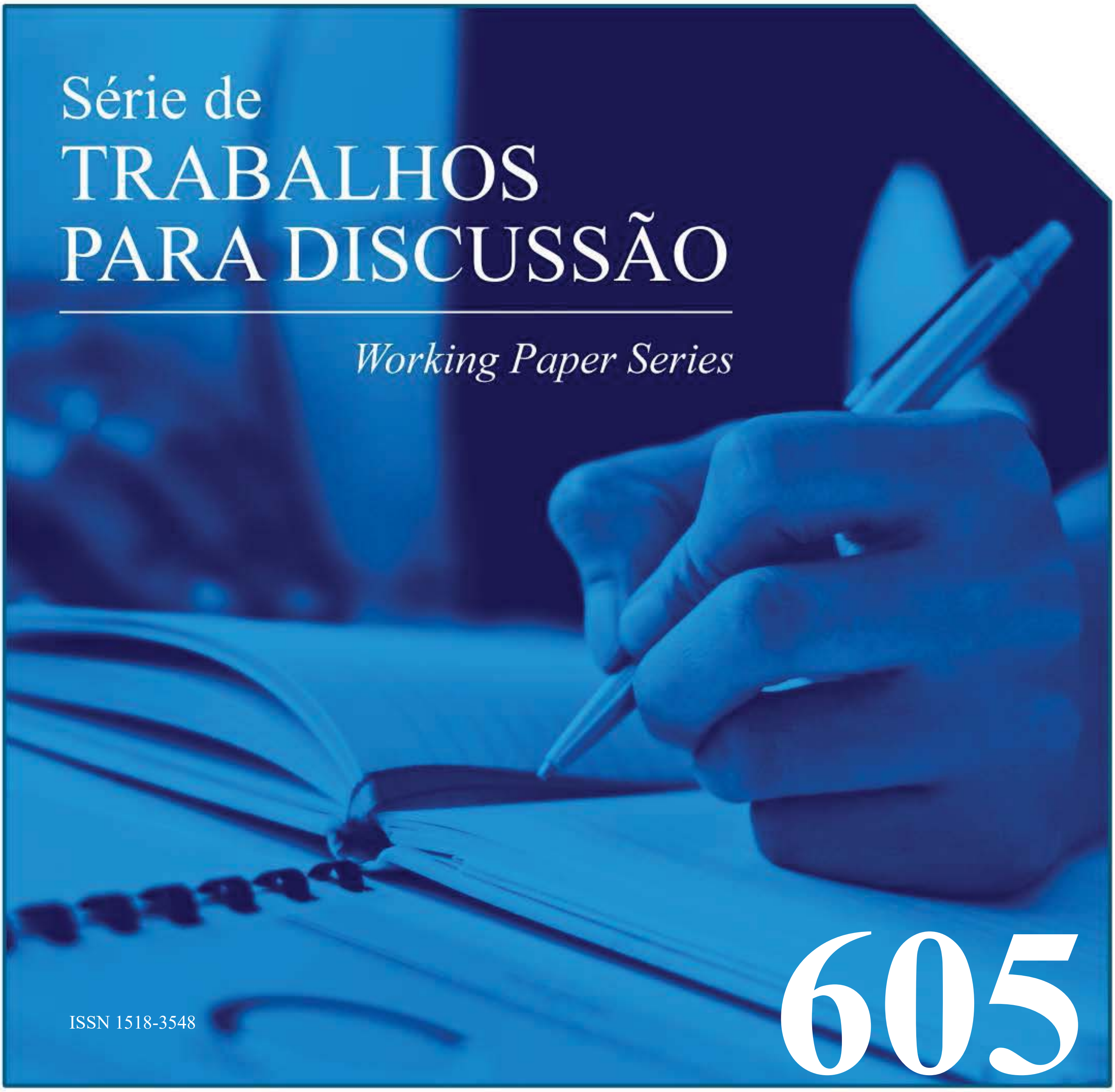

Outubro 2024

Network Analysis of Exchange Rate Shocks: implications for financial stability in Brazil

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BANCO CENTRAL DO BRASIL

ISSN 1518-3548
CGC 00.038.166/0001-05

Working Paper Series	Brasília	no. 605	Outubro	2024	p. 3-49

Working Paper Series

Edited by the Research Department (Depep) – E-mail: workingpaper@bcb.gov.br

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Non-Technical Summary

This study examines how exchange rate fluctuations affect the Brazilian economy, focusing on financial stability. By using a novel network-based framework, this research analyzes data from 2015 to 2022, covering a broad spectrum of financial and non-financial institutions. Our results highlight significant differences in how different sectors respond to exchange rate shocks. For instance, financial institutions generally benefit from a stronger dollar because of their foreign-denominated assets, while non-financial companies, especially those with substantial foreign debt, face considerable losses.

However, the study reveals that the impact of these currency shocks is far more complex than it appears at first glance. Even sectors that initially seem to benefit from the shocks can suffer substantial indirect losses due to their interconnected relationships within the financial network. This underscores the intricate and often unpredictable ways in which risks can spread across the economy, highlighting the importance of the interconnectedness component among economic agents.

One of the key contributions of this research is its ability to map out how exchange rate shocks propagate through the financial system, identifying the specific agents and sectors most vulnerable to these shocks. While certain segments, like development banks and some non-bank financial institutions, are shown to be more susceptible to these risks, the study finds the overall financial system in Brazil remains stable.

In addition to its empirical findings, the study offers a practical methodology for monitoring the resilience of the financial system to exchange rate shocks. Using network analysis, we propose a simple methodology to identify which institutions will most likely propagate risks or serve as shock absorbers. The analysis shows commercial banks play a critical role in diffusing shocks.

The relevance of this research extends beyond academic insights, offering significant implications for policymakers and regulators. By highlighting the importance of considering the network structure of financial relationships, the study suggests regulatory frameworks and stress-testing methodologies should be designed to account for the interconnected nature of financial institutions and their exposures to exchange rate risks. This approach enables a more accurate assessment of potential systemic risks and informs the development of targeted interventions to enhance financial stability.

Overall, this study offers a comprehensive characterization of how exchange rate fluctuations can impact financial stability in Brazil. It provides insights for improving regulatory frameworks, monitoring financial institutions, and enhancing the financial system's resilience. The research is particularly relevant for emerging market economies, where exchange rate volatility can pose significant risks to financial stability.

Sumário Não Técnico

Este estudo examina como as flutuações cambiais afetam a economia brasileira, com foco na estabilidade financeira. Utilizando um novo modelo baseado em redes, a pesquisa analisa dados de 2015 a 2022, abrangendo uma ampla gama de instituições financeiras e não financeiras. Nossos resultados destacam diferenças significativas na forma como diferentes setores respondem a choques cambiais. Por exemplo, as instituições financeiras geralmente se beneficiam de um dólar mais forte devido aos seus ativos denominados em moeda estrangeira, enquanto as empresas não financeiras, especialmente aquelas com dívida externa substancial, enfrentam perdas consideráveis.

No entanto, o estudo revela que o impacto desses choques cambiais é muito mais complexo do que parece à primeira vista. Mesmo setores que inicialmente parecem se beneficiar dos choques podem sofrer perdas indiretas substanciais devido às suas interconexões dentro da rede financeira. Isso ressalta as formas intrincadas e muitas vezes imprevisíveis pelas quais os riscos podem se espalhar pela economia, destacando a importância da componente de interconectividade entre os agentes econômicos.

Uma das principais contribuições desta pesquisa é a capacidade de mapear como os choques cambiais se propagam através do sistema financeiro, identificando os agentes e setores específicos mais vulneráveis a esses choques. Embora certos segmentos, como bancos de desenvolvimento e algumas instituições financeiras não bancárias, mostrem-se mais suscetíveis a esses riscos, o estudo conclui que o sistema financeiro brasileiro como um todo permanece estável.

Além dos resultados empíricos, o estudo oferece uma metodologia prática para monitorar a resiliência do sistema financeiro a choques cambiais. Utilizando a análise de redes, propomos uma metodologia simples para identificar quais instituições provavelmente irão propagar riscos ou atuar como amortecedores de choques. A análise mostra que os bancos comerciais desempenham um papel crítico na difusão dos choques.

A relevância desta pesquisa vai além dos *insights* acadêmicos, oferecendo implicações significativas para formuladores de políticas e reguladores. Ao destacar a importância de considerar a estrutura das relações financeiras em rede, o estudo sugere que os marcos regulatórios e as metodologias de teste de estresse devem ser projetados para levar em conta a natureza interconectada das instituições financeiras e suas exposições aos riscos cambiais. Essa abordagem permite uma avaliação mais precisa dos riscos sistêmicos potenciais e auxilia no desenvolvimento de intervenções direcionadas para melhorar a estabilidade financeira.

No geral, este estudo oferece uma caracterização abrangente de como as flutuações cambiais podem impactar a estabilidade financeira no Brasil. Ele fornece subsídios para a melhoria da regulação financeira, o monitoramento das instituições financeiras e o fortalecimento da resiliência do sistema financeiro. A pesquisa é particularmente relevante para economias emergentes, em que a volatilidade cambial pode representar riscos significativos para a estabilidade financeira.

Network Analysis of Exchange Rate Shocks: implications for financial stability in Brazil

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Abstract

This paper uses a network-based framework to examine the propagation of exchange rate shocks through the economy. We use a comprehensive set of supervisory, granular, and unique datasets from Brazil to construct an economy-wide network of exposures from 2015 to 2022, which includes a representative set of financial institutions, both banking and nonbanking, the corporate sector, and bilateral exposure linkages encompassing credit and funding risks. Our findings reveal significant disparities in how exchange rate shocks impact different sectors. Financial institutions generally benefit from positive exchange rate shocks due to their net foreign-denominated assets, whereas nonfinancial firms incur losses, particularly those with substantial foreign debt. However, contagion effects indicate that even sectors that are initially better off can experience substantial indirect losses, highlighting the complexity of risks in the financial network. Despite vulnerabilities in segments such as development banks and non-bank financial institutions, adequate regulatory capital maintains and supports overall financial stability. These insights underscore the importance of incorporating network structures in regulatory frameworks and stress-testing methodologies, offering crucial implications for policymakers seeking to improve financial stability and mitigate systemic risks.

Keywords: exchange rate, network model, financial stability, credit risk, funding risk.
JEL Classification: F31; C63; G01; G20; G21; G28; O16.

The views expressed in this Working Paper are those of the authors and do not necessarily reflect those of the Banco Central do Brasil.

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1 Introduction

Economies are increasingly interconnected, with exchange rate fluctuations playing an important role in influencing economic stability (Engel and West, 2005; Obstfeld et al., 2010). Financial institutions have developed a complex web of relationships with nonfinancial firms and the wider economy, resulting in calls for comprehensive models that can incorporate these nuances. This paper uses a network-based framework to examine the propagation of exchange rate shocks into the economy, focusing on the consequences of these macroeconomic shocks in terms of short-term financial stability. We use a comprehensive set of supervisory, granular, and unique datasets from Brazil to construct an economy-wide network of exposures, containing a representative set of financial institutions, banking and nonbanking, the corporate sector, and bilateral exposure linkages encompassing both credit and funding risks. With this network, we can provide a more realistic depiction of how exchange rate shocks permeate through the economy and each economic agent's balance sheet, offering valuable insights for policymakers and regulators concerned with maintaining financial stability and identifying vulnerable entities to exchange rate shocks.

Our work connects with the extensive literature that examines how exchange rate shocks affect the economy. Existing research can be categorized into two main areas. In the first, a body of the literature focuses on how different exchange rate regimes are intertwined with macroeconomic performance, including financial fragility (Chang and Velasco, 2000; Engel and West, 2005; Obstfeld and Rogoff, 1995). In the second, research models the transmission of exchange rate effects through representative agents (Devereux and Engel, 2002; Obstfeld and Rogoff, 1998; Sobolev, 2000). While convenient from a mathematical and theoretical viewpoint, this approach may mask the nuances arising from the natural heterogeneity of economic agents and their complex interconnections. Our paper, in contrast, borrows the flexibility of network models to incorporate both the natural heterogeneity of economic agents and their interconnections to examine how exchange rate shocks transmit to the economy, focusing on the financial stability implications of these macroeconomic events.

We build a comprehensive network comprising financial institutions—both banking and nonbanking—within the interbank market and their lending relationships with the corporate sector. This methodological shift aligns with the emerging literature that emphasizes the importance of the network structure as a medium of loss amplification that could lead to financial instability, as seen in the works of Allen and Gale (2000) and Acemoglu et al. (2015). This network complexity is typically absent in existing research examining the consequences of exchange rate shocks. We show stress amplification caused by the network structure can be significantly higher than the initial exchange rate shock, underscoring the importance of models that address the particularities of economic agents' interconnection patterns. Additionally, by employing a network approach, we can track the propagation of exchange rate shocks through the interconnections of economic agents, allowing us to identify agents that would be more or less affected by these macroeconomic shocks. This granular identification is important for policymakers and regulators.

We also contribute to the literature on financial networks by modeling agent-specific exposure to market risk in an integrated framework. Traditionally, network models were limited to analyzing contagion amplification in the interbank market (Battiston et al., 2012b; Eisenberg and Noe, 2001). Following the critique of Glasserman and Young (2015) that highlighted the importance of considering other forms of contagion transmission channels, researchers focused on incorporating other forms of contagion, such as introducing the corporate sector in addition to the interbank market in a unified network model (Silva et al., 2018, 2017a), overlapping portfolios (Poledna et al., 2021), and monetary policy shocks (Silva et al., 2020). Our research complements the existing literature by introducing a new contagion transmission channel: the exchange rate risk channel.

Unlike existing research that analyzes exchange rate shocks in a macroeconomic context, we model exchange rate exposure at the level of individual economic agents. Financial institutions may issue loans, borrow in foreign currencies, and engage in foreign exchange trading and speculative activities. They can also hold foreign currency assets such as bonds and equities, with exchange rate fluctuations affecting the value of these holdings. In contrast, nonfinancial firms face exchange rate risks primarily through foreign currency debt, export and import activities, and operational exposures. Our model includes comprehensive information on foreign exposures of financial and nonfinancial institutions' asset and liability sides. However, due to data unavailability, we only consider nonfinancial firms' liabilities without accounting for their foreign currency assets or hedging activities. This omission distorts the picture of these nonfinancial firms' vulnerabilities by not fully capturing their net foreign exposures. However, it also results in a more conservative estimation of risks from exchange rate shocks, potentially highlighting greater vulnerabilities by excluding mitigating factors such as foreign currency assets and hedging strategies by the corporate sector.

We also contribute methodologically by adjusting the stress propagation mechanism proposed in Silva et al. (2017a) and Silva et al. (2020) to accommodate that economic agents may profit or lose from exchange rate shocks. Exchange rate shocks are positive when the foreign currency appreciates relative to the domestic currency or negative when the opposite occurs. The net effect of an exchange rate shock depends on the economic agent's net position. If the net foreign assets are positive (negative), then the economic agent will gain (lose) from an appreciation of the foreign currency with respect to the domestic currency. We consider a more restrictive approach that allows for a clearer interpretation of the results and the presence of a unique fixed point regardless of the network structure. Economic agents may still receive negative shocks that decrease their net worth when they profit from exchange rate shocks. However, propagation will only occur when the agent migrates to a distressed state, i.e., when its net worth becomes lower than the original. This scheme aligns more with economic reasoning, as the propagation of positive shocks would effectively disseminate stability across economic agents, which is unclear from the financial contagion viewpoint.

