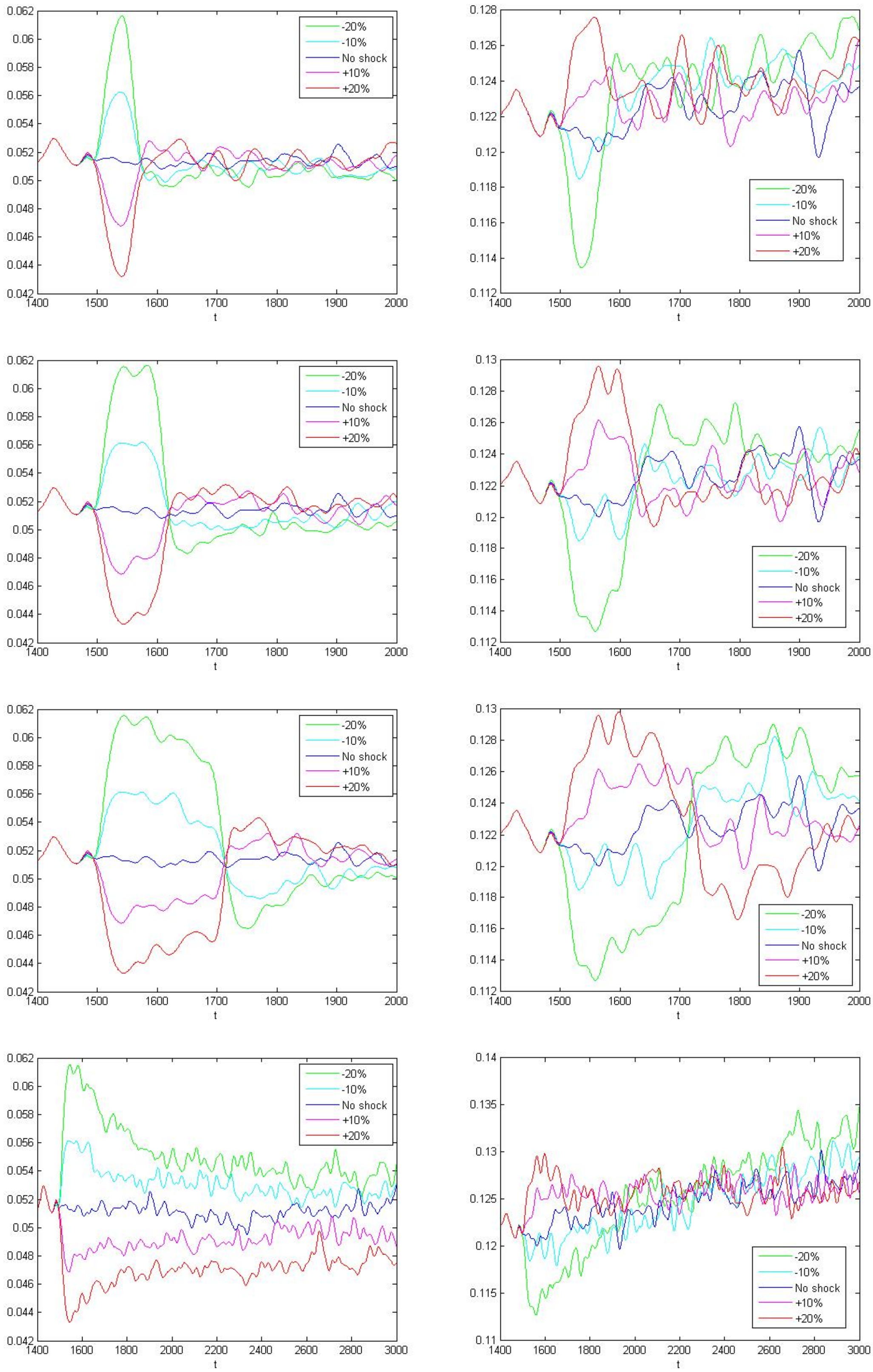


Figure 44 – *Impact of the interest rate shock on the average leverage-to-degree ratio of banks (left) and firms (right). Average of 50 simulations. Shocks last for 50 (top), 100 (2^{nd} row), 200 (3^{rd} row), and 1,500 (bottom) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

Table 9 shows the difference between the average density when there is a shock in the base interest rate and when there is not. We computed this difference for two range of periods: during the duration of the shock and between periods 2500-3000, in order to observe any long-run effect. Non-negligeable long-run effects are caused only by permanent shocks. However, the impact of a permanent interest rate shock on the financial network density seems to feature a decreasing trend over time. After some time, the density seems to start to come back to its original value. Consider, for instance, the impact of a permanent negative shock of 20% starting at period $t = 1500$. Between periods 1500 and 1600, the average density is 7% above its original value. However, between periods 2500 and 3000, this value drops to less than half (3.2%).

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	5.78***	-0.01	6.99***	-0.41***	7.61***	-0.33***	3.15***
-0.1	1.88***	0.22**	2.01***	0.09	2.81***	0.04	1.70***
0.1	-1.67***	-0.33	-3.00***	-0.09	-2.84***	-0.02	-1.78***
0.2	-4.00***	0.42***	-5.53***	0.25***	-5.48***	0.25***	-3.59***

Table 9 – *Difference between the average density when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

In Table 10, we present the elasticity of density with respect to the base interest rate. For a shock of size s, we computed the elasticity as follows:

$$\xi = \frac{dens^M_{1501-1500+D} - dens^M_{1000-1500}}{s.dens^M_{1000-1500}}, \tag{5.19}$$

where $dens^M_{a-b}$ is the average density between periods a and b (recalling that D is the duration of the shock). One can observe that density is inelastic to the base interest rate, i.e., a 1% variation in the base interest rate leads to an absolute variation of the density smaller than 1%. The elasticity is not uniform and depends on both s and D. The absolute elasticity increases with D. For negative shocks, the highest absolute elasticity is observed at the highest absolute value of s; for positive shocks, the opposite happens (except for $D = 200$). As also observed in Table 9, the effect of positive and negative shocks of the same magnitude is asymmetric. In general, the absolute elasticity is higher for negative shocks.

s	D=50	D=100	D=200
-0.2	-0.3199	-0.3868	-0.3893
-0.1	-0.2474	-0.2724	-0.2974
0.1	-0.1101	-0.2317	-0.2678
0.2	-0.1721	-0.2433	-0.2661

Table 10 – *Elasticity of the density of the financial network with respect to the base interest rate.*

In Figures 45 and 46, we present the impact of shocks to the base interest rate on the assortativity of banks and firms, respectively. It can be seen that the shocks are positively correlated to the assortativity in both cases. As the average assortativity is negative, a positive (negative) shock decreases (increases) its absolute value. The links created by negative shocks are mostly between highly-connected agents and poorly-connected agents of the oppositive type, making the network more disassortative. Similarly, positive shocks to the base interest rate tend to decrease the disassortativity of the financial network, mostly destroying the links between highly-connected agents and those with less connections of the opposite type.

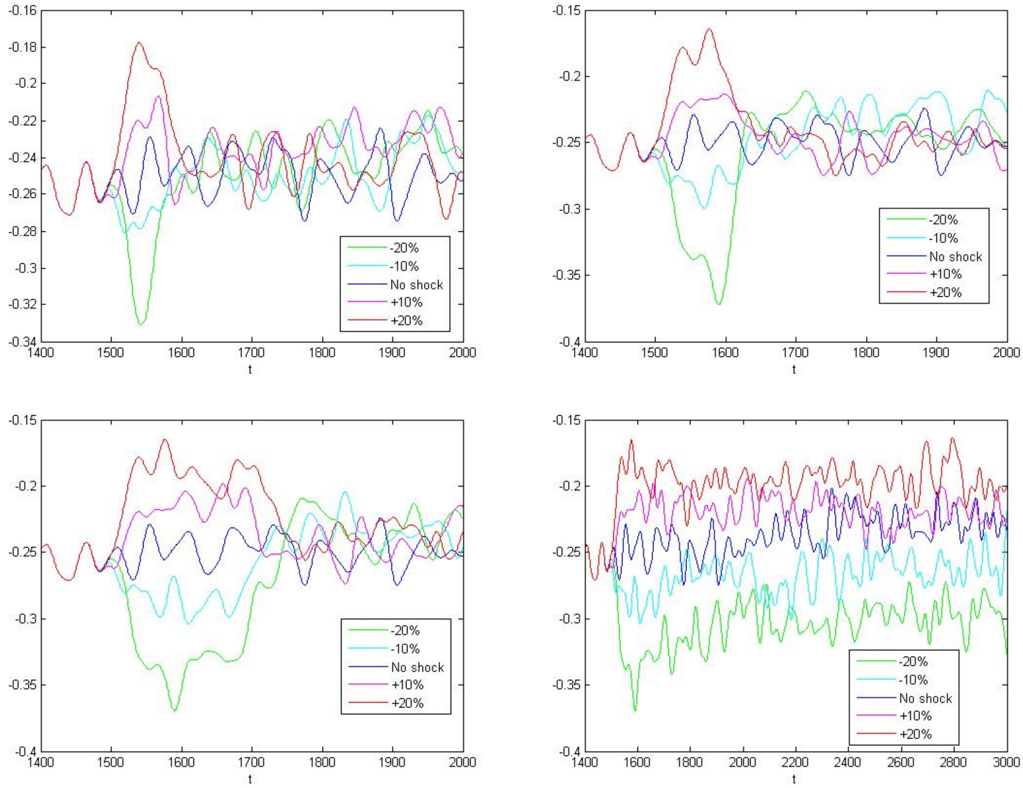


Figure 45 – *Impact of the interest rate shock on the banks' assortativity. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