Brazil is an interesting case in which to apply our methodology as an emerging country with a relatively open economy. Internal factors, such as economic downturns, political issues and concerns about the long-term sustainability of public debt, could lead to a national currency devaluation. In addition, the Brazilian currency suffers from external economic factors, such as global economic growth slowdown, trade wars, geopolitical conflicts, and the pandemic's effects. As a result, the foreign-to-Brazilian currency exchange rate has high volatility and may have expressive variations. Figure 1 illustrates this. During the Brazilian domestic recession in 2014–2016, and the process that led to the impeachment of the country's president in 2016, the US dollar appreciated almost 50% against the Brazilian Real. The uncertainties due to the COVID-19 pandemic emergence also led to a dollar appreciation.[1] Since then, the R$/US$ exchange rate has had sig-

[1] The World Health Organization (WHO) declared COVID-19 a Public Health Emergency of International Concern (PHEIC) from 30 January 2020 to 5 May 2023. From the beginning of this period to 14 May 2020, the US dollar appreciated from 4.2523 to 5.9372 R$/US$ (39.6%) and continued to fluctuate significantly after that.

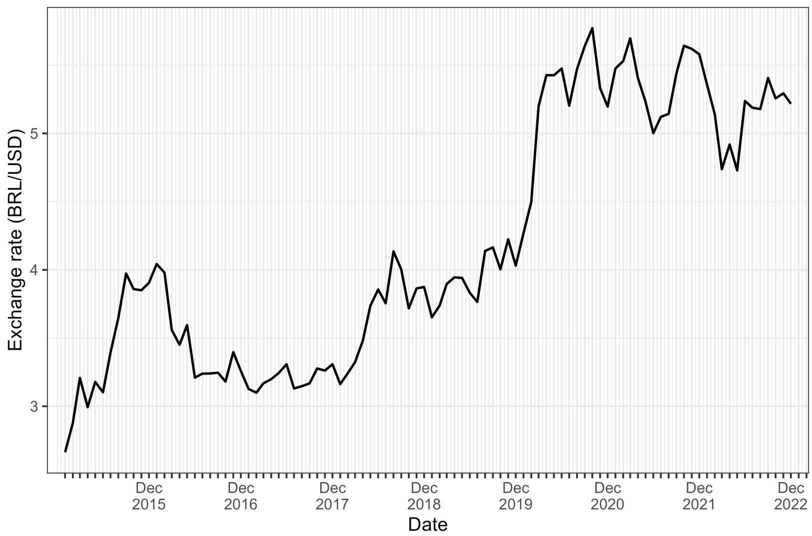


Figure 1: *Monthly R$/US$ exchange rate.*

nificant variations. Our model helps assess the extent to which abrupt changes in the exchange rate can affect the national financial system.

Our empirical results highlight significant disparities in the impact of exchange rate shocks in different sectors. While financial institutions preponderantly benefit from positive exchange rate shocks due to their net foreign-denominated assets, nonfinancial firms incur losses, especially those with substantial foreign debt. However, contagion effects reveal that even sectors that appear better off from initial shocks can experience substantial indirect losses, indicating a complex interplay of risks across the financial network. The study further establishes that while certain segments like development banks and some non-bank financial institutions are more vulnerable to these risks, overall financial stability is sound since regulatory capital is adequate to absorb such shocks. In conclusion, these findings are important for policymakers when designing targeted interventions to reduce financial instability.

We also propose a simple methodology to monitor financial system resilience to exchange rate shocks, which is crucial for regulatory frameworks aiming at ensuring stability. Leveraging network analysis, we assess economic agents' roles in shock amplification and propagation alongside their vulnerability to interconnected exposures. Our method can identify distinct and complementary roles: relevant institutions in terms of shock diffusers and shock receivers. Our findings reveal the commercial segment in the financial system has a high diffusion potential, especially during 2022, but relatively contained average impacts per lender. However, they have low shock susceptibility due to high capitalization. This nuanced understanding guides targeted regulatory interventions, integrating metrics to enhance proactive financial stability assessments and fortify against the impact of exchange rate volatility.

Our work is relevant because it enables a detailed understanding of the transmission mechanisms of financial effects of exchange rate shocks throughout the economy. By incorporating the heterogeneity of economic agents and their complex interconnections, our model offers a detailed and realistic depiction of how such shocks propagate through financial networks, highlighting vulnerabilities that traditional representative agent models overlook. This granular approach allows for identifying specific agents and sectors most susceptible to exchange rate fluctuations, providing crucial insights for policymakers and regulators.

From a policy perspective, our findings underscore the importance of considering network structures in the design of regulatory frameworks and stress-testing methodologies. The significant amplification of stress within financial networks suggests macroprudential policies should account for the interconnected nature of financial institutions and their exposures to exchange rate risks. In doing so, regulators can better anticipate potential systemic risks and implement targeted interventions to improve financial stability. Additionally, the ability to trace the contagion pathways of exchange rate shocks through the economy aids in formulating policies that mitigate the adverse effects on both financial and nonfinancial sectors, thereby safeguarding economic stability. These practical implications of our research are crucial for policymakers and regulators in their efforts to maintain financial stability.

2 Related Literature

This paper bridges two strands of literature: the impact of exchange rate shocks on firms' balance sheets and financial contagion through a network of economic agent exposures. While previous research has extensively examined these areas independently, we connect them using a network-based framework to analyze how exchange rate shocks propagate through individual financial interconnections. This approach offers a more comprehensive understanding of the systemic risks posed by exchange rate fluctuations while also allowing the identification of agents more prone to contagion risks arising from exchange rate shocks, apart from the usual initial shock in their balance sheet.

The literature on exchange rate shocks is extensive. We focus on the research most closely related to this paper: the direct effects of currency shocks on the balance sheets of firms and banks in emerging markets. Currency devaluations influence firms' investment decisions, subsequently affecting loan demand. Bonomo et al. (2003) show exchange rate shocks in Brazil from 1990 to 2001 negatively impacted firms' investment decisions and cash flows. Similarly, Aguiar (2005) examines the 1994 Mexican peso crisis, finding firms with substantial short-term foreign currency debt reduced their investment levels following devaluation. Caballero (2021) corroborates these findings, analyzing data from 15 emerging market countries from 2010-2015 and finding currency depreciation decreases firm investments.

Exchange rate shocks can also affect stock markets. Santillán-Salgado et al. (2019) use a panel of five Latin American countries from 2009 to 2016 and find exchange rate depreciation is associated with lower market returns for listed stocks. Bebczuk et al. (2010) use a panel of 57 countries to show the aggregate effects of currency devaluation on balance sheets can affect the macroeconomy.

Additionally, the amplification of losses from currency devaluations through balance sheets has been well-documented. Krugman (1999) and Céspedes et al. (2004) study how balance sheets amplify losses from currency devaluations. Abbassi and Bräuning (2023) use the 2016 Brexit referendum and subsequent British pound depreciation as a natural experiment to study its impact on the German financial system, finding it affected both firms and banks, leading to a credit contraction. Our paper complements these studies by showing how the network structure can amplify the effects of exchange rate shocks beyond individual balance sheets.

Research also highlights the potential for currency depreciation to exacerbate financial instability. Aghion et al. (2001, 2004) show currency depreciation affects the net worth and borrowing capacity of firms, potentially leading to further depreciation and loss of production, leading to a currency crisis. Schneider and Tornell (2004) show credit and exchange rate risks can arise endogenously and reinforce each other. Niepmann and Schmidt-Eisenlohr (2022) indicate how foreign currency exposures increase credit risk for banks. Our study builds on these insights by modeling the dynamic feedback mechanisms within a network framework, providing a more comprehensive view of potential financial instability.

The literature on financial contagion through interbank loans begins with the seminal paper by Allen and Gale (2000), analyzing how different network structures affect the spread of financial contagion. Early developments focus on interbank claims, as seen in Gai et al. (2011), Nier et al. (2007), and Georg (2013). Battiston et al. (2012a) introduce the DebtRank measure for analyzing financial distress spread, further developed by Bardoscia et al. (2015). Caccioli et al. (2017) provide a comprehensive overview of such models. Our research extends these models by integrating exchange rate shocks into the analysis of financial contagion within the network.

Expanding the scope of contagion models, Elliott et al. (2014) and Acemoglu et al. (2015) introduce more general economic network models than financial claims. Elliott et al. (2014) analyze contagion through cross holdings, while Acemoglu et al. (2015) provide a framework for evaluating the macroeconomic state of an economy by aggregating the microeconomic state of agents in a network. Our study expands this approach by focusing on how exchange rate shocks can propagate through these networks, affecting the macroeconomic state.

This paper aligns with the literature on multi-layered financial networks, as our model is based on Silva et al. (2020, 2017a). Cifuentes et al. (2005) examine how asset value losses through mark-to-market accounting can lead to increased liquidity demand from banks, causing financial contagion through interbank loans. Aoyama et al. (2013) extend the DebtRank measure to firms in a bivariate loan network. Ding et al. (2017) analyze contagion through a two-layered financial network: the standard interbank layer and an information layer. Our work further develops these multi-layered models by introducing exchange rate risk as an additional layer of analysis.

The connection between macroeconomic trends and financial networks is also explored. Gao et al. (2022) connect macroeconomic trends to a financial network with two layers: an interbank layer and a layer connecting banks and firms. In this model, macroeconomic trends affect firms, which in turn impact banks both directly and indirectly. Our research builds on this by analyzing how exchange rate shocks as a macroeconomic trend impact the financial network, providing a more detailed and dynamic understanding of these interactions.

3 Methodology

This section discusses the methodology to evaluate the resilience of the Brazilian financial system to exchange rate shocks. The framework we present here is built on top of those proposed in Silva et al. (2020, 2017a), which, in turn, extend Battiston et al. (2012b) and Bardoscia et al. (2015). Roughly speaking, from the point-of-view and scope of our paper, Battiston et al. (2012b) and Bardoscia et al. (2015) propose and enhance the stress propagation mechanism in a network model in which agents have mutually exposed balance sheets and receive an exogenous shock, which enters the model as a net worth loss. Silva et al. (2017a) and Silva et al. (2020) study an economy with different types of agents and exposures using this mechanism to study stress amplification processes in real-world settings. The process defined here is built on top of the foundations provided by these papers.

Before proceeding, it is important to clarify the term *resilience* with the previously used term *stress*, defined as the ratio of loss to the capital of a given economic agent or group of economic agents. When computing stress for a group of agents (which is extensively done in our discussion of the results), we sum up the losses of each agent in the group and divide by the group sum of capitals. Resilience is the opposite of stress: if stress after a shock is high, then resilience is low, and vice-versa. Then, if we define that stress varies from 0% (zero – undistressed) to 100% (default), the corresponding interval for resilience would be from 100% to 0% (zero). In this case, an agent close to defaulting with stress equal to 90% would show a resilience of 10%. Although it is important to interpret stress in terms of the resilience of an agent, group of agents, or the entire economy, we use the term *stress* throughout this paper to maintain consistency with the existing literature.

Another important reason we do not emphasize the term *resilience* despite its inference from stress is that the DebtRank methodology measures stress only after an initial loss. DebtRank computes additional stress from a given shock and does not provide a stress measure for financial systems that have not experienced losses. For example, consider two financial systems with the same financial exposures, where in one system, each agent has three times more capital than in the other. The more capitalized system is more resilient, regardless of external shocks. However, without an external adverse shock, DebtRank cannot compare their resilience: they would be equal in the methodology. DebtRank's stress measure is relative, not absolute. Thus, while it is not possible to directly compare the resilience of two financial systems (or the same system under different conditions), it is possible to compare them indirectly by observing which system becomes more stressed after a shock. This is useful, as it allows us to say an economy is resilient to a particular shock if the resulting total stress is within an acceptable range, indicating the financial system's soundness in that specific shock. Therefore, we evaluate the resilience of a financial system *to a given shock*, which aligns with the stress computation described below.

3.1 Overview: agents, time scale and exogenous shocks

The economy for which we evaluate stress comprises a group of heterogeneous economic agents spanning various economic sectors and roles within the financial system. We evaluate an economy formed by financial institutions and nonfinancial firms comprising the financial and corporate sectors. However, our model does not incorporate the sector's inputs, outputs, and human resources. Instead, it analyzes only monetary quantities and relationships among agents within the financial system, thus providing a financial system analysis. This analysis is performed at a specific point in time, meaning the network structure and state of agent data reflect only the conditions at the time of analysis. Additionally, the exogenous shock that initiates the stress propagation process affects agents simultaneously, with stress propagation occurring on a shorter time scale than that of network changes. Therefore, our conclusions are valid for the short term only.

Our model evaluates the buildup of stress in an economy in response to exogenous exchange rate shocks. The proposed framework translates these shocks into changes in net worth for individual agents in case of any exposures. Specifically, exchange rate shocks can impact agents exposed to foreign currencies, whether as assets or liabilities, leading to gains or losses that, after mark-to-market adjustments, affect the agent's net worth. These gains or losses serve as the initial shock that triggers the contagion process in the model. We highlight that the framework for exchange rate shocks can be adapted to any exposure arising from market risk.

3.2 Model structure

Using a network model, we evaluate the effects of exchange rate shocks on systemic risk in a financial system. The financial system is represented as a network of interconnected balance sheets, where pairwise exposures link the financial health of one agent to others. Initially, we assume the system is in equilibrium, with all agents able to meet their obligations and no stress propagation occurring. The initial shock, a single event in time, simultaneously impacts the financial health of a group of agents, causing changes in their financial stability. These changes trigger stress propagation to connected agents until a new equilibrium is reached. The stress levels of agents in this new equilibrium are then used to compute systemic risk conditional on the initial shock.

3.2.1 Core model

Our model is built on the baseline framework provided by the DebtRank model (Bardoscia et al., 2015; Battiston et al., 2012b) and the feedback additions of Silva et al. (2017a) and Silva et al. (2020). An important issue of Battiston et al. (2012b)'s original model was that it could underestimate stress evaluation, as its stress propagation simulation blocks second- and high-order rounds of impact diffusion that occur when the network has cycles. Bardoscia et al. (2015) addressed that issue by allowing banks to propagate stress increments at each interaction to fully attain the final equilibrium stress for each agent.

Our model relies on this previous research and uses the same definitions, intuitions, types of information, and propagation process. This framework has a methodology based on these key definitions:

1. *Stress*: The concept of stress reflects the financial health of an agent and ranges from 0 to 1. An agent is undistressed when they have a positive net worth and have not incurred losses before the shock. Stress is measured as the ratio of incurred losses to capital. If losses equal capital, the agent defaults (capital becomes zero after accounting for losses), and stress reaches 1. Stress is capped at 1, even if losses exceed capital. In essence, stress measurement requires comparing losses against an undistressed state and the agent's net worth.

2. *Stress propagation*: Stress propagation involves iterative steps. In each iteration, the methodology checks if any agent has additional losses compared to the previous iteration. If so, the methodology calculates the corresponding stress level and the amount that the agent will not be able to repay creditors, imposing losses on these creditors in the subsequent iteration. This process continues until the network stabilizes at an equilibrium of incurred losses by its agents.

   To determine the amount of debt not repaid due to stress, the methodology assumes an undistressed agent can fully meet their debt obligations. In contrast, a defaulted agent cannot repay any debt. If in a given time t, an agent's stress level is below 1 (not in default), the methodology considers its repayments are proportional to $(1 - stress)$. The unpaid amount, represented by $debt \times stress$, becomes an additional loss on its creditors in the subsequent iteration $t+1$.

Our model is grounded in this established framework. Our approach involves simplifying a complex array of agents, exposure types, interactions, and external shocks into a format suitable for stress propagation calculations using the DebtRank framework. Additionally, we introduce an enhancement to the DebtRank propagation process. Specifically, we ensure that agents who have gained do not have their debts increased beyond their original amounts, aligning more closely with real-world scenarios. In the following sections, we will elaborate on these contributions in detail.

3.2.2 Financial system modelling

We model the financial system in a multilayer network setting. Vertices of each network layer are economic agents from a specific economic sector (financial institutions or nonfinancial firms, in our case). Links between economic agents represent financial exposures to counterparty or funding risk. Our model has two layers: the financial sector and the corporate sector. Financial institutions are the vertices in the financial sector, and nonfinancial firms are the vertices in the corporate sector.

3.2.3 Exposure to exogenous changes in the exchange rate

In this model, economic agents are exposed to exogenous market risk, specifically to changes in the exchange rate compared to the current exchange rate at the time of evaluation. Before these changes, the financial system network is in equilibrium and undistressed. In this state, we simulate a sudden change in the exchange rate (the initial shock), which simultaneously affects all the network agents. This shock triggers the stress propagation process. In our model, only one exogenous shock occurs: the initial shock.

Exchange rate fluctuations generate shocks that affect network agents as follows. Financial institutions or nonfinancial firms will experience changes in the market value of these exposures if exposed to foreign currency-denominated debt or assets. We assume these exposures are marked-to-market, and losses and gains are immediately accounted for in the profit and loss account, impacting the economic agent's net worth. This net worth impact on each agent is the initial shock in our model.

Network agents may be exposed to many foreign currencies, including the US Dollar. In our data sources, these exposures are aggregated and denominated in Reais. For our study, we simulate exogenous changes in the USD/BRL exchange rate, representing the value of 1 US Dollar in Brazilian Reais. This approach is rooted in the predominance of dollar-denominated foreign assets and liabilities among network agents.

Next, we describe how the different economic agents are exposed to exchange rate shocks. Financial institutions are significantly exposed to exchange rate risks through various channels. They may issue loans or borrow in foreign currencies. Some financial institutions specialized in investment may also engage in foreign exchange trading and speculative activities, where adverse exchange rate movements can result in substantial trading losses. They can also hold foreign currency assets such as bonds and equities, and fluctuations in exchange rates can impact the value of these holdings. In contrast, nonfinancial firms face exchange rate risks primarily through foreign currency debt, export and import activities, and operational exposures. Domestic currency depreciation increases the domestic currency value of the debt, raising firms' debt servicing costs and financial distress. Exporters benefit from a depreciated domestic currency due to increased international competitiveness, whereas importers suffer from higher raw materials and components costs, squeezing profit margins. Firms with substantial foreign revenue face variability in earnings arising from the exchange rate risk volatility. Additionally, international supply chains expose firms to exchange rate risks, influencing input costs and final product prices. Unlike financial institutions, nonfinancial firms often have less sophisticated risk management practices for handling exchange rate risks.

3.2.4 Exposures to contagion

After receiving the initial shock, a network agent may experience an increase in net worth (if the exchange rate variation leads to a gain after mark-to-market adjustments) or a decrease (loss). If an agent gains, no stress propagation occurs, as we will see later. In case of a loss, this will trigger a contagion propagation process. The basics of this process are a pair of agents in which at least one is exposed to the other. In this paper, we detail the main types of pairwise exposures between the different types of agents that we consider in the contagion propagation process, following mostly Silva et al. (2017a). These exposures can be interpreted as standard contagion exposures and used to evaluate the financial system's financial stability.

In our model, we include financial institutions and nonfinancial firms. Despite the information required for both types of agents being the same, their capital (net worth) and bilateral exposures, their role in the financial system and the nature of the financial exposures are distinct. Financial institutions are exposed to other financial institutions in the interbank market and to nonfinancial firms in the traditional credit market through unsecured lending operations, giving rise to counterparty risk. Nonfinancial firms are exposed to funding risk if the financial sector is unwilling to roll over short-term debt due to financial distress. The counterparty and funding risk channels between the financial and corporate sectors originate a stress feedback mechanism between both sectors, similar to the Bernanke et al. (1999)'s financial accelerator concept but in a network environment.

When modeling financial contagion, we consider two types of risk: counterparty risk and funding risk. Counterparty risk in this model is the same as uncollateralized credit risk. The debtor agent issues a debt instrument to a creditor agent with an expected repayment cashflow. Until the instrument matures, the creditor is exposed to the debtor in the outstanding amount of the instrument. The risk incurred by the creditor is that the debtor is stressed and cannot make the payments due. The creditor agent is exposed to the stress of the debtor agent by the debtor's liability amount. Funding risk is different. Suppose we have an exposure of a creditor agent to a debtor maturing soon, and the debtor counterparty decides to roll over its short-term debt. The creditor counterparty might be expecting to receive cash and will not receive it, which may lead him to incur liquidity issues. Thus, to prevent liquidity problems, the creditor counterparty performs precautionary hoarding and requires the debtor to repay its short-term debt partially or in full. Thus, the risk incurred by the debtor is that the creditor is stressed and requires a partial or full repayment from the debtor when he was not prepared to do so. The debtor agent is exposed to the stress of the creditor by the short-term liability amount.

The economic rationale for stress propagation is as follows. For counterparty risk, economic agents reprice down investments solely based on debtors' net worth variation (creditworthiness) in a linear fashion. Economic agents update their balance sheets with changes related to fluctuations in the default probability of their debtors. These default probabilities are estimated since each creditor monitors its investments. We assume a creditor is able to measure or at least estimate the stress related to the net worth conditions of its debtors. Suppose the creditor sees a decrease in one of its debtors' net worth. In that case, the creditor will reprice down its investments toward that debtor to reflect the new increased default probability due to a deteriorated credit quality. That creditor will see a decrease in the value of these investments and will update its balance sheet with a reduction in its net worth. In the next step of stress propagation, it will be the time for the creditors of the creditor mentioned in the beginning to monitor their debtors and repeat this process.

For funding risk, financial interconnections are rationalized by agents' precautionary liquidity hoarding as they approach insolvency. The hoarding is operationalized as a credit crunch, in which creditors do not roll over outstanding short-term credit to their debtors. The extent of the agent's liquidity hoarding is negatively related to its distance to insolvency. This distance to insolvency is given by the agent's stress. Suppose that $\mathbf{L}_{ij}$ is the outstanding short-term liability of debtor i towards creditor j. The potential cash outflow in the short term from i to j will be in the range from 0 to $\mathbf{L}_{ij}$. If creditor agent j is undistressed, it fully rolls over the credit to i, and no lack of liquidity exposure occurs in the short term. On the other hand, if j is fully stressed and defaults, then it does not roll over any credit. Consequently, i must repay its debt in full in the short term. Having to pay back a debt does not make the debtor i incur any losses in itself, as it would occur in the case of a counterparty risk, but may produce a loss under some circumstances. To take this into account, instead of considering as risk exposure the full debt, as we do for counterparty risk, we consider the risk exposure is given by part of the debt $\mathbf{L}_{ij}$, given by $\alpha_{ij}\mathbf{L}_{ij}$, in which $\alpha \in [0,1]$, so that only part of the computed liquidity constraint is converted to loss. α_{ij} depends on, for instance, the liquidity conditions of debtor i and creditor j and on the ability of economic agent i to replace the funding counterparty j with another one. Finally, although our model provides infrastructure for estimating losses from funding risk in an adequate fashion, we are adopting $\alpha_{ij} = 1$ in this study.[2]

3.2.5 Stress propagation process

We treat financial institutions and nonfinancial firms indistinctively as economic agents. Our model evaluates stress from exchange rate shocks on a single date. The shock occurs at the date and triggers a propagation process that is a dynamic system that may take several iterations before converging. Although the propagation process is not instantaneous, we say the computation is performed on a single date as the time-lapse of propagation is much shorter than the time in which the relevant variables and the interconnections in the network change.

We note as t the current iteration of the dynamic system. We assume $t = 0$ represents the economy's state before the exchange rate shock. At $t = 1$, the exchange rate abruptly changes, leading to immediate changes in net worth for economic agents with open net exposures to exchange rate risk. 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 the network. Hence, the dynamic system is a contracting map, converging to a fixed point. In other words, the final equilibrium of agents' stresses exists and is unique.

The balance sheet of economic agent i at iteration t consists of three elements: assets $\mathbf{A}_i(t)$, liabilities $\mathbf{L}_i(t)$, and net worth $\mathbf{E}_i(t) = \mathbf{A}_i(t) - \mathbf{L}_i(t)$. The economic agent defaults at t when $\mathbf{E}_i(t) \leq 0$. We decompose net worth losses of economic agent i up to iteration t by using a differential version of the fundamental accounting equation:

$$\Delta\mathbf{E}_i(t) = \Delta\mathbf{E}_i^{(\mathrm{ct})}(t) + \Delta\mathbf{E}_i^{(\mathrm{f})}(t) \tag{1}$$

[2] This will overestimate losses and stresses. However, this overestimation will not be relevant due to the relatively small exposures related to counterparty risks and the fact that only nonfinancial firms may be exposed.

in which $\Delta\mathbf{E}_i^{\text{(ct)}}(t)$ and $\Delta\mathbf{E}_i^{\text{(f)}}$ indicate potential losses due to counterparty risk and funding risk, respectively. As explained in Section 3.2.4, Silva et al. (2017a) rationalize counterparty risk losses in this stress propagation mechanism due to the marked-to-market downward repricing of assets held against debtors within the network that lost net worth. They show that:

$$\Delta\mathbf{E}_i^{\text{(ct)}}(t+1) = \sum_{j \in \mathscr{A}(t-1)} \frac{\mathbf{A}_{ij}^{\text{(in)}}(0)}{\mathbf{E}_j(0)} \left[\mathbf{E}_j(t) - \mathbf{E}_j(t-1)\right] \tag{2}$$

in which $\mathbf{A}_{ij}^{\text{(in)}}(0)$ and $\mathbf{E}_j(0)$ are exogenous variables representing the initial exposure of i to j and the net worth of j, respectively. Exposure here is the amount of credit issued by the lender. The term $\mathscr{A}(t-1)$ indicates the set of economic agents that have not defaulted until iteration $t-1$.

Silva et al. (2017a) model funding risk from nonfinancial firms' inability to rollover short-term debt issued by financial institutions. They show variations in net worth due to funding risk can be written as:

$$\Delta\mathbf{E}_i^{\text{(f)}}(t+1) = \sum_{j \in \mathscr{A}(t-1)} \frac{\alpha_{ij}\mathbf{L}_{ij}^{\text{(in-st)}}(0)}{\mathbf{E}_j(0)} \left[\mathbf{E}_j(t) - \mathbf{E}_j(t-1)\right], \tag{3}$$

in which $\mathbf{L}_{ij}^{\text{(in-st)}}(0)$ is the initial short-term liabilities of the nonfinancial firm i to the financial institution j and $\alpha_{ij} \geq 0$ modulates the funding risk arising from the short-term liability.

Denote as $\mathbf{s}_i(t)$ the financial stress of economic agent i in iteration $t \geq 0$, which is the fraction of losses (or gains) with respect to its initial net worth, i.e.:

$$\mathbf{s}_i(t) = \frac{\mathbf{E}_i(0) - \mathbf{E}_i(t)}{\mathbf{E}_i(0)}. \tag{4}$$

When the exchange rate shock occurs at $t = 1$ and in subsequent periods, the economic agent can face four states:

$$state_i(t) = \begin{cases} \text{Better off,} & \text{when } s_i(t) < 0, \\ \text{Undistressed,} & \text{when } s_i(t) = 0, \\ \text{Distressed,} & \text{when } 0 < s_i(t) < 1, \\ \text{Defaulted,} & \text{when } s_i(t) = 1. \end{cases} \tag{5}$$

At every iteration t, each economic agent i faces shock transmission from its distressed counterparties j as follows:

$$\mathbf{s}_i(t+1) = \min \left[1, \mathbf{s}_i(t) + \sum_{j \in \mathscr{S}} \mathbf{V}_{ij}(\text{AS}) \Delta \mathbf{s}_j^+(t) + \mathbf{V}_{ij}(\text{LS}) \Delta \mathbf{s}_j^+(t) \right], \tag{6}$$

in which $\mathscr{S}$ is the set of all economic agents, $\mathbf{V}(\text{AS})$ and $\mathbf{V}(\text{LS})$ are the vulnerability matrices that encode how financial contagion propagates from each economic agent's asset and liability sides, and $\Delta \mathbf{s}_j^+(t)$ is the net worth reduction (as a share of the initial value) of the counterparty j if it is in the distressed state. Mathematically, it is given by:

$$\Delta \mathbf{s}_j^+(t) = \max \left[0, s_j(t) \right] - \max \left[0, s_j(t-1) \right]. \tag{7}$$

Effectively, Equations (7) combined with (6) only allow for shock propagation from economic agent j proportional to the amount of the net worth reduction after it reaches the distressed state. Consider that $s_j(t) = -0.1$ and $s_j(t+1) = 0.2$. The economic agent j will not propagate stress until it crosses the 0 (undistressed state) mark. Therefore, between iterations t and $t+1$, it will only propagate $\max(0, 0.2) - \max(0, -0.1) = 0.2$, which represents the net worth reduction it experienced after entering the distressed state. This flexible scheme allows the "better off" state to preclude shock propagation while permitting shock absorption from its counterparties.

We highlight important differences regarding our shock propagation rule and existing research, such as in Silva et al. (2017a) and Silva et al. (2020). In the first, the authors only consider shocks that reduce economic agents' initial net worth, which is a usual assumption when dealing with systemic risk measurement in a contagion context. In this case, shocks are typically idiosyncratic defaults, credit downgrades, or economic downturns. In the second, the authors permit shocks that increase or decrease the economic agents' initial net worth but in a different context: the transmission of monetary policy shocks. In their shock propagation scheme, stress can propagate as long as the economic agent's net worth from one iteration to the other decreases, irrespective of its current state. In this work, we consider a more restrictive approach that allows for a clearer interpretation of the results and the presence of a unique fixed point: shocks can only propagate when economic agents are distressed. When they are in a "better off" state, they may receive negative shocks that decrease their net worth.[3] However, propagation will only occur when the agent migrates to a distressed state. This scheme aligns more with economic reasoning, as the propagation of positive shocks would effectively disseminate stability across economic agents, which is unclear from the financial contagion viewpoint.