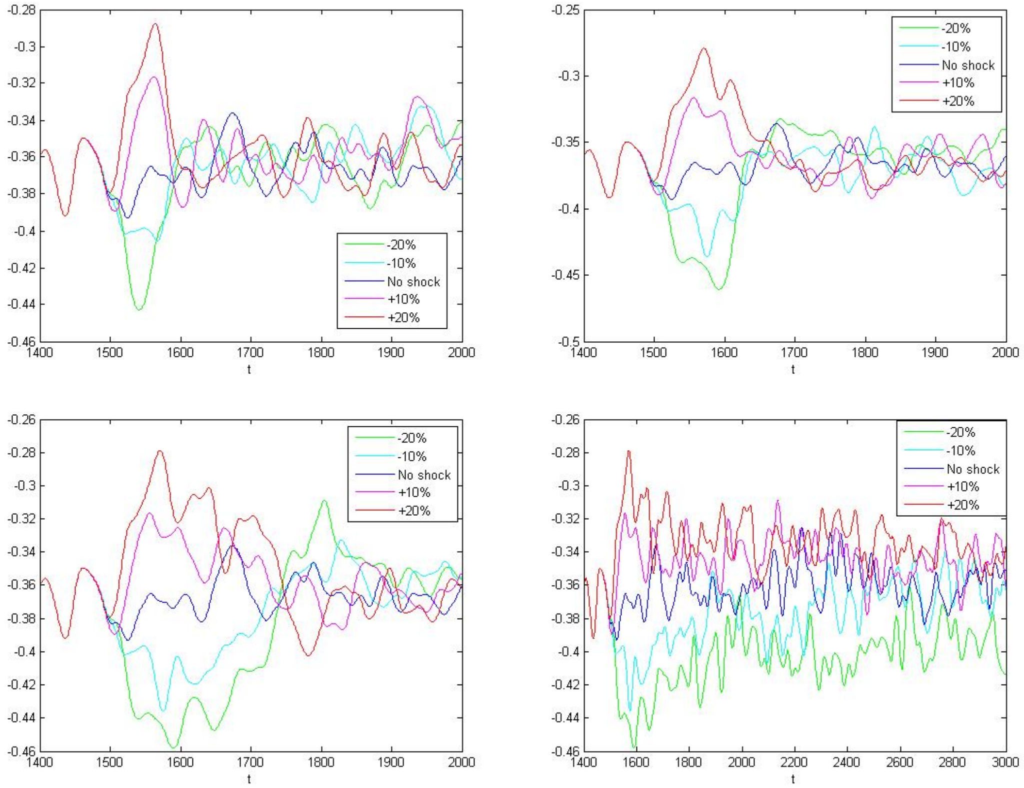


Figure 46 – *Impact of the interest rate shock on the firms' assortativity. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

Tables 11 and 12 corroborate the results presented in Figures 45 and 46. Positive shocks to the base interest rate decrease the absolute value of assortativity and negative shocks have the opposite effect. In general, the impact of base interest rate shocks is higher in banks' assortativity than in firms' assortativity. In some cases, there are significant long-run effects of temporary shocks (e.g., the long-run impact of a shock of magnitude -0.2 and duration 200 on banks' assortativity) and non-decreasing effects of permanent shocks (e.g., the impact of permanent negative shocks on banks' assortativity). The higher impact of shocks to the base interest rate on banks' assortativity is confirmed through the computation of the respective elasticities (Tables 13 and 14).

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	14.8***	-0.39	29.1***	-3.71***	30.8***	4.42***	29.4***
-0.1	7.68***	-0.97	11.7***	-4.14***	14.5***	0.52	13.6***
0.1	-6.98***	-3.81***	-8.89***	2.68***	-11.8***	-1.13	-3.03***
0.2	-20.4***	-0.68	-22.6***	0.30	-21.9***	0.67	-15.1***

Table 11 – *Difference between the average banks' assortativity when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	7.92***	-3.01***	14.46***	-0.97**	16.9***	-1.44***	8.53***
-0.1	3.04***	-1.47***	7.46***	-1.45***	10.1***	-1.78***	-0.07
0.1	-5.99***	-1.66***	-9.17***	-0.98**	-6.98***	-1.01**	-4.20***
0.2	-12.5***	1.32***	-15.7***	-1.76***	-13.4***	-0.55	-6.57***

Table 12 – *Difference between the average firms' assortativity when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

s	D=50	D=100	D=200
-0.2	-0.7106	-1.2551	-1.2954
-0.1	-0.7086	-0.8253	-1.0210
0.1	-0.7492	-1.1687	-1.5124
0.2	-1.0394	-1.2471	-1.2404

Table 13 – *Elasticity of the banks' assortativity with respect to the base interest rate.*

s	D=50	D=100	D=200
-0.2	-0.5794	-0.8101	-0.8006
-0.1	-0.6550	-0.9096	-0.9302
0.1	-0.2795	-0.7787	-0.7655
0.2	-0.4785	-0.7227	-0.7017

Table 14 – *Elasticity of the firms' assortativity with respect to the base interest rate.*

The resilience of the financial network, as measured by its largest component, is negatively related to the magnitude of the interest rate shock (Figure 47). A positive interest rate shock destroys some links, creating more isolated components in the financial network. However, this impact is very small (Table 15). The elasticity is always smaller than 3% and larger for smaller changes in absolute value, probably because in this case the denominator is smaller (Table 16). It is worth noting that a permanent interest rate shock seems to have an increasing impact on the largest component. Consider, for instance, the impact of a permanent interest rate shock of –20% on the largest component. Between periods 1501 and 1550, the average largest component will be 0.21% above the value of the no interest rate shock case. This value increases through the length of time of the simulation, reaching 1.06% between periods 2500-3000.

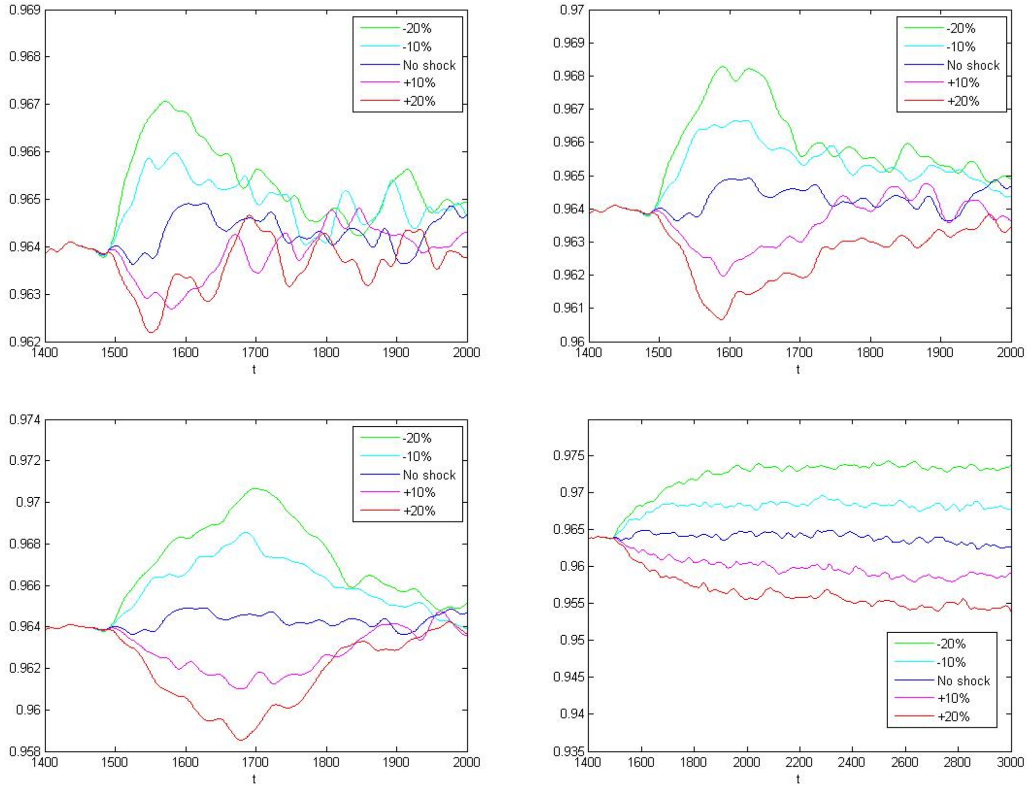


Figure 47 – *Impact of the interest rate shock on the largest component. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed applying the HP filter.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	0.21***	0.01**	0.28***	0.01	0.38***	0.02***	1.06***
-0.1	0.13***	0.00	0.17***	0.01**	0.25***	0.05***	0.51***
0.1	-0.06***	-0.01**	-0.13***	-0.01	-0.22***	0.02**	-0.48***
0.2	-0.11***	0.02***	-0.23***	-0.02***	-0.39***	-0.01	-0.89***

Table 15 – *Difference between the average largest component when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

s	D=50	D=100	D=200
-0.2	-0.0071	-0.0120	-0.0185
-0.1	-0.0063	-0.0130	-0.0233
0.1	-0.0125	-0.0175	-0.0238
0.2	-0.0088	-0.0135	-0.0202

Table 16 – *Elasticity of the largest component with respect to the base interest rate.*

Concerning the impacts of shocks to the base interest rate on the kurtosis of the degree distribution (Tables 17 and 18), some suggestive conclusions can be drawn from our results: i) while the short-term effects of temporary shocks are ambiguous, they have a clear long-term impact, which is a decrease (in most of the cases) in the kurtosis of the degree distribution of both banks and firms. This suggests that the impact of negative and positive shocks is asymmetric; ii) while permanent negative (positive) shocks decrease (increase) the kurtosis of banks' degree distribution, this relationship is the opposite in the case of the firms. This effect is asymmetric, in the sense that it is stronger for firms and in the case of negative shocks. The rationale behind these results seems to be the following: a higher supply of credit, brought by a negative interest rate shock, take the form of more banks supplying credit to the more credit-demanding firms. Therefore, there are new links being created between isolated banks and these firms (i.e., an increase along the extensive margin); iii) lasting positive shocks (100 periods or more) also decrease significantly the kurtosis of the firms' degree distribution.

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	-0.0009	-1.7939	-0.5619	-0.2524	-0.8008	-1.0273	-3.7803
-0.1	0.4126	-0.9312	1.3628	-1.2479	1.6223	-1.9575	-3.6683
0.1	0.4707	-1.3735	0.0767	-0.9854	1.0659	-1.5866	0.1786
0.2	-0.2820	-0.9564	-0.2964	-1.7028	1.1315	-1.2400	1.7987

Table 17 – *Difference between the average kurtosis within the mentioned period interval of banks' degree distribution when there is an interest rate shock and when there is not (in %). The computation considers 2,500 values (50 banks times 50 simulations). Period P corresponds to that in which the shock starts, thus P=1500.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	4.1026	-0.5896	-1.2149	-9.9445	0.6089	9.1163	24.2379
-0.1	0.4113	-3.0865	-1.3341	-10.2206	1.1731	-0.1723	16.6770
0.1	-4.2716	-10.8553	-2.1998	3.7021	-0.9814	-10.7725	-1.7572
0.2	-0.6702	-10.2046	-3.9324	-2.1713	-8.8474	-3.9199	-13.2025

Table 18 – *Difference between the average kurtosis within the mentioned period interval of firms' degree distribution when there is an interest rate shock and when there is not (in %). The computation considers 25,000 values (500 firms times 50 simulations). Period P corresponds to that in which the shock starts, thus P=1500.*

5.5 Concluding remarks

An important question raised by many studies on financial networks is how the propagation of shocks through the financial network is driven by its topological features. In this paper, we address a different but related and equally relevant question. More precisely, we assess how exogenous shocks to the policy interest rate affect some key topological measures of a bank-firm credit network.

In order to perform this task, we develop an ABM in which banks extend loans to consumption-good firms. The bank-firm credit network evolves endogenously according to plausible behavioral assumptions, in the sense that both firms and banks are always willing (but not always able) to close a credit deal with the network partner perceived to be less risky. After assessing some artificial time series generated by the model (output, banks' and firms' leverage, non-performing loans etc.), we show that our model is able to reproduce several key stylized facts of bank-firm credit networks: for example, i) the degree distributions are fat-tailed; ii) the bipartite bank-firm credit network is characterized by a disassortative behavior; and iii) the correlation between the size of the node and its degree is positive.

Going through the literature on the subject, we identified that the propagation of shocks through a financial network depends mainly on three key topological features: degree distribution, assortativity, and density. We then assessed how positive and negative exogenous shocks of different magnitudes and durations to the base interest rate affect these topological features. Moreover, we included in our analysis the largest component, which is a proxy for the financial network resilience.

We have found that the density of the financial network decreases with positive interest rate shock and increases with negative ones. Therefore, the increase in the flow of credit between banks and firms, as a result of a negative interest rate shock, results in the creation of new links. Similarly, when the flow of credit decreases in face of a positive interest rate shock, some links of the financial network are destroyed. Assessing the relationship between the density of the network and the leverage of banks and firms, we observed that, in the case of the banks, changes along the extensive margin (number of partners) and intensive margin (average flow of credit per partner) occur in the same direction. However, in the case of firms, changes along the extensive and intensive margin occur in opposite directions: an increase (decrease) in the average number of partners is accompanied by a decrease (increase) in the average flow of credit (as a fraction of the firms' net worth) granted by each partner.

Another interesting result is that negative shocks to the base interest rate make the financial network formed by banks and firms more disassortative (i.e., the absolute value of the negative assortativity increases), while positive shocks generate the opposite effect. This implies that the links created by negative shocks are mostly between highly-connected agents and poorly-connected agents of the opposite type. On the other hand, the links destroyed by positive shocks are mostly those between highly-connected agents and that of the opposite type with less connections.

Finally, we have found that interest rate shocks have a long-term impact on the kurtosis of the degree distribution of both banks and firms. The type of impact depends on the duration of the shock. Usually, temporary shocks lead to a decrease in the kurtosis of the degree distribution. This suggests an asymmetry in the impact of negative and positive shocks. Meanwhile, permanent negative (positive) shocks decrease (increase) the kurtosis of banks' degree distribution. In the case of the firms, this relationship is the opposite one. A possible explanation for these results is that a higher supply of credit, caused by a negative interest rate shock, takes the form of more banks supplying credit to the more credit-demanding firms – that is, an increase in the flow of credit along the extensive margin.

Our results have important implications with respect to the role played by financial networks in driving economic outcomes. It is widely recognized that the effect of some processes in the economic system depends on the topological structure of the financial networks embedded in such a system. For instance, in network models of systemic risk, the considered effect is computed as the potential loss of economic value generated by an exogenous shock. In these models, the topology of the financial network is usually assumed to be fixed and exogenous. However, our study robustly suggests that the topology of a financial network both affects and is affected by shock propagation in a complex coevolutionary way. Therefore, understanding how the topology of a financial network coevolves with a given shock propagation is crucial to more properly and precisely compute the impact of the considered shock, and our study sheds some suggestive light on such a key issue.

Appendix: Parameters and initial conditions

Symbol	Meaning	Value
Parameters:		
N^F	Number of firms	500
η	Labor productivity parameter	3
ψ_w^{min}	Nominal wage adjustment parameter (Eq. 5.1)	0.5
ψ_w^{max}	Nominal wage adjustment parameter (Eq. 5.1)	1.1
ψ_l^{max}	Target leverage adjustment parameter (Eq. 5.3)	0.2
l^{max}	Firms' maximum leverage	5
l^{min}	Firms' minimum leverage	0.5
N^B	Number of banks	50
κ	Banks' maximum leverage ratio	0.04
α	Banks' capital buffer sensitivity to financial fragility (Eq. 5.4)	0.5
t_D	Duration of debt (in periods)	10
λ	Probability of choosing a bank at random	0.1
f^{min}	Minimum fraction of credit to be supplied in each credit deal	0.2
i^B	Base interest rate	0.02
β	Interest rate markup parameter (Eq. 5.5)	0.25
γ	Risk premium parameter (Eq. 5.5)	0.2
f_{RI}	Fraction of investment randomly shared among firms (Eq. 5.6)	0.1
ε	Investment distribution parameter (Eq. 5.6)	2
ϕ	Sensitivity of firms' markup to a change in market share (Eq. 5.9)	0.2
ψ_ρ	Propensity to consume parameter (Eq. 5.11)	0.02
f_{RD}	Fraction of the aggregate demand randomly distributed among firms (Eq. 5.12)	0.1
θ	Sensitivity of firms' market share to relative price (Eq. 5.14)	1
s^{max}	Maximum market share	0.04
δ	Proportion of profits distributed as dividends	0.15
τ	Tax rate	0.15
ψ_ζ	Sensitivity of government spending to the growth rate (Eq. 5.18)	0.05
ζ^{min}	Minimum fraction of government spending (Eq. 5.18)	0.02
$g*$	Growth rate target (Eq. 5.18)	0.03
Initial conditions:		
$NW_{i,0}$	Firms' initial net worth	$NW_{i,0} \sim N(10,2)$
$\mu_{i,0}$	Firms' initial markup	$\mu_{i,0} \sim N(0.15,0.03)$
$l^*_{i,0}$	Firms' initial target leverage	$l^*_{i,0} \sim U(1.5,2)$
$NW_{j,0}$	Banks' initial net worth	$NW_{j,0} \sim N(10,2)$
R_0^H	Households' initial cash	1,000
Γ_0	Government initial surplus	1,000
w_0	Initial nominal wage	1
ζ_0	Initial fraction of government spending (Eq. 5.18)	0.04

CHAPTER

6

RISK-DEPENDENT CENTRALITY IN THE BRAZILIAN STOCK MARKET

6.1 Introduction

Centrality is one of the key topological features of nodes in complex networks (Rodrigues (2019), Comin *et al.* (2020)). It refers to how important and influential a given node is for the whole network. Central nodes play an important role concerning dynamical processes throughout complex networks, e.g., the spreading of news in social networks or the propagation of shocks in financial networks. Moreover, the removal of a central node is supposed to cause a significant change in the structure of the network; otherwise (for instance, if it is a dead-end node), its removal will have no further consequences. Consider the simple example depicted in Figure 48. The removal of node V will break the network into two disconnected components, implying that it is a very central node. Notice that this node is not highly connected and, therefore, not only hubs are considered as central.