We follow Silva et al. (2017a) and define $\mathbf{V}(\text{AS})$ and $\mathbf{V}(\text{LS})$ as follows:

$$\mathbf{V}_{ij}(\text{AS}) = \frac{\mathbf{A}_{ij}^{(\text{in})}(0)}{\mathbf{E}_i(0)}, \tag{8}$$

$$\mathbf{V}_{ij}(\text{LS}) = \frac{\alpha_{ij}\mathbf{L}_{ij}^{(\text{in-st})}(0)}{\mathbf{E}_i(0)}. \tag{9}$$

We allow the dynamic system to iterate until the Frobenius norm of stress changes from the previous iterations is below a certain positive threshold, after which we say the equilibrium has been reached:

$$\|\mathbf{s}(t) - \mathbf{s}(t-1)\|_F < \varepsilon \tag{10}$$

in which $\mathbf{s}(t)$, $\mathbf{s}(t-1)$ are the stress vectors in iterations t and $t-1$, given by $\mathbf{s}(t)$, $\mathbf{s}(t-1)$: $s_i^+(t), s_i^+(t-1), i \in \mathscr{S}$, $\mathscr{S}$ is the set of all economic agents, and ε is a positive threshold.

[3] Note that economic agents will receive negative shocks only by construction since the shock propagation is limited to originate from distressed agents.

We evaluate systemic risk in terms of the aggregate net worth loss experienced by economic agents after equilibrium has been reached, say, at iteration $t = t_e$. Then, the systemic risk SR arising from the exchange rate shock is:

$$SR = \sum_{i \in \mathscr{S}} \mathbf{s}_i(1)\mathbf{E}_i(0) + \sum_{i \in \mathscr{S}} \left(\mathbf{s}_i(t_e) - \mathbf{s}_i(1)\right)\mathbf{E}_i(0) = SR_{\text{exchange rate}} + SR_{\text{contagion}}, \tag{11}$$

in which $SR_{\text{exchange rate}} = \sum_{i \in \mathscr{S}} \mathbf{s}_i(1)\mathbf{E}_i(0)$ and $SR_{\text{contagion}} = \sum_{i \in \mathscr{S}} \left(\mathbf{s}_i(t_e) - \mathbf{s}_i(1)\right)\mathbf{E}_i(0)$. Both $SR_{\text{exchange rate}}$ and $SR_{\text{contagion}}$ are in monetary values. The net worth loss due to contagion is associated with the initial exchange rate shock. Conceptually, while the net worth loss due to the exchange rate shock directly impacts economic agents' balance sheets through immediate marked-to-market accounting, the net worth loss due to contagion is the additional impact transmitted through the financial interconnections.

In our empirical results, we show systemic risk results as the capital-weighted stress average, as this gives the idea of how close to default the whole system, the segment, or a group of agents is. These stress measures can be referred to as the total net worth (capital) losses by specific economic system's segments as a share of the segment's total net worth for the group of agents considered. These stress measures, for the initial shock and after contagion are given by:

$$S^I_{\mathscr{G}} = \frac{\sum_{i \in \mathscr{G}} \mathbf{s}_i(1)\mathbf{E}_i(0)}{\sum_{i \in \mathscr{G}} \mathbf{E}_i(0)}, \tag{12}$$

$$S^C_{\mathscr{G}} = \frac{\sum_{i \in \mathscr{G}} \left(\mathbf{s}_i(t_e) - \mathbf{s}_i(1)\right)\mathbf{E}_i(0)}{\sum_{i \in \mathscr{G}} \mathbf{E}_i(0)}. \tag{13}$$

in which $S^I_{\mathscr{G}}$ and $S^C_{\mathscr{G}}$ are stress measures computed for the group $\mathscr{G}$ of agents, be the group all of the economic agents, a segment, an economic sector, etc. The superscript I stands for the initial shock (exchange rate shock), and C stands for contagion in the final equilibrium. These stress measures are the same as the "Loss (% capital)" measures reported in Section 5.

4 Data

Our methodology requires data on the economic agents' balance sheets and their mutual exposures to compute stress propagation in the financial system in a given month. To incorporate the effects from exogenous sources of market risk, such as changes in the exchange rate,[4] it is necessary to translate these shocks into changes in the agents' balance sheet variables. To this end, the methodology uses the exposures to these shocks computed from account balances in the balance sheet. Roughly speaking, these exposures are foreign currency assets or liabilities converted to the domestic currency (Brazilian Reais – BRL).

At the time of the data used in this research, there was an issue concerning hedging exchange rate exposures in Brazil. Gains and losses on foreign assets from fluctuations in exchange rates were not recognized for income tax purposes, whereas gains and losses on domestic derivatives used to hedge foreign exposures were recognized for income tax purposes. This discrepancy resulted in an imperfect hedge, requiring an overhedge in domestic positions to offset taxes. Operationally, this setup achieved a perfect hedge in accounting terms: gains in derivatives were taxed, and losses provided tax credits. For instance, with a 15% income tax rate and a 100 USD foreign asset, a 117.65 USD hedge was required. A 10% drop in the USD value led to a 10 USD loss in the foreign asset and a 11.77 USD gain in the derivative, taxed at 15%, resulting in a net gain of 10 USD after 1.77 USD taxes. While this approach was perfect from an accounting perspective, it impacted regulatory capital, as tax credits were excluded. From an exposure standpoint, there remained an unhedged position. Due to its lack of impact on accounting, these exposures were not included in the study. This rule is no longer applicable, as gains and losses on foreign assets are now recognized for income tax purposes.

4.1 Data sources and application

This section describes the data sources our methodology requires.

We use three types of data:

- Economic agents data, corresponding to end-of-month balance sheet data (total assets, cap-

[4]The methodology could be adapted to study the effects of similar market risks, such as the shocks on the monetary policy interest rate, provided that it is possible to obtain data on exposures to these risks.

ital) of agents and meta-information of agents, such as type of agent, type of financial institution (if it is an FI), economic sector, and industry (for firms).

- Mutual end-of-month exposures among agents, such as bank credit issuances to firms or interbank market operations between financial institutions. These exposures are aggregated for each pair (lender, borrower) regardless of the type of instrument or time to maturity, as the methodology only uses information on total bilateral exposures for each point in time.

- Exposures to the external exchange rate shock, corresponding to end-of-month and dollar-denominated assets and liabilities. We define a positive (negative) exchange rate shock as the appreciation (depreciation) of the dollar (USD) relative to the local currency (in the case of Brazil, BRL). These shocks are denominated in percentual terms of the current observed exchange rate. That is, if 1 USD = 5 BRL, after a +10% shock, the exchange rate will be 5.50 R$/US$.

These data are extracted from proprietary databases maintained by the Central Bank of Brazil, which are as follows:

- Entities of Interest to the Central Bank of Brazil (Unicad). We extract from this dataset meta-information of financial institutions, such as type of control, size, and prudential segment;

- Consolidated financial statements from the Accounting Plan of the Institutions of the National Financial System (Cosif). We extract from this dataset balance sheet information at the institution level;

- Nonfinancial companies (NFCs) database, encompassing public and non-public, accounting and non-accounting information from more than 42 thousand accounting entities (see Docha and Rodrigues (2023) for more detail). We extract NFC's meta-information and balance sheet information required by our methodology, including foreign debt.

- Credit Information System (SCR). We extract from this dataset credit operations granted by financial institutions to the firms in the network, aggregating for each pair (lender, borrower) the outstanding amount issued and the credit cashflow with time-to-maturity until 90 days;

- Interfinancial exposures database. From this dataset, we extract the aggregated exposures for pairs of financial institutions (lender and borrower). We do not net out the bilateral exposures as it would reduce the stress measure of the financial institutions in the pair;

- Exposures of financial institutions in foreign currency, both in the asset and liability side, which we use as the financial institution's exposure to exchange rate shocks.

Table 1: *Average number and total assets of the economic agents*

Economic agent (segment)	Type of institution	N	Total assets (R$ bi)
Commercial	Financial, bank	97	6820.0
Development	Financial, bank	4	840.7
Investment	Financial, bank	36	135.7
Brokers	Financial, non-bank	141	8.5
Credit Companies	Financial, non-bank	123	99.5
Credit Unions	Financial, non-bank	964	338.3
Finance Companies	Financial, non-bank	109	2.2
Payment Institutions	Financial, non-bank	9	72.0
Accommodation and food services	Firm	171	25.1
Administrative and support services	Firm	554	348.7
Agriculture	Firm	225	104.2
Construction	Firm	516	207.2
Education	Firm	114	48.6
Electricity and gas	Firm	344	709.7
Human health and social work	Firm	287	92.2
Information and communication	Firm	867	448.3
Manufacturing	Firm	3035	3131.1
Mining	Firm	134	691.1
Professional, scientific and technical	Firm	895	129.4
Public administration and defence	Firm	6	24.5
Real estate	Firm	359	53.5
Transportation and storage	Firm	491	373.0
Water supply and sanitation	Firm	104	161.7
Wholesale and retail trade	Firm	2127	794.1

Our methodology requires extensive use of granular data to model each component. They are discussed as follows:

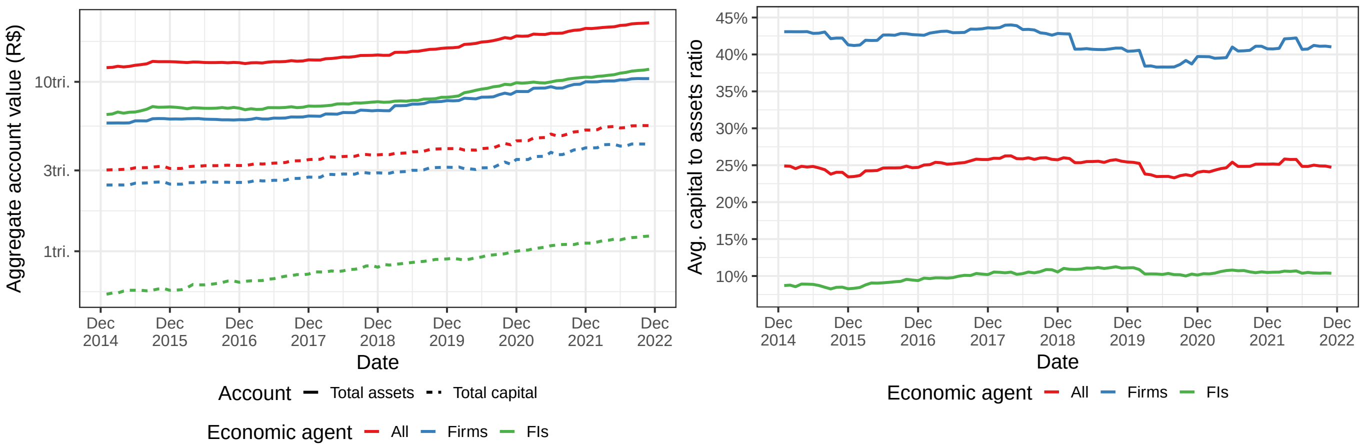
- Agents. We form the exposure network of financial institutions and nonfinancial firms. The financial institutions we consider are those for which we have accounting and exposure data. These institutions are banks (universal, commercial, investment, and federal savings banks), credit unions, credit companies, finance companies, payment institutions, and brokers. For these institutions, we consider bank conglomerates and individual banking institutions that do not belong to a conglomerate. Regarding the sample of nonfinancial firms, they are extracted from the Nonfinancial companies database. Our sample includes those who are borrowers in credit operations and have the required accounting data. Table 1 shows the average number of agents and their total assets by agent type (financial institution or nonfinancial firm) from 2015 to 2022.

- Network exposures. We form the network exposures from information from two sources. One of these sources is the Interfinancial Exposures database. From this source, we aggregate bilateral exposures between pairs of agents (lender and borrower). We only consider non-collateralized financial instruments to compose the bilateral exposure. The other source is the Credit Information System database. From there, we also take the bilateral outstanding credit between each financial institution that issued the credit (lender) and the corresponding nonfinancial firm (borrower). These exposures (bank-bank and bank-firm) form the counterparty risk in the model. We also take the nonfinancial firm's exposure to funding risk by aggregating outstanding credit maturing in the following 90 days for the pair (nonfinancial firm, financial institution granting credit). Due to a lack of data, we do not consider the trade network between nonfinancial firms and investments that firms have in securities issued by financial institutions.

- Initial shocks. We compute initial shocks from the exposures of financial institutions and firms in foreign currency and the exchange rate shock (expressed as a percentage change of the US Dollar exchange rate). These shocks are losses incurred by the exposed agents. Thus, to compute the initial shocks, we multiply the exchange rate shock (positive if the US Dollar appreciates) by the exposure of each agent (if the exposure is a liability, the signal is positive; if it is an asset, it is negative). The shock is computed considering the exchange rate varying from the current observed value at the computation date. Thus, the idea is that the simulated shock is a sudden exchange rate event apart from what we have already observed in the economy up to a particular point. We note that we do not have data on asset-side firm exposures. Finally, we perform the simulations applying exchange rate shocks varying from -40% to +100% of changes in the exchange rate in steps of 5 p.p.

4.2 Economic agents: relevant information

Table 1 shows the average number of institutions by type and total assets across time. If the agent is a financial institution, we divide it into bank and non-bank. The banking sector comprises financial institutions specialized in financial intermediation—accepting deposits and issuing credit—in addition to custodying customers' money. It also provides financial services to customers, such as withdrawals and investments. The largest segments in terms of total assets



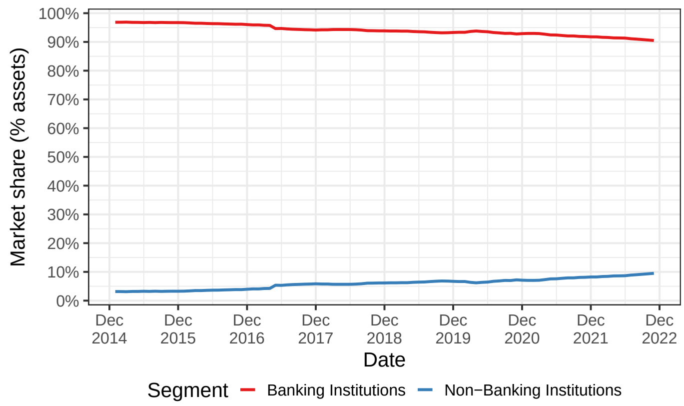
***(a)** Assets and capital of financial institutions and firms*

***(b)** Average capital to assets ratio of financial institutions and firms*

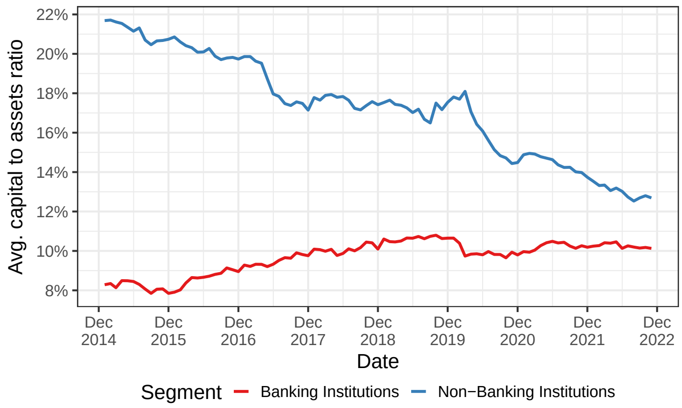
***Figure 2:** Total assets and capital aggregated for financial institutions and firms that form the network over time. In (a), we report aggregated assets and capital for financial institutions and firms in nominal R$. In (b), we report the average capital to total assets ratio, computing these variables for the entire segment (financial institutions or firms) prior to calculating the ratio.*

are commercial banks and manufacturing. However, the segments with the highest average total assets per institution are commercial and development banks. It is noteworthy that the total assets of the corporate sector are roughly equivalent to those of the financial sector (financial institutions), as shown in Figure 2a, but the corporate sector has a lower average total assets per institution compared to the financial sector as it comprises a greater number of firms. From Figure 2a, we also see the aggregated capital for financial institutions is much smaller than that of firms. This is confirmed by the evolution of the average capital-to-assets ratio shown in Figure 2b.