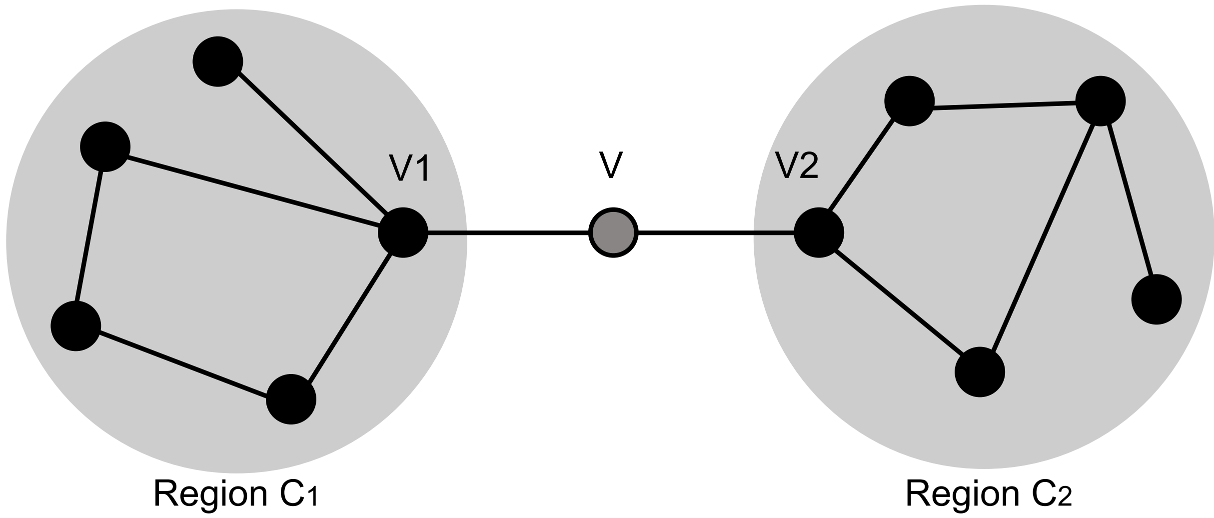


Figure 48 – *The removal of node V will break the network into two disconnected parts. Moreover, all shortest paths from one region to another has to go through node V.*

There are many centrality measures to characterize the networks structure (Rodrigues (2019)). Particularly, three classical ones are (i) the degree (the number of direct neighbors of a given node), (ii) the betweenness centrality (the fraction of shortest paths[1] going through a given node), and (iii) the closeness centrality (the average of the shortest path distances from a given node to every other node in the network).[2] The eigenvector centrality (Bonacich (1972)) is not restricted to shortest paths. It is given by the components of the main eigenvector of the adjacency matrix representing the network. Other centrality measures include the subgraph centrality (Estrada and Rodríguez-Velázquez (2005)), and the PageRank centrality (Gleich (2015)).

The use of centrality measures in the analysis of economic and financial networks has proved to be quite fruitful. It has shed light on a wide range of important issues. Several studies (e.g., Martinez-Jaramillo *et al.* (2014), Kuzubas, Omercikoglu and Saltoglu (2014), León and Pérez (2014), Chan-Lau (2018), Ghanbari, Jalili and Yu (2018)) have attested the relevance of centrality measures in identifying systemically important nodes in financial networks. D'Errico *et al.* (2009) studied the shareholding network of the Italian Stock Market. By using some centrality measures, they detected central companies according to two criteria: informational flow and absorption of external shocks (less asset volatility in central companies). Rossi *et al.* (2018) found a positive correlation between network centrality and portfolio performance in a delegated investment management setting. Temizsoy, Iori and Montes-Rojas (2017) shows that

[1] The shortest path between two nodes is the one in which the sum of the weights of the constituent edges is minimized. There are some excellent textbooks the reader unfamiliar with the complex networks concepts may refer to, as Estrada (2012) and Barabási (2016).

[2] They are not necessarily correlated, hence the necessity of considering more than one measure of centrality. Coming back to Figure 48, node V has a small degree (just two direct neighboring nodes). However, all shortest paths from C1 to C2 - and vice versa - has to go through node V, which implies it has a high value of betweenness centrality.

funding rates in the e-MID market are significantly affected by banks' network centrality in the interbank market. The temporal centrality measure, developed by Zhao *et al.* (2018), proved to be an efficient portfolio optimization and risk management tool.

A shortcoming of the existent measures of centrality is that they are based on a static view of the network. Networks are subject to elements that can cause significant changes in relatively short periods of time. For instance, changes in the external risk will alter the centrality ranking of the banks in an interbank network (Bartesaghi *et al.* (2020)). Based on the Susceptible-Infected epidemiological models (Pastor-Satorras *et al.* (2015)) and on the communicability functions (Estrada and Hatano (2008)), Bartesaghi *et al.* (2020) derived a new centrality measure called *risk-dependent centrality* (RDC). This node centrality measure depends on both the topology of the network and the external risk the whole network is submitted to.

Bringing the analysis into the financial realm, the RDC accounts for both the probability of the node becoming financially vulnerable, as well as propagating negative shocks to other nodes. The RDC is positively correlated with the level of external risk. For instance, the current SARS-CoV-2 pandemic (as of June 2021) has increased the external risk, imposing a higher level of stress on the nodes in a given financial network. The most interesting point concerning this new centrality measure is that the RDC of each node is differently affected by the external risk. Some nodes are quite central at low levels of external risk, becoming less central than other nodes as the level of external risk increases, and vice versa. Therefore, not only the RDC, but also the *ranking* of the nodes based on it, is affected by the external risk. Assessing two real-world financial networks – the *S&P 100* assets network and the U.S. top corporates network –, Bartesaghi *et al.* (2020) corroborated this point.

The purpose of this paper is to calculate the RDC assessing the Brazilian stock market. Following Bartesaghi *et al.* (2020), we extract the minimum spanning tree (MST) from the correlation matrix of daily returns of assets traded at the Brazilian stock market. The period ranges from January 2008 to June 2020. The RDC is computed for each asset at different levels of external risk. We observe that the ranking of assets based on the RDC depends on the external risk: assets which are central at low levels of external risk are less central when this level increases, and vice versa.

Additionally, we compute the RDC employing an empirically-computed external risk level, based on the *Emerging Markets Bond Index* (EMBI+) index. Thus, rather than assuming different values, the external risk level is unique at each time window. We show that the average RDC of some economic sectors deviates from that of others in crisis periods, being quite similar in non-crisis periods. Notably, assets of the oil, gas, and biofules and financial sectors become more central than the others in periods of crisis. Also, we find a strong and positive correlation between the volatility of the RDC and the external risk level. The same result was not observed when we computed the correlation between the volatility of other centrality measures and the external risk level. This result shows that the volatility of the RDC is a better proxy for the external risk level than those of other centrality measures.

Besides this introduction, this paper has three other parts. Section 6.2 presents the methodology and the data set. General results are discussed in Section 6.3. Section 6.4 presents results concerning the empirically-computed external risk level. Some concluding remarks take Section 6.5.

6.2 Methodology and data set

6.2.1 The data set

Our data set is comprised of daily closure prices of the assets traded at the Brazilian stock market (BMF&BOVESPA) between January 2008 and June 2020. Following Bartesaghi *et al.* (2020), we used moving six-months windows, in which the window is rolled one month forward. The first time window covers all trading days from January 1^{st}, 2008 to June 30^{th}, 2008; the second one, from February 1^{st}, 2008 to July 31^{st}, 2008; and so on, until the last time window, from January 1^{st}, 2020 to June 30^{th}, 2020. Hence, we have obtained a total of 145 time windows.

In each window, we have considered only those assets whose number of observations is at least 80% of the number of trading days in the period. This is to assure that the returns correlation can be properly calculated. The number of assets in each time window varies from 196 to 249 and is depicted in Figure 49.

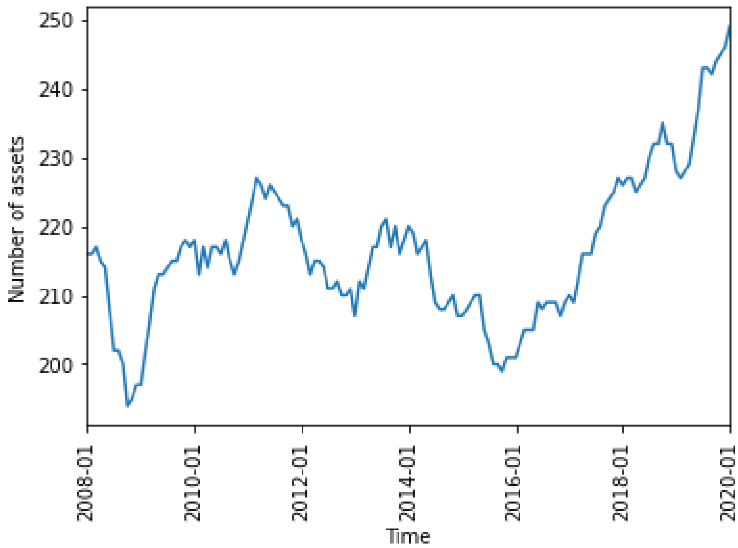


Figure 49 – *Number of assets used in each time window. The time period in the horizontal axis corresponds to the first month of the time window.*

6.2.2 Methodological issues

Once the data was retrieved, we first calculated the logarithmic returns of the assets:

$$r_i^t = \ln P_i^t - \ln P_i^{t-1}. \tag{6.1}$$

In Equation 6.1 above, P_i^t is the closure price of asset i at time t. Then we computed the Pearson cross correlation coefficient ρ_{ij} between the returns of each pair of assets. Finally, we transformed the correlation coefficients ρ_{ij} into the distance coefficients d_{ij} according to the following equation (Mantegna (1999), Peron and Rodrigues (2011), Peron, Costa and Rodrigues (2012)):

$$d_{ij} = \sqrt{2(1-\rho_{ij})}. \tag{6.2}$$

The higher the correlation between the returns of two different assets, the closer they will be. In fact, d_{ij} reaches its minimal value (0) when ρ_{ij} is 1, and the distance will be maximal (2) when the correlation is minimal (-1). The coefficients d_{ij} form the distance matrix D, which constitutes the adjacency matrix of graph Γ.

The minimum spanning tree (MST) T is extracted from graph Γ. A spanning tree connects all nodes of the graph without forming loops. Among all existing spanning trees, that whose sum of weights of the edges is the lowest is MST. Figure 50 illustrates this point. The weights of the edges of the MST (in bold) amount to 32. It can be seen that it is not possible to connect all the vertices of the graph through a shortest path of edges and without loops. MST is an approach extensively applied to financial networks (e.g., Gilmore, Lucey and Boscia (2008), Kwapień *et al.* (2017)), as it highlights the most relevant piece of a graph, bearing only its essential information.[3]

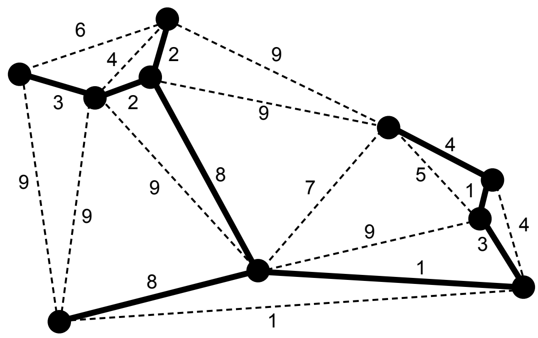


Figure 50 – *A graph and its MST represented by the edges in bold.*

The final step is the calculation of the RDC. In the undirected network represented by the MST, the RDC of each node i is calculated according to the following equation:[4]

$$R_i = \sum_j (e^{\zeta A})_{ij}, \tag{6.3}$$

[3] We performed this analysis also on the entire distance matrix. However, differently from what happens with the MST (as we will show later), the ranking of the nodes based on the RDC is barely affected by the external risk. Thus, the presence of less relevant information blurs the real relationship between RDC and the level of external risk. Recalling that circulability – the weighted sum of all closed walks starting and ending at a given node – is null in MSTs, the RDC corresponds to the transmissibility in this case.

[4] For more details on the RDC formula, see Bartesaghi *et al.* (2020).

where A is the adjacency matrix representing the MST, and ζ is the level of risk the entire network is submitted to, and $(e^{\zeta A})_{ij}$ is the number of walks starting at i and ending elsewhere (including i itself) weighted by $\frac{\zeta^k}{k!}$, where k is the length of the walk.[5] Formally, ζ is defined as $\gamma(1-\beta)$, where β is the probability of a given node to be infected at the beginning (i.e., to be the one from which the epidemic starts) and γ measures the risk of infection on the network, where $\gamma = 0$ corresponds to the no infection case (i.e., isolated nodes).Figure 51 depicts a simple network composed of five nodes. The path *abcdb* is a possible walk starting at node *a* and ending at node *b*. Assuming all edges are of length 1, this walk is of length 4. The RDC is the sum of two components: the *circulability*, i.e., the weighted sum of all closed walks starting and ending at node *a*, and the *transmissibility*, the weighted sum of all closed walks that start at *a* and end elsewhere.

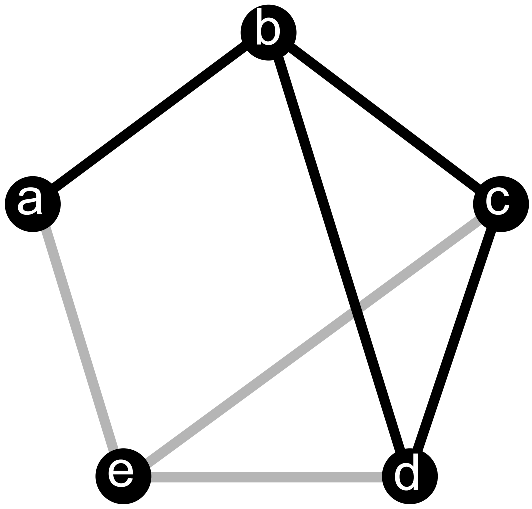


***Figure 51** – The path abcdb is a possible walk starting at a and ending at b (length=4).*

6.3 Results

6.3.1 General results

For each time window, we followed the steps described in Section 6.2.2. The ranking position of each asset based on the RDC is computed varying the value of the external risk ζ in the interval (0,1] with step 0.01.

The result for the time window 2008-01 (January 2008-June 2008) is depicted in Figure 52. In most cases, the ranking position changes significantly according to different values of ζ. Some assets become less central when the external risk increases. For instance, TIM (telecommunications, number 192 in Figure 52) moved from position 9 to 107 when ζ increases

[5] In order to solve Equation 6.3, we rely on the following properties of symmetric matrices (as this is the case of A): there is an invertible matrix Q and a diagonal matrix Λ such that $A = Q\Lambda Q^{-1}$; and all A eigenvalues are real. It implies the following exponential matrix property: $e^{\zeta A} = Qe^{\zeta\Lambda}Q^{-1}$. For details, see Moler and Loan (2003).

from 0.01 to 1. In contrast, other assets climbed in the ranking with the increase in ζ, as *F. Guimarães* (textile, number 79, from 146^{th} to 27^{th} place) and *Embratel* (telecommunications, number 68, from 119^{th} to 15^{th} place). Other assets are very central even under high levels of external risk. The airline *Gol* (number 87) always occupies the first place, regardless the value of ζ. Other quite central assets are, for instance, the electric power company *Light* (number 113, worst ranking equal to 3) and the gas distribution company *Comgas* (number 46, worst ranking equal to 5). On the other hand, some assets have a very low level of centrality independently of the external risk. The companies *Vale* (mining, number 203), *Lojas Americanas* (retail, number 116), *B2W Digital* (e-commerce, number 17), and *Gerdau* (metallurgy, number 85) are always among the four least central assets.

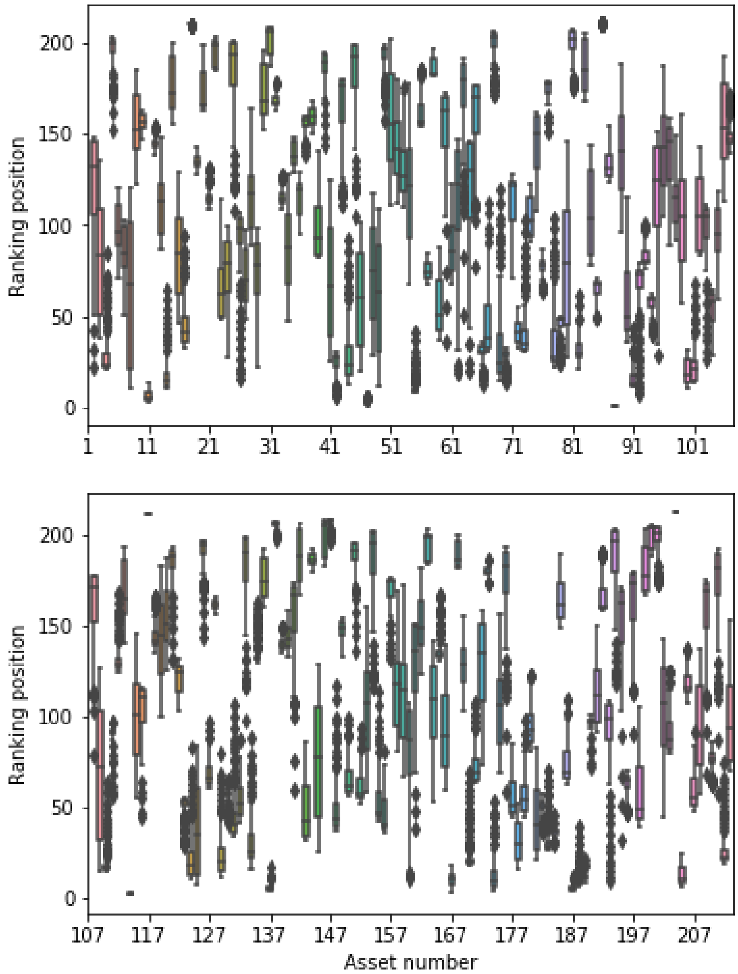


Figure 52 – *Distribution of assets' rankings based on the RDC with respect to ζ. Results regard to the time window 2008-01 (January 2008-June 2008). For the sake of better visualization, results are being presented in two subplots.*

We investigated the correlation between the assets' ranking based on the RDC and the level of external risk ζ. We did not find a consistent correlation between these two variables. How the external risk affects the assets' rankings depends on the network topology and, hence, varies across different time windows. In Figure 53, we depict two examples. For the time window

January-June 2008, the asset *Abyara* (on top, construction sector) became more central as far as ζ increased. It climbed from position 140 to 40 in the ranking based on the RDC. However, in the time window July-December 2008, the increase in ζ had an opposite effect on the asset's ranking. It lost 100 positions in the ranking based on the RDC. The effect of the increase in ζ on the asset *AES ELPA* (on bottom, electric power sector) was the inverse in the two time windows: it moved up (down) in the ranking in January-June 2008 (July-December 2008).