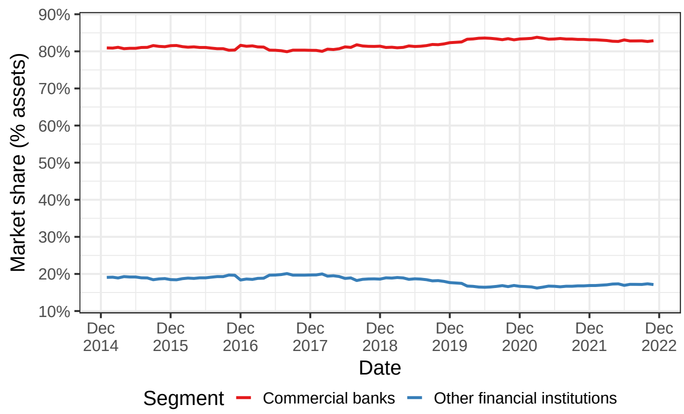
Figures 3a–3d show a closer view into the financial sector. Figure 3a portrays the market share of banking and nonbanking institutions within the financial sector. The financial sector's assets are strongly concentrated in the banking sector. Within the banking sector, assets are concentrated in the commercial banking segment. Figure 3c provides a comparison over time of the market share of commercial banks and the group of all the other financial institutions, showing the market share of commercial banks was kept above 80% along the period of study. Figure 3d provides a drill-down on the segment of the financial sector formed by all the financial institutions that are not commercial banks. We highlight three effects: the decrease in the market share of development banks, the significant increase in credit unions' share, and the launch of payment institutions in the first half of 2017. Finally, Figure 3b compares the average capital to total assets ratio of banking and nonbanking financial institutions, making clear banking institutions have lower ratios along the period of study and the ratios of banking and nonbanking financial institutions have



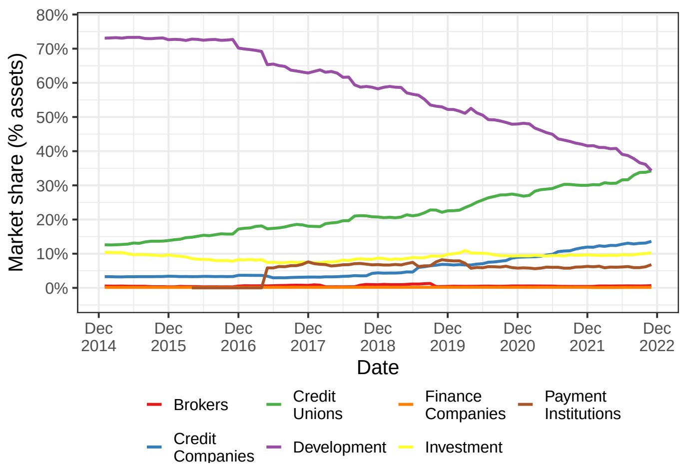
(a) *Market share of banking and nonbanking institutions in the financial sector*



(b) *Average capital to assets ratio of banking and nonbanking institutions*



(c) *Market share of banks and other financial institutions*



(d) *Market share of all segments except commercial*

Figure 3: *A closer view into the financial sector. Figure (a) displays the market share, over time, of banking and nonbanking institutions in terms of total assets, and Figure (b) shows the average capital to total assets ratio for these segments. Figure (c) categorizes the sample in (a) a different way, showing that among banking institutions, commercial banks hold at least 80% of financial sector assets, leaving the remainder to the other institutions. Finally, Figure (d) details the market share of the types of financial institutions that are not commercial banks.*

been converging over time.

Figure 4 provides a closer view of the market shares of the economic agents from the corporate sector, categorized by industry. One of the items provided by the Nonfinancial companies (NFCs) database as meta-information is the national economic activity code (CNAE) provided by the Brazilian Institute of Geography and Statistics (IBGE). We use the CNAE to define the industry to which agents belong. The figure shows the Manufacturing industry has, by far, the largest average market share.

Figure 5a explores the agents' exposures to exchange rate risk over time. This figure reports aggregated assets and liability exposures as a percentage of aggregated capital for financial institutions. In the case of firms, we only have information on the liability side. These exposures

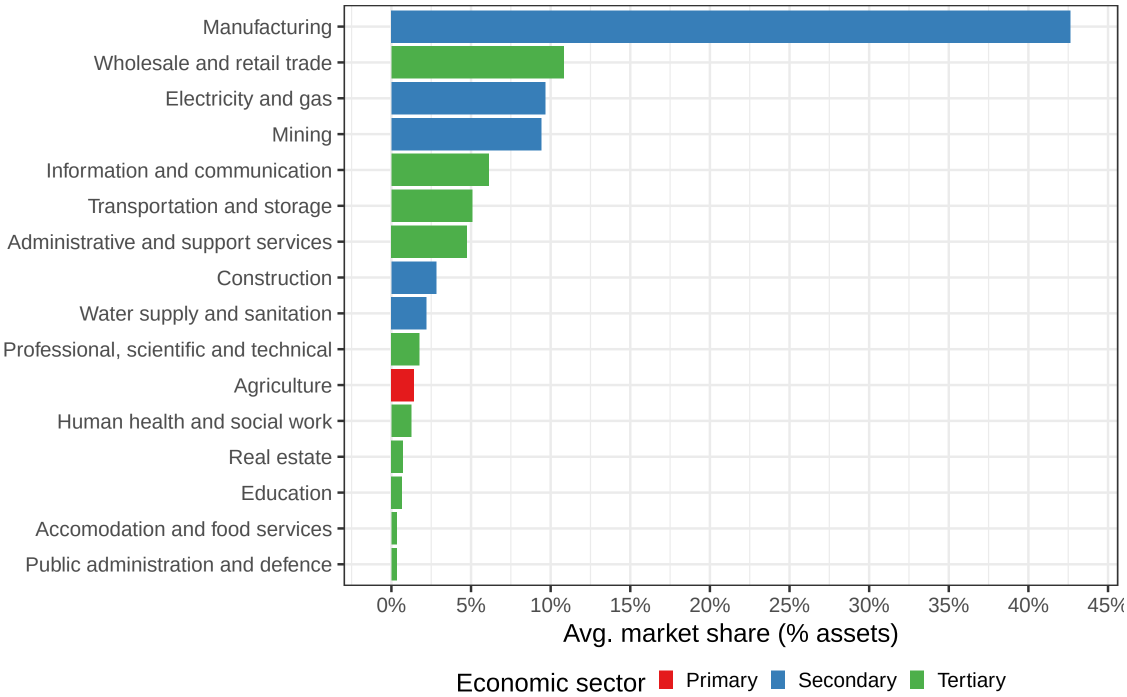


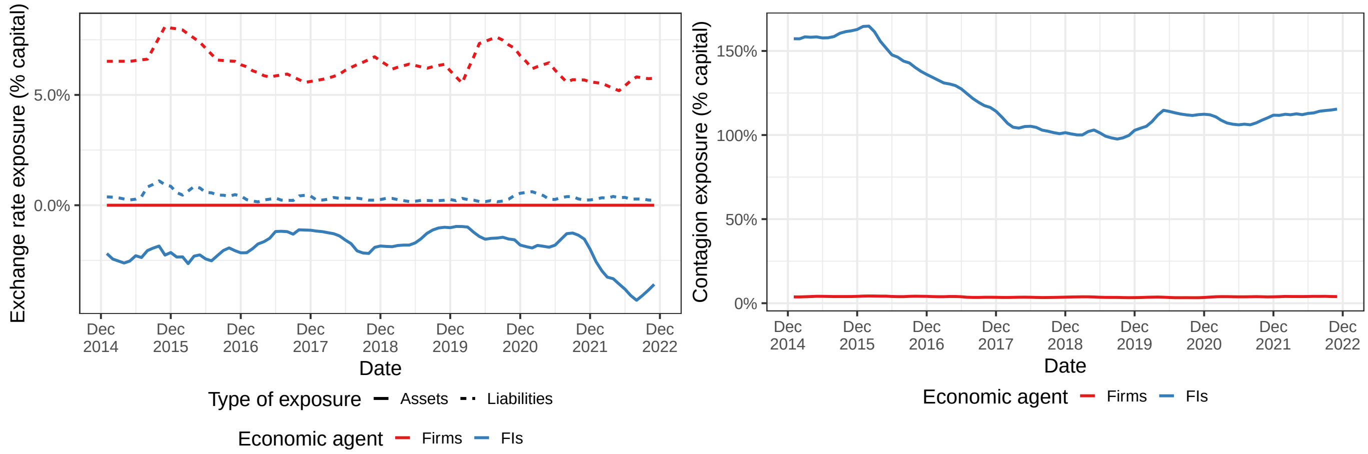
Figure 4: *Average market share of the corporate sector by industry during the analyzed period.*

comprise the initial stress for our contagion model. Liability-side exposures are reported as being positive, given that they result in losses under positive exchange rate shocks. All the amounts are below 10% in absolute value, meaning exposures to exchange rates, on average, are not high for these agents. Firms' liability-side exposures are larger than financial institutions (recall we do not have hedging). Asset-side exposures of financial institutions are larger than liability-side ones. In turn, Figure 5b explores the agents' exposures to contagion losses. Differently from the exposures reported in the previous figure, exposures to contagion are high, comparable to the agents' capital, for financial firms. This is related to the high degree of interconnection among these agents due to the interbank market. Conversely, we do not have significant contagion exposures by firms as, due to a lack of data, the only exposure sources are derived from financial institutions' funding risk in credit operations.

5 Results

5.1 Exchange rate shocks and financial stability

This section examines how simulated exchange rate shocks affect the financial and corporate sectors. We evaluate losses in terms of the direct losses caused by the exchange rate shock



***(a)** Exchange rate exposures over time - assets and liabilities*

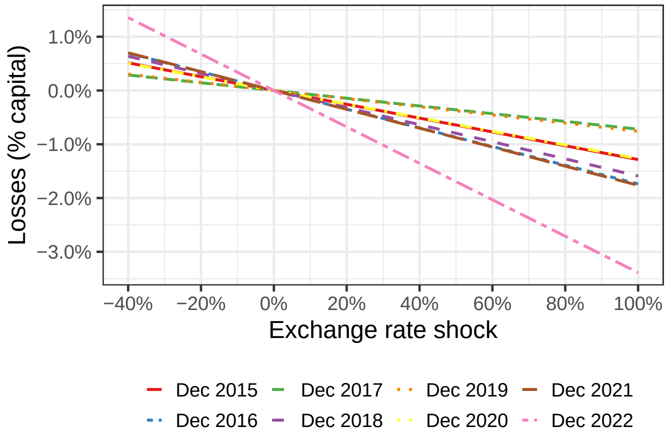
***(b)** Contagion exposures over time*

***Figure 5:** Risk exposures by type of economic agent over time. In (a), we report exposures to exchange rate shocks for firms and financial institutions. We report asset-side and liability-side exposures separately because, given an exchange rate shock, only one of these components will result in losses (if not zero). These exposures are reported as capital percentages for each segment. In (b), we also report contagion exposures as percentages of the segment's capital. Contagion exposures arise from exposures among the network agents. Contagion exposures are greater for banks due to operations in the interbank market.*

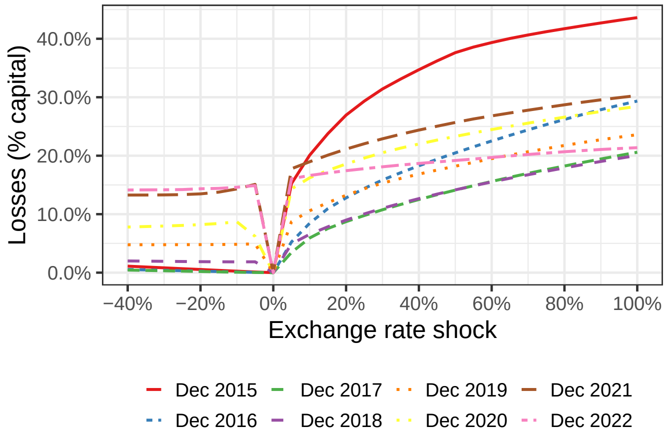
and the additional losses that may arise due to financial exposures.

We performed a sensitivity analysis of financial institutions' and firms' potential net worth losses due to simulated exchange rate shocks. We consider both the direct and indirect (contagion) effects. We examine the effects of negative and positive exchange rate shocks on banks and firms' foreign currency exposures, mostly dollar-denominated. We simulate shocks ranging from -40% up to 100% of the actual observed exchange rate, with steps of 5 p.p. A negative value stands for a shock that leads to a devaluation of the U.S. dollar against the Brazilian Real. We first assess the potential capital loss due to the direct effects of the shock. We then evaluate the potential losses due to contagion (See Equations (12) and (13)).

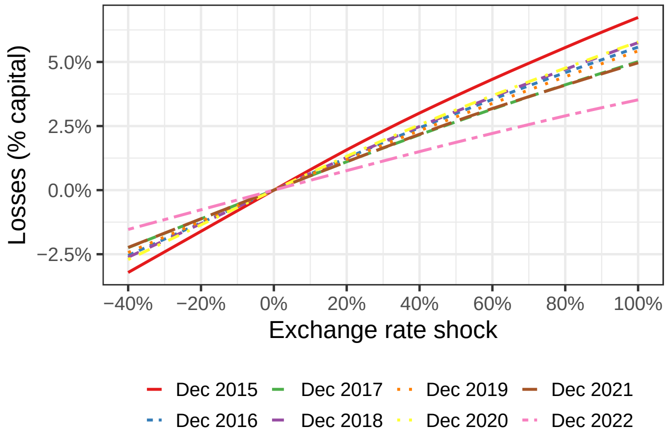
Figures 6a and 6c show the direct impact of different simulated sudden exchange rate shocks. We show total losses over the segment's total capital, which correspond to the sum of each individual loss as a ratio of the total capital in the segment. Negative losses indicate gains for the economic agent, which occur when the agent has a positive net asset position relative to the foreign currency. Exchange rate shocks have opposite direct effects on the financial and corporate sectors. The potential loss trajectory for the financial sector decreases as the shock magnitude increases, suggesting the financial sector has positive net foreign-denominated assets. For the corporate sector, it is the opposite. This is expected since we only have firms' foreign debt.