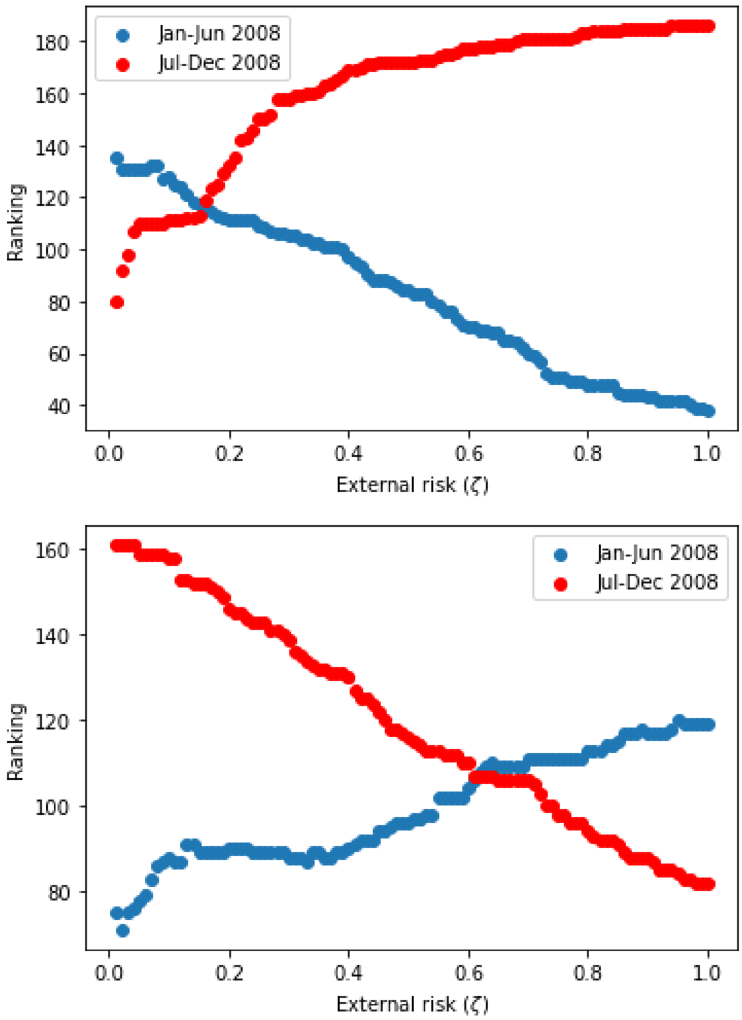


***Figure 53** – Scatter plot of assets' rankings based on the RDC and ζ for two assets: Abyara (top) and AES Elpa (bottom). Results are presented for two different time windows: January-June 2008 (blue) and July-December 2008 (red).*

We calculated the average standard deviation of assets' rankings based on the RDC for each time window. As each time window has a different number of assets, we computed the standard deviation normalized according to the number of assets. This avoids any size effects and allows the comparison between different time windows. Both the standard deviation and the normalized standard deviation are shown in Figure 54. There was a peak of rankings' volatility in the midst of the 2007-2008 financial crisis, whose climax was the Lehman Brothers bankruptcy. The period between mid-2014 and end-2018, during which Brazil experienced a harsh economic-political crisis, is also characterized by a roughly continuous increase in rankings' volatility.

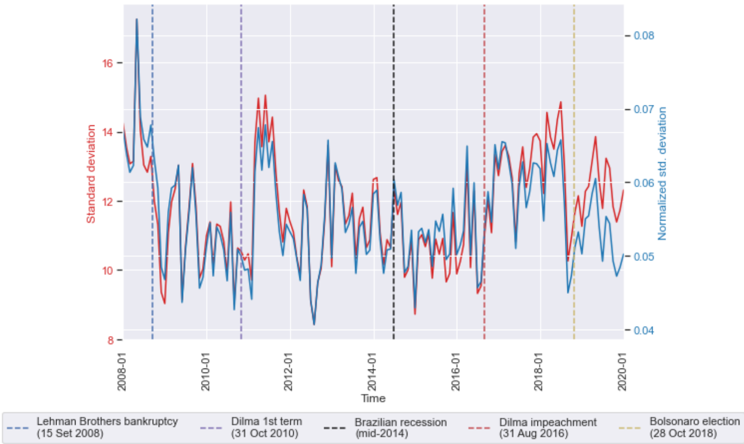


Figure 54 – *Average standard deviation of assets' rankings based on the RDC. The time period in the horizontal axis corresponds to the first month of the time window.*

6.3.2 RDC and crisis

According to Bartesaghi *et al.* (2020), the centrality of nodes is more affected by ζ in shock periods. Therefore, the average standard deviation of assets' rankings based on the RDC should be higher in periods of crisis. We computed the correlation between the average standard deviation of assets' rankings based on the RDC and two crisis indicators: the *Ibovespa* average daily return and the EMBI+ for Brazil. In both cases, we computed the average for each time window.

The *Ibovespa* is the main performance indicator of the stocks traded in the Brazilian stock market (B3). It results from a theoretical portfolio of stocks, which is reassessed every four months, and accounts for about 80% of the stock market (in terms of both number and volume of transactions). The EMBI+ for Brazil measures the difference between the yields carried by debt instruments issued by the Brazilian government and the yields of U.S. Treasury securities. As riskier bonds need to offer higher yields, this is a good proxy for the country risk. Every 100 points corresponds to 1%. For instance, if the EMBI+ is equal to 400, this difference – the spread – is equal to 4%.

We have found a negative, albeit low, correlation in the case of the *Ibovespa* average return. This correlation is more significant (both in terms of absolute value and p-value) when the normalized standard deviation is considered (Table 19). This result suggests a higher volatility of assets' rankings based on the RDC in crisis periods. However, there is not a significant correlation between the volatility of assets' rankings and the EMBI+ index.

	Ibovespa avg. return	EMBI+
Standard deviation	-0.1762	-0.0622
Normalized std. dev.	-0.2207	0.1206

Table 19 *– Correlation between the average standard deviation of assets' rankings based on the RDC and two crisis indicators: the Ibovespa average daily return and the EMBI+. Red: significant at the 1% level. Green: significant at the 5% level.*

We present in Figure 55 the distribution of the normalized standard deviation of assets' rankings according to the RDC for two time windows. We chose the time window 2009-10, that had the highest average *Ibovespa* daily return (0.47%), and 2008-05, with the lowest (-0.44%). As expected, the average standard deviation is smaller in the first case (0.055 against 0.081), with a p-value around 1.8×10^{-9}.

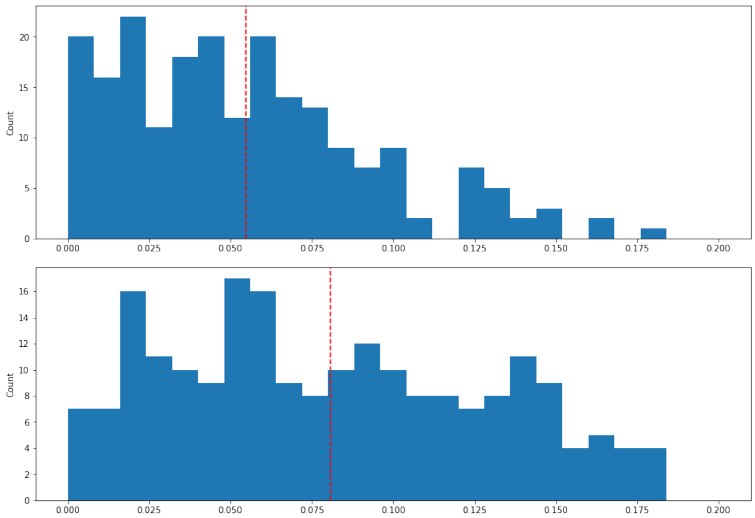


Figure 55 *– Distribution of normalized standard deviation of assets' rankings based on the RDC for two time windows: with the highest average Ibovespa daily return, 2009-10 (above), and with the lowest one, 2008-05 (below). The dashed lines represent the average standard deviation in each time window.*

As a last exercise, we ranked the time windows according to the *Ibovespa* average daily return. We formed two groups: the five time windows with the highest and the lowest average daily return (top 5 and bottom 5, respectively). Finally, we compared the average normalized standard deviation of assets' rankings based on the RDC between time windows of different groups. The results are presented in Table 20. As expected, no time window in the bottom 5 group has an average standard deviation smaller than any time window in the top 5 group. Moreover, in the majority of the cases, the p-value is smaller than 5%.