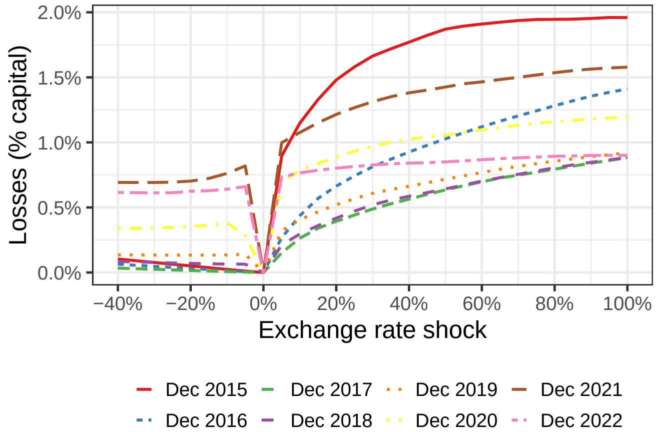
***(a)** Financial sector's direct losses (from the initial shock)*



***(b)** Financial sector's indirect potential losses (from contagion)*



***(c)** Corporate sector's direct losses (from the initial shock)*

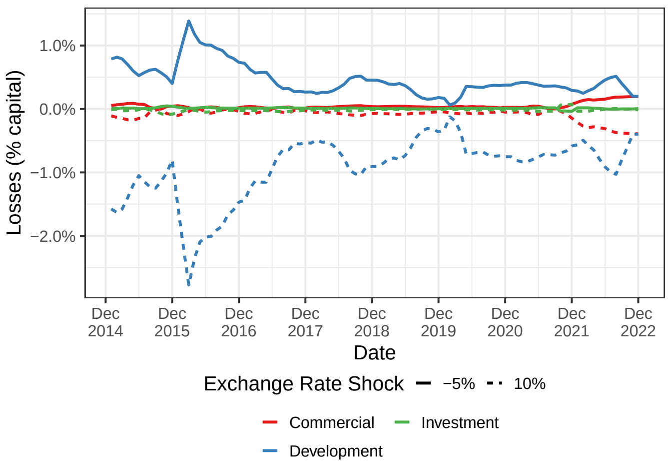


***(d)** Corporate sector's indirect potential losses (from contagion)*

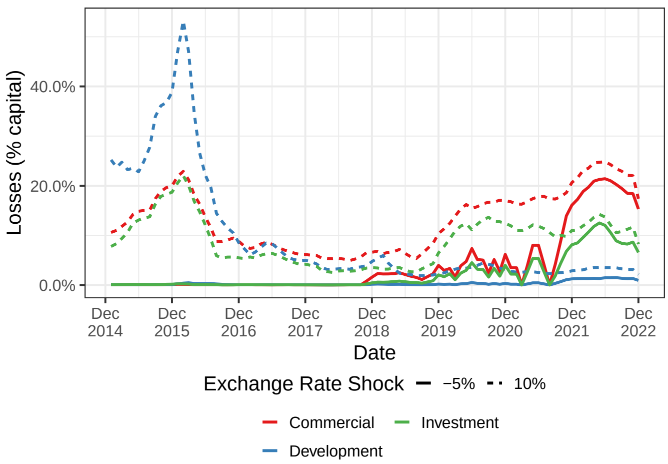
***Figure 6:** Sensitivity analysis of losses in the financial (upper row) and corporate (bottom row) sectors in response to varying magnitudes of exchange rate shocks. Positive exchange rate shocks denote an appreciation of US dollars to Brazilian reais (unit: BRL/USD). Figures (a)–(d) show how losses computed on different dates behave in response to different magnitudes of exchange rate shocks. Figures (a) and (c) show direct losses from the initial shock, and (b) and (d) show indirect losses through contagion. The impact is measured considering the total capital within the associated sector (financial or corporate). Figures (b) and (d) show a kink for exchange rate shocks equal to zero as the network propagates losses but not gains. For a given date, some agents incur losses in case of negative exchange rate shocks while others lose in case of positive ones, originating different contagion patterns and magnitudes for negative and positive exchange rate shocks.*

While the financial sector could be better off in case of positive exchange rate shocks, firms could face potential losses higher than 5% of the capital of the whole corporate sector depending on the shock magnitude and shock year. Regarding negative shocks, the potential losses of the financial sector would be less than 1% of the capital of the whole sector, except for 2022, the year of worst results for the financial sector in terms of direct potential losses. It is worth noting the effects of the initial shock on the firm's capital are overestimated since we do not have the amount of the firm's foreign currency assets.

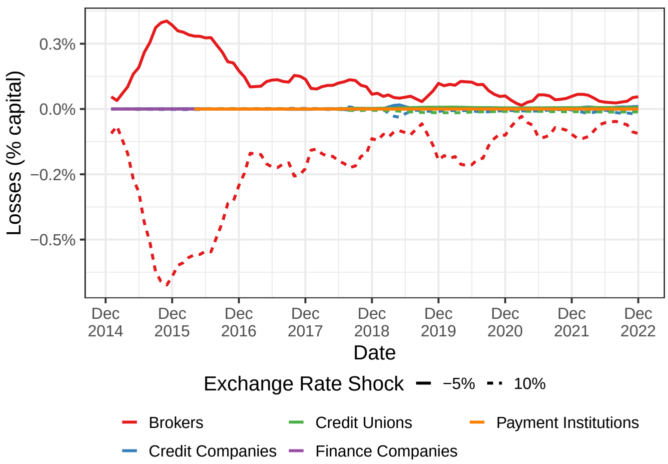
Each sector's year of higher losses and gains depends on its net exchange rate exposure (liabilities exchange rate exposure - assets exchange rate exposure). As shown in Figure 5a, the higher net exchange rate exposure as a capital percentage for the firms and financial institutions



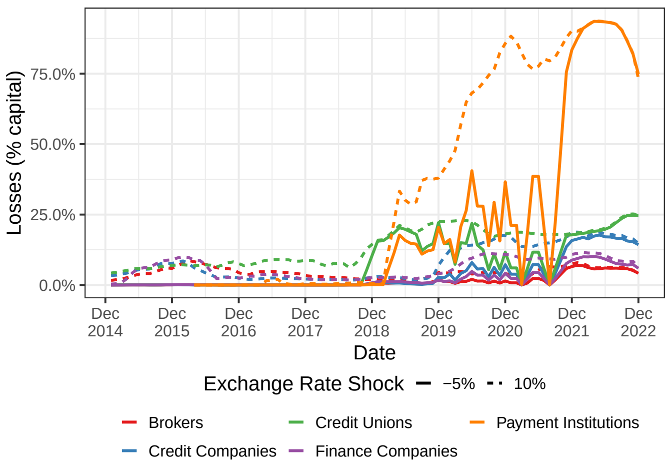
***(a)** Banking institutions' direct losses (from the initial shock)*



***(b)** Banking institutions' indirect potential losses (from contagion)*



***(c)** nonbanking institutions' direct losses (from the initial shock)*

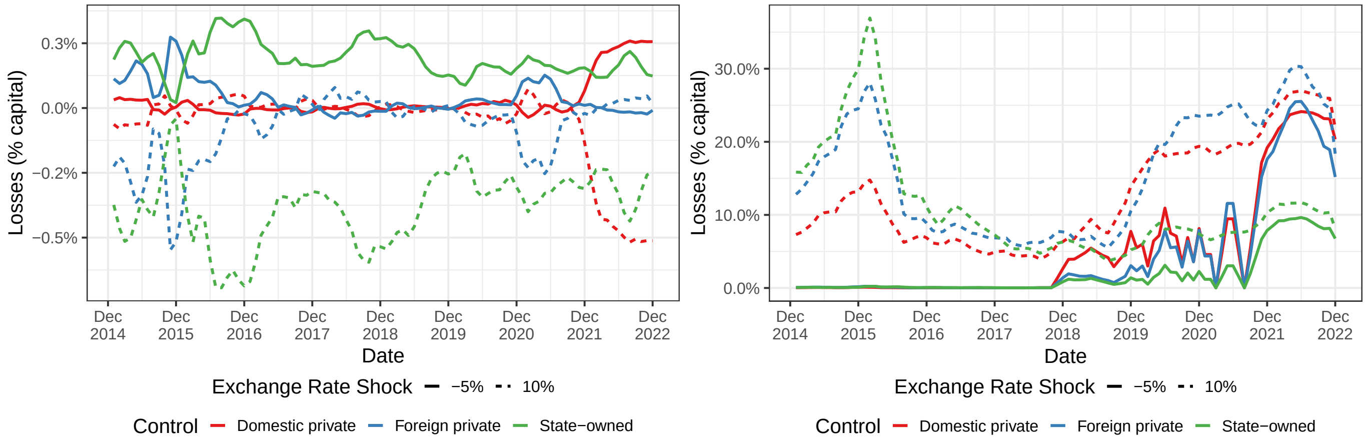


***(d)** nonbanking institutions' indirect potential losses (from contagion)*

***Figure 7:** Direct losses and contagion potential losses arising from exchange rate shocks computed for financial sector segments. Figures (a) and (b) show losses for banking institutions segments (commercial, investment, development banks), whereas Figures (c) and (d) show them for nonbanking institutions segments (brokers, credit companies, credit unions, finance companies, payment institutions). We depict net worth losses caused by exchange rate shocks (direct effect) and the contagion losses that follow (indirect effect) in financial institutions from 2015 to 2022 quarterly. We use two exchange rate shocks, -5% and $+10\%$, evaluated over the observed exchange rate at each time point. Losses (the sum of individual losses in a specific segment) are in percentage terms of the total net worth of institutions in a specific segment.*

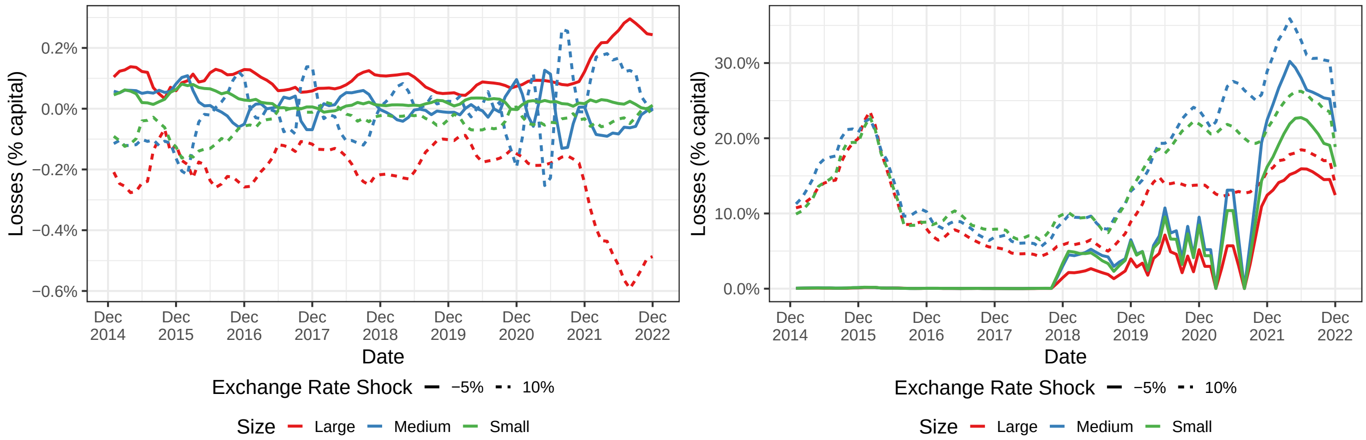
occurs in 2015 and 2022, respectively. Even in those years, the minimum capital regulations would be enough to cover the direct losses that could occur in case of an exchange rate shock materializing.

Even though the financial sector (corporate sector) is better off in case of negative (positive) exchange rate shocks, some financial institutions (firms) could experience capital losses. This fact explains why the contagion results show capital losses for both the financial and corporate sectors for negative and positive shocks. According to our methodology, only capital losses due to the initial shock are propagated to other agents by contagion. Financial institutions or firms that eventually gain from exchange rate shocks add them to their net worth.



***(a)** Financial sector's direct losses (from the initial shock)* ***(b)** Financial sector's indirect potential losses (from contagion)*

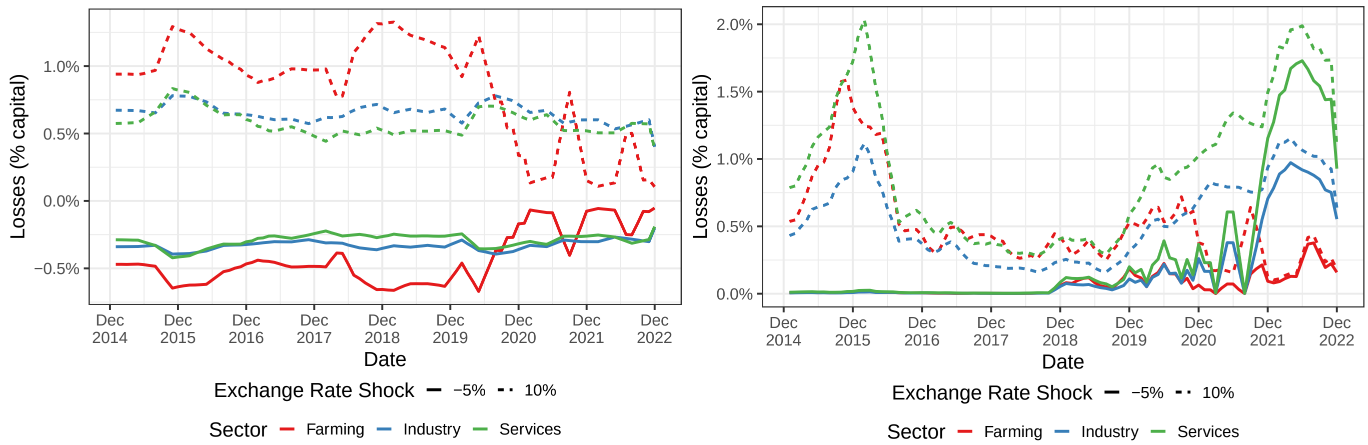
***Figure 8:** Direct losses and contagion potential losses arising from exchange rate shocks segregated by financial institutions' type of control (domestic private, foreign private, state-owned). We depict net worth losses caused by exchange rate shocks (direct effect) and the contagion losses that follow (indirect effect) in financial institutions from 2015 to 2022 quarterly. We apply two exchange rate shocks, -5% and $+10\%$, evaluated over the observed exchange rate at each time point. Losses (the sum of individual losses in a specific segment) are computed as a percentage of the total net worth of the institutions in a specific segment.*



***(a)** Financial sector's direct losses (from the initial shock)* ***(b)** Financial sector's indirect potential losses (from contagion)*

***Figure 9:** Direct losses and contagion potential losses arising from exchange rate shocks segregated by financial institutions' size (large, medium, small). We depict net worth losses caused by exchange rate shocks (direct effect) and the contagion losses that follow (indirect effect) in financial institutions from 2015 to 2022 quarterly. We apply two exchange rate shocks, -5% and $+10\%$, evaluated over the observed exchange rate at each time point. Losses (the sum of individual losses in a specific segment) are computed as a percentage of the total net worth of the institutions in a specific segment.*

In contrast to the distinct potential loss trajectories for financial institutions and firms arising from initial shocks, the contagion results show similar evolution for paths of potential losses as the shock magnitude increases for both agent types (Figures 6b and 6d). This similarity arises because, in the region of positive exchange rate shocks, the magnitude of potential losses is largely determined by the agents' passive exposure in the network (which remains constant) and varies almost linearly with the shock intensity across all dates and agent types. However, the financial sector's potential indirect losses are higher due to its elevated contagion exposure (Figure 5b).