Top 5 \ Bottom 5	2008-05	2008-09	2008-07	2008-06	2008-08
2009-10	0.026	0.012	0.010	0.013	0.009
2009-11	0.036	0.022	0.020	0.023	0.019
2009-07	0.031	0.017	0.015	0.018	0.014
2016-11	0.027	0.013	0.011	0.014	0.010
2009-09	0.020	0.006	0.004	0.007	0.003

Table 20 – *The values in the table correspond to the difference between the average standard deviation of assets' rankings based on the RDC of the time window in the bottom 5 group (columns) and that of the time window in the top 5 group (rows). Red: significant at the 1% level; Green: significant at the 5% level.*

6.4 Empirically-computed external risk

In the previous section, we computed the RDC assuming an abstract external risk level. In this section, we assess the dynamics of the assets' RDC in face of an empirically-computed external risk. Thus, rather than assuming multiple values, the external risk will be an unique value at each time window. At time window t, the external risk is equal to

$$\zeta_t = \frac{EMBI+_t - min(EMBI+_t)}{max(EMBI+_t) - min(EMBI+_t)}. \tag{6.4}$$

Thus, we compute $EMBI+_t$, the average EMBI+ index for time window t. Then, we subtract the minimum $EMBI+_t$ over all time windows. Finally, we divide the result by the difference between maximum and minimum $EMBI+_t$. This procedure ensures ζ_t will range between 0 and 1. There was two main crisis periods, in which the EMBI+ index reached the highest values (Figure 56): the first one in the midst of the 2008 financial crisis, and the second one during the Brazilian economic-political crisis of 2015-2016.

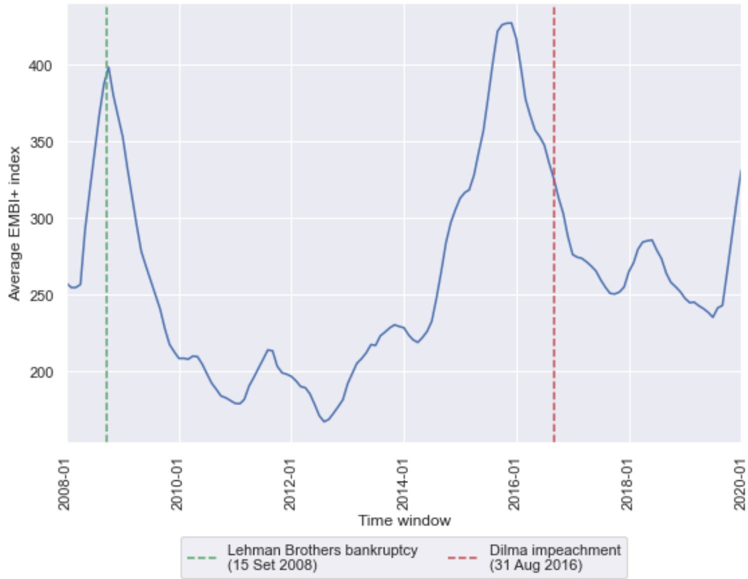


***Figure 56** – Average EMBI+ index.*

In Figure 57, we show the distribution of the assets' rankings based on the RDC with respect to ζ_t over all time windows. Comparing these results with those of Figure 52, one can observe that, in this case, the volatility of the assets' rankings is higher. There are no assets which are always at the top or the bottom of the ranking. The few assets which present a low volatility are those that appear in a small number of time windows. This result is expected, as now the topology of the network is not fixed and changes across different time windows.

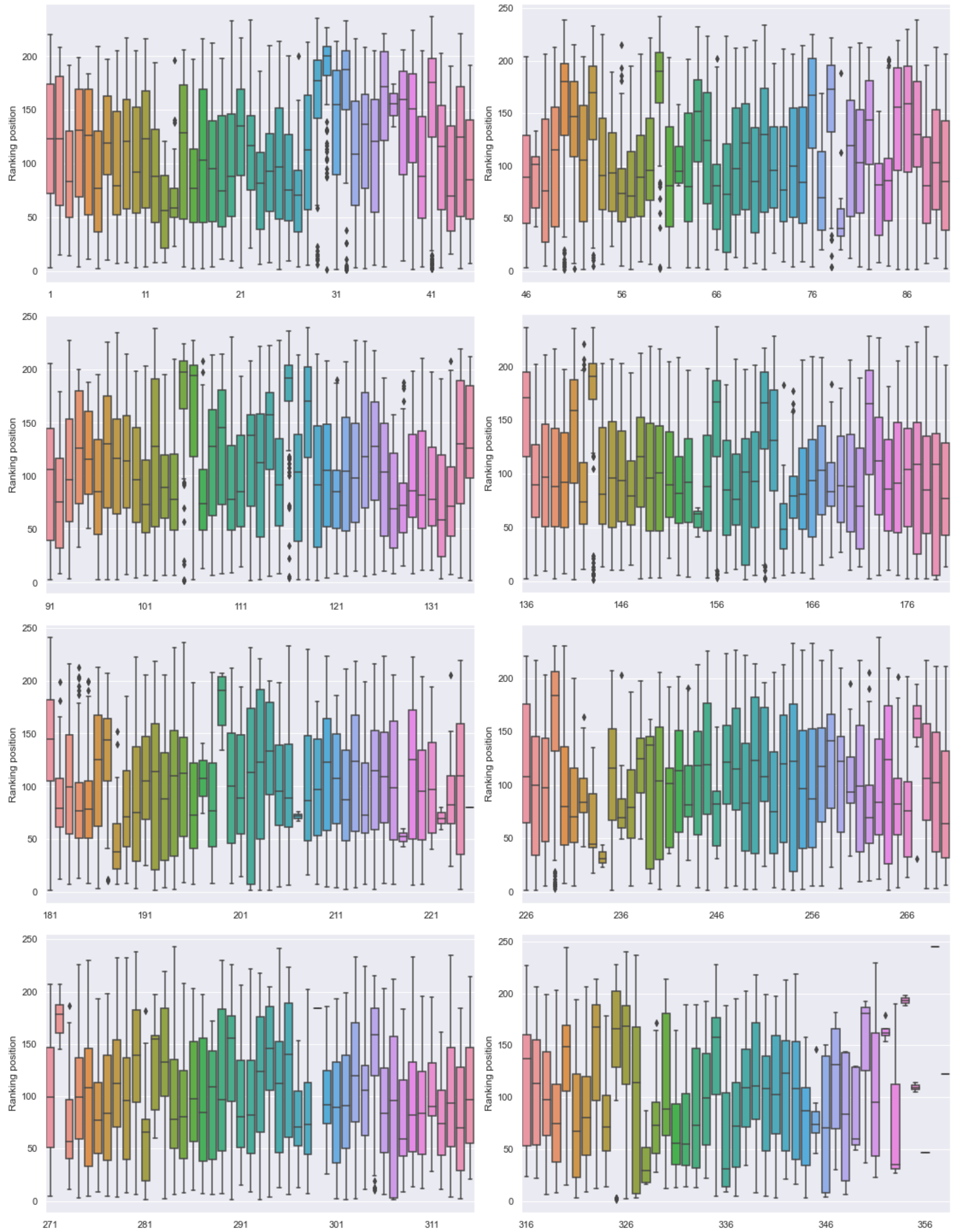


***Figure 57 –** Distribution of assets' rankings based on the RDC with respect to ζ_t over all time windows.*

Figure 58 depicts the average assets' RDC by economic sector. One can observe that, in crisis periods, the average RDC of some sectors deviates from that of the others. Notably, the oil, gas, and biofuels and financial sectors become more central than other economic sectors during periods of crisis. In non-crisis periods, the difference between the average RDC of the economic sectors is much less noticeable.

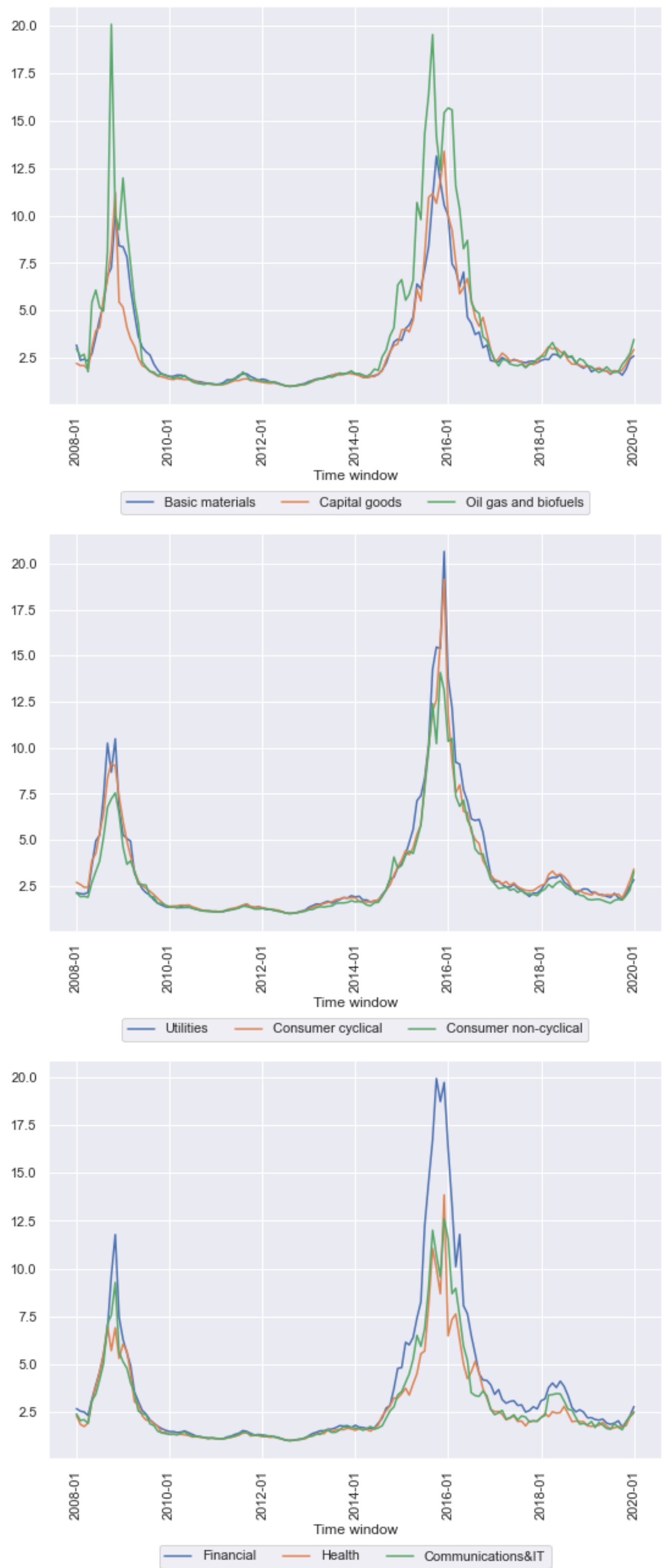


Figure 58 – *Average RDC for economic sector.*

We further investigate this assumption by computing the correlation between the RDC volatility and the external risk ζ_t. Moreover, we also compute other centrality measures (CM) of the MST (average degree, closeness centrality, betweenness centrality, and PageRank) and then the correlation between their volatility and ζ_t. We consider two measures of volatility: the standard deviation (SD) and the coefficient of variation (CV). Results are presented in Table 21. The correlation of the RDC, both in terms of standard deviation and coefficient of variation, is high and positive. This means that the volatility of the RDC increases in crisis periods. Furthermore, the volatility of the other CMs is much less correlated with ζ_t. Therefore, the volatility of the RDC is a better proxy for the external risk level than that of other centrality measures.

CM	corr(ζ_t,SD)	p-value	corr(ζ_t,CV)	p-value
RDC	0.88	5.6×10^{-47}	0.94	8.9×10^{-70}
K	0.13	0.12	0.13	0.12
CC	0.35	1.6×10^{-5}	0.12	0.14
B	-0.16	0.05	0.05	0.53
PR	0.26	0.00	0.06	0.46

Table 21 – *Correlation between ζ_t and the standard deviation (SD) and coefficient of variation (CV) of the centrality measures (CM). Legend: RDC: risk-dependent centrality; K: average degree; CC: closeness centrality; B: betweenness centrality; PR: PageRank.*

6.5 Concluding remarks

We computed the RDC for the Brazilian stock market, replicating the results presented in Bartesaghi *et al.* (2020) for the U.S. stocks constituents of the *S&P* 100 index. In most of the cases, not only the RDC, but also the assets' rankings based on it, change significantly with the level of external risk. Assets lose or gain positions in the centrality ranking when the external risk level varies. Few assets remain at the top or at the tail of the ranking independent of the external risk.

Additionally, we assessed the relationship between crisis and RDC. Bartesaghi *et al.* (2020) pointed that the centrality of nodes is more affected by the external risk in periods of crisis. Comparing the Jan-Jun 2001 time window with the two networks covering the 2007-2008 crisis period (end of 2007 and end of 2008), they show that the volatility of assets' ranking based on the RDC is significantly higher in the crisis period. We tested this hypothesis through an alternative approach. We investigated the relationship between the volatility of assets' rankings based on the RDC and two crisis indicators: the *Ibovespa* index average daily return and the EMBI+ index. We found a negative correlation between the average standard deviation of assets' rankings and the *Ibovespa* index average daily return, mainly when we considered the standard deviation normalized by the number of assets. Moreover, tests of mean difference have shown that time windows in the bottom 5 of average daily return present an average normalized standard deviation higher than most of those in the top 5. However, the correlation between the volatility of assets' rankings and the *Ibovespa* returns is not high (-0.22 for the normalized standard deviation). Moreover, there is not a significant correlation between the assets' volatility and the EMBI+ index.

Finally, we assessed the dynamics of the RDC under an empirically-computed external risk level ζ_t. We relied on the EMBI+ index to compute this external risk level. One can observe that the average RDC of the economic sectors are quite similar in normal times, but the RDC of some sectors deviates from that of others in crisis periods. Notably, assets of the oil, gas, and biofules and financial sectors become more central than the others in periods of crisis. A posterior analysis shows that there is a strong and positive correlation between the volatility of the RDC and the external risk level. The same result was not observed when we computed the correlation between the volatility of other centrality measures and the external risk level. Therefore, this result justifies the computation of the RDC, as its volatility captures better the dynamics of the external risk level than those of other centrality measures.

An important question concerns the determinants of the impact of the external risk level on the assets' ranking based on the RDC. As we have shown in Figure 53, the effect of the external risk on the ranking of a given asset is not necessarily the same across different time windows. An interesting exercise would be to try to predict this effect using topological (e.g., centrality measures) and non-topological (e.g., economic sector) features as explanatory variables. It would show which characteristics determine the correlation between the external risk and the asset's ranking based on the RDC. It is a topic to be explored in a follow-up article.

CHAPTER

7

CONCLUSION

In this thesis, we have made some contributions concerning contagion and risk in economic networks. In Chapter 2, we assessed the impact of monetary policy shocks on financial stability. We developed a model which allows us to compute both first- (impact on banks' net worth through the trading book channel) and second-round (contagion) effects of changes in the interest rate. With this tool, we can identify economic sectors and banks that would be more sensitive to sudden interest rate changes. This framework was applied in a comprehensive database of Brazilian banks and firms. Our main results are the following: i) interest rate shocks affect more strongly financial stability in periods of monetary policy tightening (i.e., an increase in the interest rate; ii) the effects of positive and negative interest rate shocks in the Brazilian economy are asymmetric, with positive interest rate shocks affecting more financial stability; iii) the relationship between interest rate changes and financial stability is non-linear, reinforcing the need to mitigate monetary policy shocks through interest rate smoothing and adequate communication and transparency to society.

The financial institution(FI)-specific determinants of systemic risk (SR) have been assessed in Chapter 3. First, the SR has been computed for different levels of the initial shock for FI in the Brazilian interbank market. Then, we explored individual determinants of SR through machine learning techniques: random forest, XGBoost, and Shapley values. Among the potential explanatory variables, there are topological and financial features. Our results show that systemic impact – i.e., the potential loss caused by a shock in a given FI – is mainly driven by topological features. The importance of topological features to the prediction of the systemic impact of banks increases with the level of the initial shock, while it decreases for credit unions. Moreover, the systemic vulnerability – i.e., the potential loss suffered by a given FI due to a shock in the system – is mainly determined by financial features, whose importance increases with the initial shock level for both banks and credit unions.

A simplifying – but unrealistic – assumption adopted by SR models is that losses are imposed on creditors proportionally to the loan extended to the debtor under distress. In Chapter

4, we have shown what happens when more realistic assumptions concerning loss distribution by distressed debtors are adopted. According to empirical studies, debtors are more likely to default on fragile creditors. For a Brazilian multilayer credit network (interbank credit network and bank-firm credit network), we showed that SR increases substantially when the heterogeneous loss distribution is adopted. Under this heterogeneous loss distribution rule, creditors are ranked in ascending order according to some criterion (equity, out-degree, loan extended, or randomly). A possible explanation for this is that, when the homogeneous loss distribution is abandoned, the shock transmission effect of the financial network gains relative importance over the risk-sharing effect. A further investigation corroborated this hypothesis. When losses are mostly transmitted to more fragile creditors, the density has a positive impact on SR, which does not happen under the homogeneous loss distribution rule. It suggests that, under the heterogeneous rule, the financial network acts mainly as a shock transmission channel.

It is widely accepted in the literature that shock propagation is driven by the topological features of the financial network. However, little is known about the other way around – i.e., whether the topology of the financial network is affected by shocks. In Chapter 5, we shed some light on this issue. We developed an agent-based model (ABM) in which a bank-firm credit network evolves endogenously according to plausible behavioral assumptions. We then assess how three topological features of the bank-firm network, which are key drivers of shock propagation – density, assortativity, and degree distribution – are impacted by shocks on the base interest rate. Our simulations show that the impact of shocks to the policy interest rate on such topological features of the bank-firm credit network varies quantitatively and qualitatively with the sign, magnitude, and duration of the shocks. For instance, negative shocks to the base interest rate increase the density of the financial network formed by banks and firms and make it more disassortative.

Finally, Chapter 6 deals with the Brazilian network of correlated assets. Bartesaghi *et al.* (2020) derived a new centrality measure called risk-dependent centrality (RDC), which depends on both the topology of the network and the external risk the whole network is submitted to. We computed the RDC for assets traded on the Brazilian stock market between January 2008 and June 2020 at different levels of external risk. We observed that the ranking of assets based on the RDC depends on the external risk. Rankings' volatility is related to crisis events, capturing the recent Brazilian economic-political crisis. Moreover, we computed the RDC employing an empirically computed external risk level, relying on the Emerging Markets Bond Index index. We show that some economic sectors (oil, gas and biofuels, and financial) become more central during crisis periods. Moreover, the volatility of the RDC is positively correlated with the external risk level.

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