***(a)** Corporate sector's direct losses (from the initial shock)*

***(b)** Corporate sector's indirect potential losses (from contagion)*

***Figure 10:** Direct losses and contagion potential losses arising from exchange rate shocks segregated by nonfinancial institutions' (wide) sector (farming, industry, services). We plot net worth losses caused by exchange rate shocks (direct effect) and the contagion losses that follow (indirect effect) in nonfinancial institutions from 2015 to 2022 quarterly. We apply two exchange rate shocks, -5% and $+10\%$, evaluated over the observed exchange rate at each time point. Losses (the sum of individual losses in a specific segment) are computed as a percentage of the total net worth of the institutions in a specific segment.*

***Figure 11:** Direct losses and contagion potential losses arising from a decrease of 5% in the exchange rate (USD depreciates relatively to the BRL) segregated by nonfinancial institutions' sectors (according to the letter-based CNAE structure in Brazil). We depict net worth losses caused by exchange rate shocks (direct effect) and the contagion losses that follow (indirect effect) in nonfinancial institutions from 2015 to 2022 quarterly. We perform computations for the exchange rate shocks, -5%, evaluated over the observed exchange rate at each time point. Losses (the sum of individual losses in a specific segment) are computed as a percentage of the total net worth of the institutions in a specific segment.*

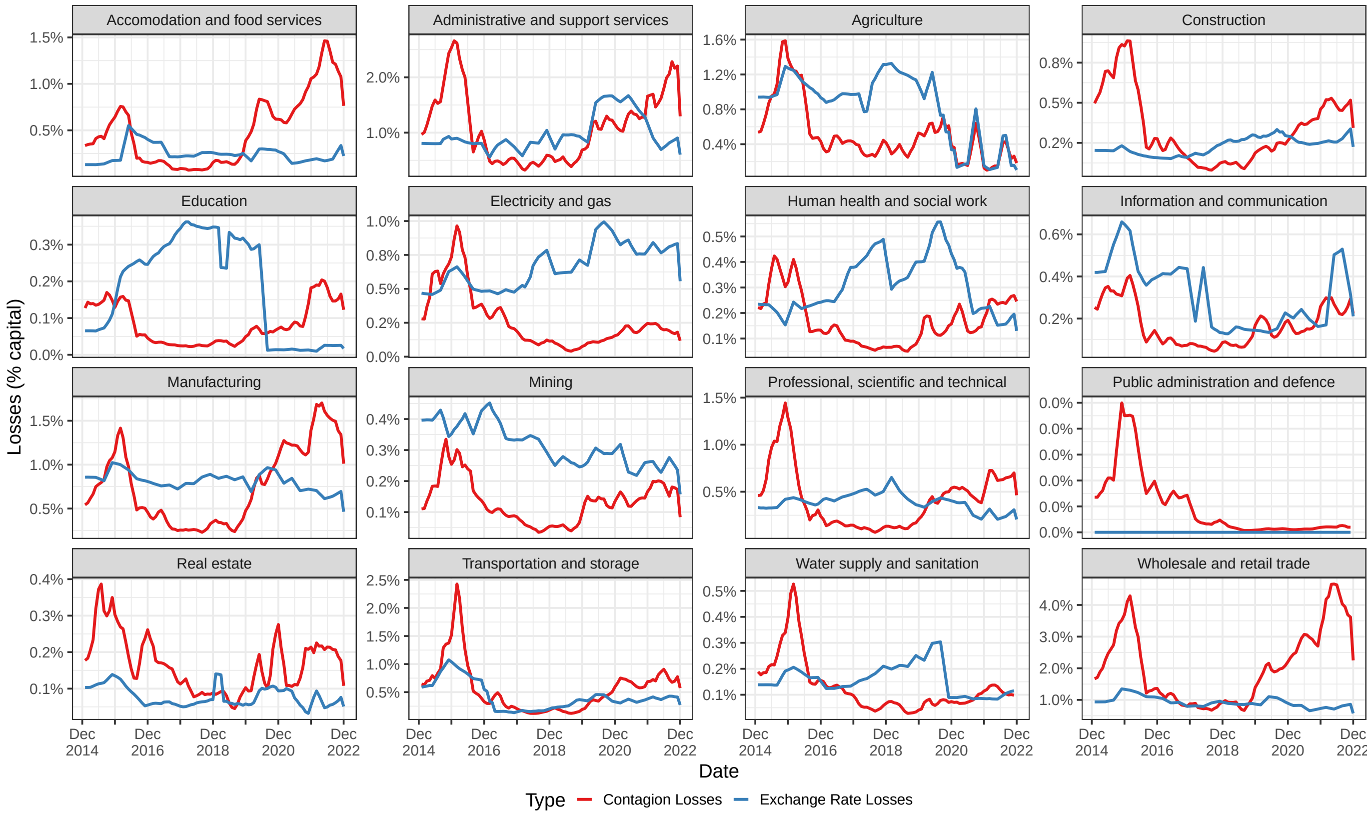


Figure 12: *Direct losses and contagion potential losses arising from an increase of 10% in the exchange rate (USD appreciates relatively to the BRL) segregated by nonfinancial institutions' sectors (according to the letter-based CNAE structure in Brazil). We depict net worth losses caused by exchange rate shocks (direct effect) and the contagion losses that follow (indirect effect) in nonfinancial institutions from 2015 to 2022 quarterly. We perform computations for the exchange rate shocks,* $+10\%$*, evaluated over the observed exchange rate at each time point. Losses (the sum of individual losses in a specific segment) are computed as a percentage of the total net worth of the institutions in a specific segment.*

Since we only have data for loans from financial institutions to firms, the potential contagion losses for the corporate sector can be underestimated if there is foreign currency credit among the firms.

In Figure 6b, we observe that the potential losses in the 2015 curve exceed those of other dates' curves for positive exchange rate shocks but not for negative shocks. This discrepancy arises because, in the case of positive shocks, the curve is driven mostly by passive currency exposures, which peaked in 2015 (see Figure 5a). Conversely, in the case of negative shocks, the curve is driven by active currency exposures, which reached their highest level for financial institutions in 2022.[5]

If no agent went bankrupt, the trajectories for potential contagion losses would be linear as

[5]This statement is based on the following model assumptions: 1) Positive exchange rate shocks (dollar appreciation) generate losses for agents with net passive currency exposure and profits for those with net active exposures; and 2) Agents experiencing losses propagate risks (potential losses) to their counterparties, according to the methodology. Conversely, agents with profits become more resilient to losses but do not propagate financial stress. As a result, the curves for potential losses from positive exchange rate shocks differ from those resulting from negative shocks.

the exchange rate shock increases, as in the case of the initial shock. The trajectories of potential contagion also depend on network cyclicality,[6] the average vulnerability of the agents and the shock size (Silva et al., 2017b).

An important question is whether these potential losses can jeopardize financial stability. To address this, we proceed with a more granular analysis. First, we analyze the losses by financial sector segments. Due to the size differences among the segments, we divided the financial sector into banking and nonbanking institutions to improve the results' visualization (Figure 7). The potential losses from initial shocks are significantly higher for development banks. However, the losses diminished from 2015, when they reached their maximum, up to 2019. Probably because of the COVID-19 pandemic effects, the potential losses increased in 2020 and remained relatively stable since then (Figure 7a). Regarding nonbanking institutions, the most impacted by initial shock are the brokers. They also reached the maximum potential losses in 2015, but the losses were low in the last years of the analysis period. We can note potential losses for nonbanking institutions are about one-third of potential losses for banking institutions (Figure 7c). The contagion is more relevant for banking institutions in case of positive shock, although the relevance of negative exchange rate shock increases significantly for commercial banks after 2021. While the higher potential losses from contagion could come from development banks up to 2016, from 2017 onwards, potential losses arising from commercial banks are more relevant. In 2021, both Commercial and Investment banks experienced a sharper increase in their potential losses, reaching respectively 20% and 10% of the capital from the whole banking segment (Figure 7b).

Regarding contagion effects on nonbanking institutions, there also is a significant increase in potential losses for payment institutions, reaching more than 80% of the capital of the whole segment. However, these potential losses do not jeopardize the financial stability since the payment institutions have a low share of the financial system (Figure 7d).

Looking at the results of financial institutions' control, state-owned financial institutions are the most vulnerable to the first impact of negative exchange rate shocks during almost the whole analysis period. The exceptions are in 2015, when foreign financial institutions were exposed to higher potential losses, and after 2021, when domestic private financial institutions became

[6] Network cyclicality measures to what extent a network has cyclic routes. A formal definition of network cyclicality can be found in Silva et al. (2017b).

more vulnerable (Figure 8a). Regarding size, the potential losses are higher for large financial institutions. However, as the level of potential losses reaches about 3% of the capital of the financial system, we find initial shock losses do not jeopardize financial stability (Figure 9a). The contagion effects have similar patterns for the control and size of financial institutions. The higher potential losses could occur in 2015 and after 2020, reaching up to 30% of the financial system capital (Figures 8b and 9b).

The granular analysis for the corporate sector shows direct potential losses for farming sector firms were the highest until 2020. After that year, they dropped and started oscillating. The industry and services sectors show more stable trajectories of direct potential losses (Figure 10a). The potential contagion losses follow a similar pattern to those of the financial sector but on a smaller scale. While losses from contagion could reach up to 30% for the financial sector, the maximum loss for the corporate sector is 2%. The sector most affected by contagion is the services sector, followed by industry (Figure 10b). A more granular analysis shows the sectors Wholesale and retail trade and Administrative and support services are the most affected in case of both negative and positive exchange rate shocks, mainly utilizing contagion (Figures 11 and 12). Overall, losses from the exchange rate would not provoke severe financial damage in the corporate sector.

5.2 Monitoring the system's resilience to exchange rate shocks

This section proposes a simple methodology to monitor the system's resilience to exchange rate risks. It may complement the regulators' toolkit to ensure financial stability and act proactively to safeguard it in case of heightened vulnerabilities. Our method uses the network topology and comprises two dimensions: (i) identifying how capable each economic agent can diffuse and amplify a simulated exchange rate shock; and (ii) assessing how fragile the network is given the financial interconnections. Both dimensions give complementary views relevant to gauging financial stability.

Our analysis is built upon the concept of an economic agent's criticality. Consider Figure 13, which shows a hypothetical lending network in the left panel. Economic agents are the vertices and are identified by uppercase letters. Their capital is enclosed in green within parenthesis. Links denote financial exposures, illustrated here by lending operations for didactic purposes. We

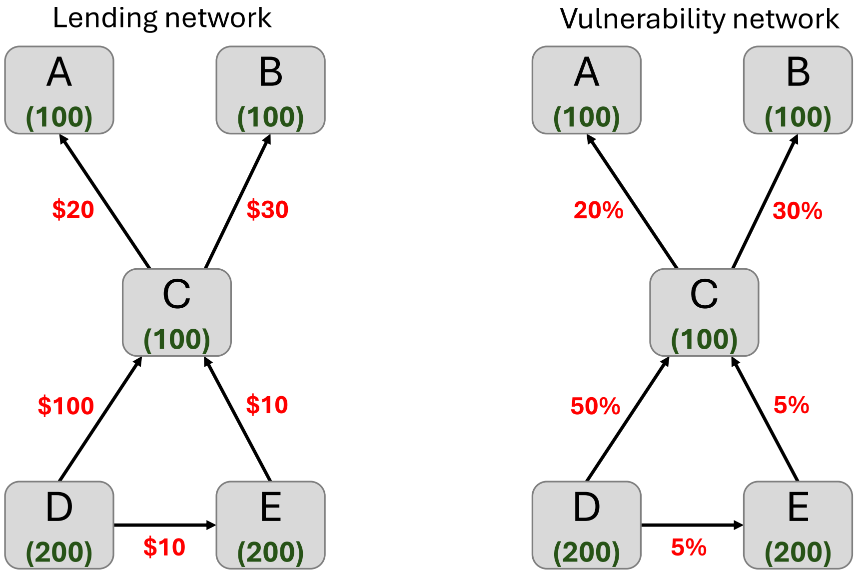


Figure 13: *Schematic of a lending network (left panel) and the associated vulnerability network (right panel). Vertices are denoted with uppercase letters from A to E. Capital is enclosed in green within parenthesis below the vertex label. (a) Lending network: links are lending operations (it could also be funding risk in the model). The amount lent is shown in red near each link. (b) Vulnerability network: links are the financial vulnerability (credit risk in our case of lending operations) of the lender (link origin) to the borrower (link destination), given by percentage amount of the lending operation with respect to the lender's capital.*

construct the vulnerability network arising from these financial exposures in the right panel. Each link now represents the vulnerability of the lender (link origin) to the borrower (link destination), given by the percentage amount of the lending operation with respect to the lender's capital. The vulnerability network provides information on the extent of losses the lender would be subject to in case of default from the borrower. This interpretation directly connects with how fragile it is to other economic agents.

An economic agent's criticality can be defined in terms of an agent that promotes shock diffusion—termed here as criticality as a shock diffuser—or its susceptibility to receiving shocks from the neighbors—criticality as a shock receiver. We define the economic agent i's criticality as a shock diffuser $C_i^{\text{(diffuser)}}$ and as a shock receiver $C_i^{\text{(receiver)}}$ as follows:

$$C_i^{\text{(diffuser)}} = \sum_{j \in \mathscr{L}_i} V_{ji}, \tag{14}$$

$$C_i^{\text{(receiver)}} = \sum_{j \in \mathscr{B}_i} V_{ij}, \tag{15}$$

in which i indexes the economic agent. The terms $\mathscr{L}_i$ and $\mathscr{B}_i$ are the sets of lenders and borrowers of economic agent i (financial and nonfinancial firms), and V_{ji} represents the financial vulnerability of j towards i. Our model described in Section 3.1 considers two types of vulnerabilities: counterparty risk (see Equation (8)) and funding risk (see Equation (9)). A lender's vulnerability to counterparty risk is the amount lent to the borrower in terms of the lender's capital. Figure 13 only depicts vulnerabilities arising from counterparty risk. For instance, the vulnerability of C to A is 20% because C would lose 20% of its capital in case A defaults. Funding risk exposure goes the opposite way: it is the vulnerability that the borrower faces in case the lender is not willing to roll over short-term debt, considering the current borrower's liquidity conditions. The economic agent's criticality as a shock diffuser is simply the sum of losses as a percentage of each lender's capital that the economic agent would inflict on the network. Conversely, the economic agent's criticality as a shock receiver is the sum of losses it would receive if all borrowers defaulted.

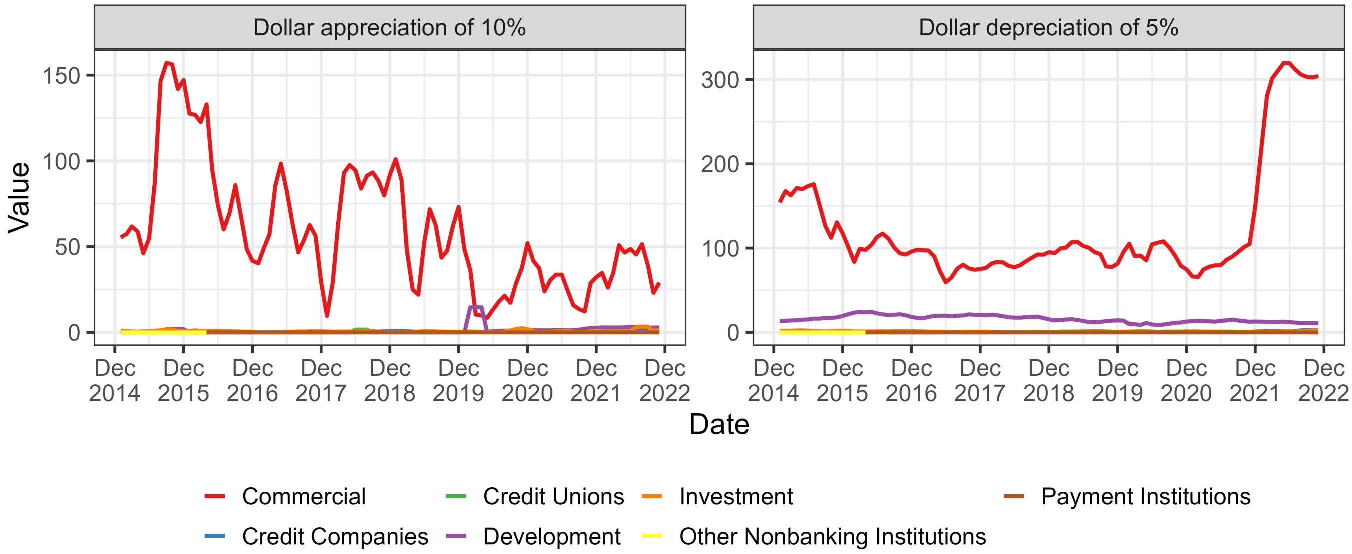
The unscaled version of criticality that sums across vulnerabilities of an economic agent's neighborhood (lenders or borrowers) gives a direct sense of losses that would propagate to or be received by direct neighbors. However, the unscaled criticality grows as the economic agent has more lenders or borrowers. We also analyze a scaled version of the criticality by normalizing the unscaled version by the number of lenders and borrowers, which provides a sense of the average amount lost by direct lenders in terms of their own capital. Mathematically, the scaled criticalities $Scaled\ C_i^{\text{(diffuser)}}$ and $Scaled\ C_i^{\text{(receiver)}}$ are given by:

$$Scaled\ C_i^{\text{(diffuser)}} = \frac{1}{|\mathscr{L}_i|} \sum_{j \in \mathscr{N}_i} V_{ji}, \tag{16}$$

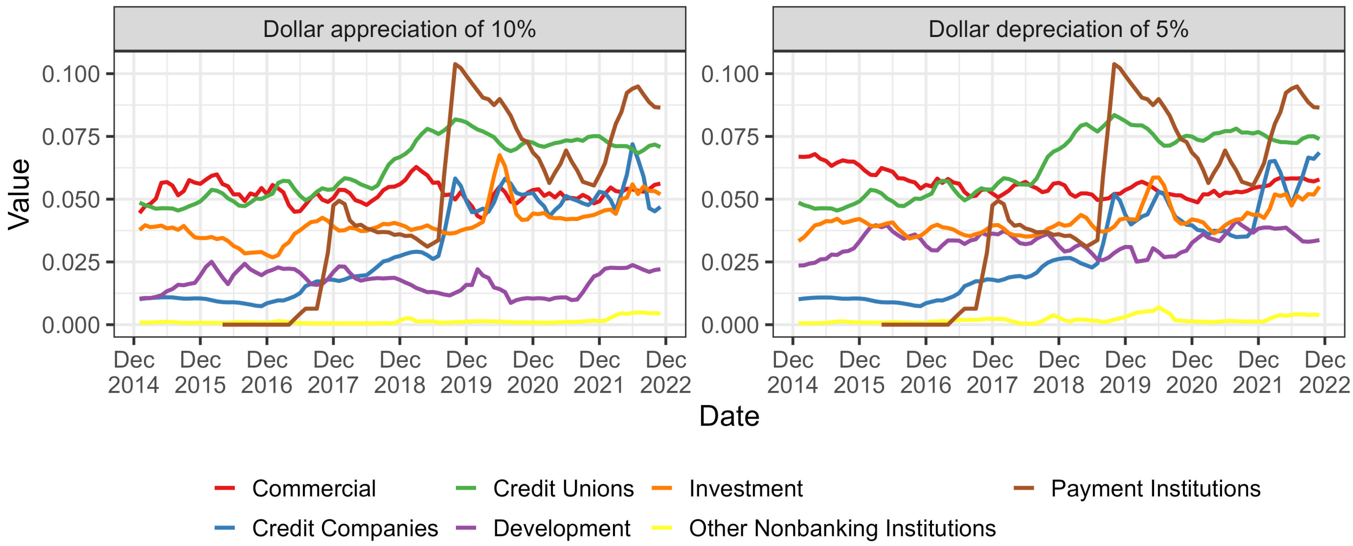
$$Scaled\ C_i^{\text{(receiver)}} = \frac{1}{|\mathscr{B}_i|} \sum_{j \in \mathscr{N}_i} V_{ji}, \tag{17}$$

in which $|\mathscr{L}_i|$ and $|\mathscr{B}_i|$ denote the number of lenders and borrowers of economic agent i.

Figure 14 shows the (a) unscaled criticality – as in Equation (14) – and (b) scaled criticality – as in Equation (16) – by segment of the financial sector over time from the perspective of shock diffusion. We take the average of the individual unscaled and scaled criticality as a shock diffuser weighted by each financial institution's loss due to the simulated exchange rate shock within its segment. This analysis includes only financial institutions that would lose capital due



***(a)** Unscaled criticality as a shock diffuser (weighted by exchange rate shock loss)*



***(b)** Scaled criticality as a shock diffuser (weighted by exchange rate shock loss)*

***Figure 14:** Average criticality as a shock diffuser over time by the financial institution's segment. (a) Unscaled (total) criticality (as defined in Equation (14)) and (b) scaled criticality (as defined in Equation (16)). Criticalities are computed for scenarios involving a 10% appreciation (left panel) and a 5% depreciation (right panel) of the dollar relative to the Brazilian Real. The figure displays average values for each segment, with both scaled and unscaled criticalities weighted by the financial institution's net loss due to the initial exchange rate shock. Financial institutions profiting from the exchange rate shock are excluded from the computations, as they would not propagate financial stress within the network.*

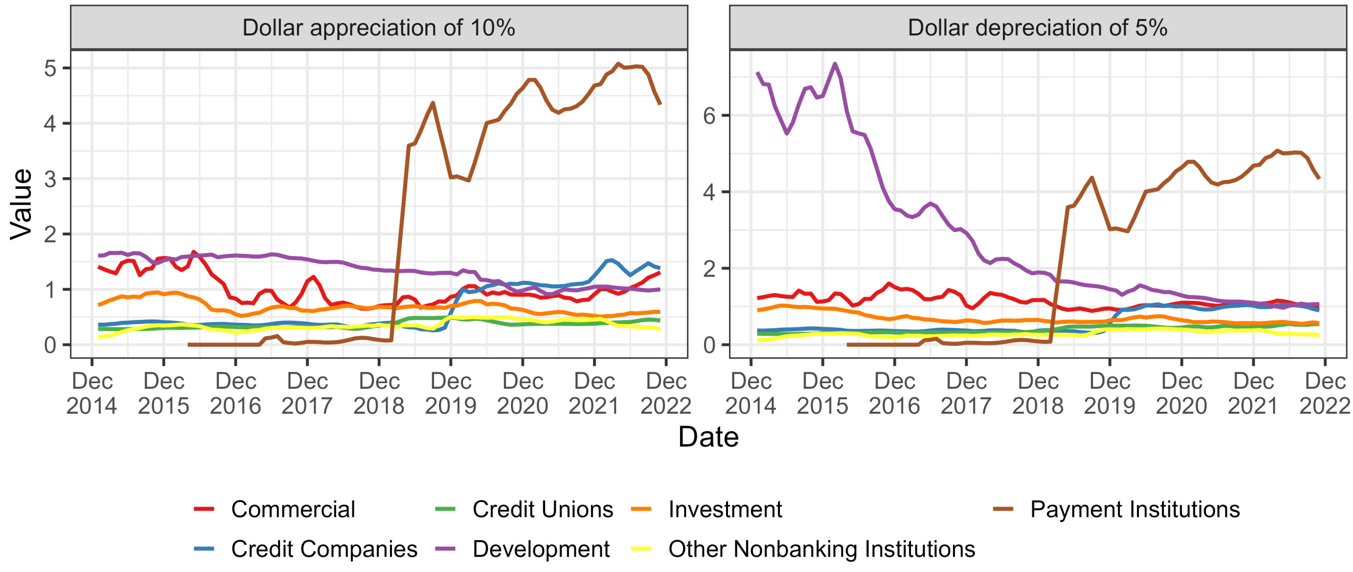
to the exchange rate shock scenarios: an appreciation of 10% (left panel) and depreciation of 5% (right panel) of the dollar relative to the Brazilian Real. Financial institutions that would profit from the simulated exchange rate shock are excluded, as they would not, in principle, propagate financial stress within the network.

The commercial segment exhibits high unscaled criticality as a shock diffuser, primarily because commercial financial institutions tend to have many lenders. By weighting the criticality as a shock diffuser according to its loss due to the exchange rate shock, we effectively measure how significantly the shock targets institutions with a high propensity to diffuse financial stress. There is a substantial increase in unscaled criticality as a shock diffuser for the commercial segment during 2022, triggered by the 5% depreciation shock of the dollar against the Brazilian Real. This suggests this particular exchange rate shock would affect financial institutions with high criticality as shock diffusers, which can amplify the dissemination of financial distress across the network.

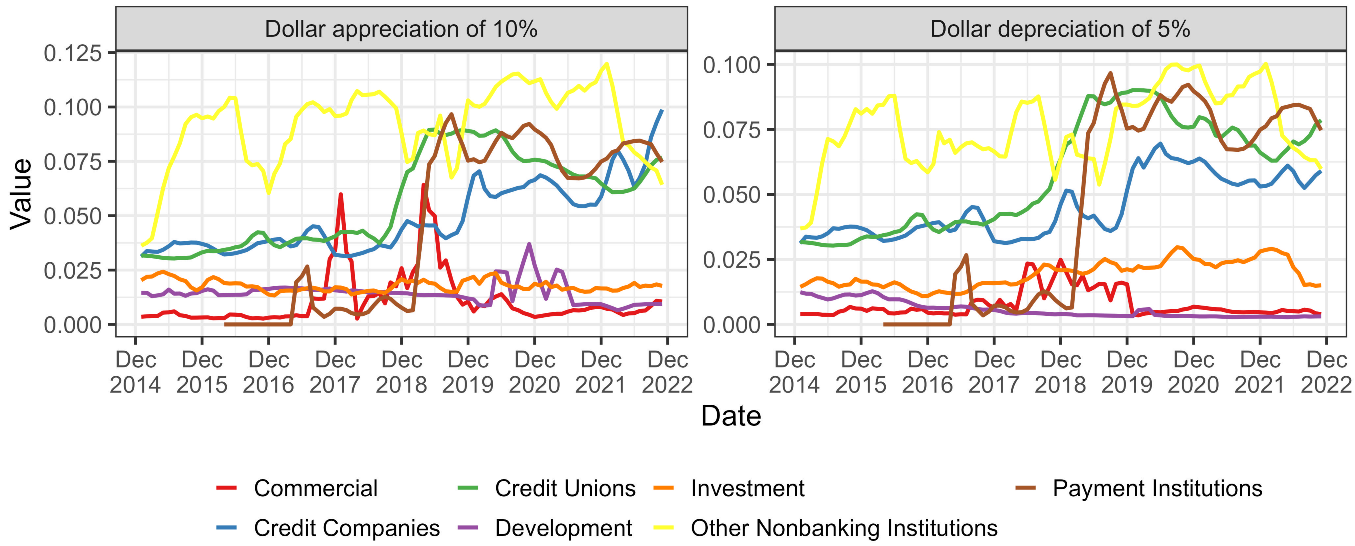
Conversely, the scaled criticality as a shock diffuser for the commercial segment indicates the average loss inflicted on each lender would be approximately 5% of its capital for both 10% appreciation or 5% depreciation of the dollar relative to the Brazilian Real. This highlights while the total potential for shock diffusion is high, the average impact per lender remains relatively contained. Additionally, the increasing scaled criticality as a shock diffuser of payment institutions and credit unions during the analyzed period suggests a growing borrowing trend in these sectors.

Figure 15 shows the (a) unscaled criticality (as in Equation (15)) and (b) scaled criticality (as in Equation (17)) by segment over time from the perspective of receiving shocks. We now consider all financial institutions (and not only those that lose from the exchange rate shock). We take average criticality values for each segment weighted by each financial institution's capital. We change the weighting strategy because, from the perspective of receiving shocks, we are more concerned with entities that could lose more in the network, irrespective of whether they would be directly or indirectly affected by the exchange rate shock. We see that despite the high criticality in diffusing shock for commercial financial institutions, they have a low susceptibility to receiving shocks due to their high capitalization. Regarding receiving shocks, development banks had a high susceptibility to receiving shocks during the Brazilian recession, but it steadily decreased over time. Since 2018, payment institutions' susceptibility to receive shock has increased, but the average value is low.

The criticality analyses complement the contagion results and can be useful for monitoring financial stability. Financial institutions with many lenders can diffuse significant losses triggered by an exchange rate shock, potentially harming financial stability. Similarly, a weak financial institution that lent to many borrowers could be highly susceptible to shocks. Our criticality measure helps identify these financial institutions. For instance, Figure 7b shows the contagion potential



***(a)** Unscaled criticality as a shock receiver (weighted by capital)*



***(b)** Scaled criticality as a shock receiver (weighted by capital)*

***Figure 15:** Average criticality as a shock receiver over time by the financial institution's segment. (a) Unscaled (total) criticality (as defined in Equation (15)) and (b) scaled criticality (as defined in Equation (17)). Criticalities are computed for scenarios involving a 10% appreciation (left panel) and a 5% depreciation (right panel) of the dollar relative to the Brazilian Real. The figure displays average values for each segment, with both scaled and unscaled criticalities weighted by the financial institution's observed capital at each point.*

losses for the commercial banking segment increase from 2021 in case of a 5% dollar depreciation. This effect can be partially explained by the exchange rate shock generating losses to financial institutions with a high potential to propagate shocks (Figure 14a). Their potential losses spread to their lenders, increasing the total losses for the commercial segment, even though the individual lenders' losses are, on average, not high (Figure 14b). The commercial segment has a low susceptibility to receiving exchange rate shocks (Figures 15). However, for the payment institutions segment, both diffusers and receivers are relevant to explain the potential contagion losses due to exchange rate shock (Figure 7d). For instance, the average individual losses for diffusers and receivers are about 10% for a dollar appreciation as well a dollar depreciation (Figures 14b and 15b.

Our methodology can be used to monitor financial stability, allowing the regulator to take measures on two fronts. Reducing the potential power of shock diffusion of institutions and enhancing the resilience of financial institutions susceptible to receiving shocks in the network due to exchange rate shocks (financial institutions with high criticality as shock receivers). Policymakers can leverage this methodology to prioritize monitoring and intervention efforts, ensuring proactive measures are taken to mitigate systemic risk. Additionally, this approach can be integrated into existing regulatory frameworks to enhance the dynamic assessment of financial stability, thereby improving the robustness of the financial system against exchange rate volatility.

6 Conclusions

This paper examines the propagation of exchange rate shocks in a comprehensive network comprising various financial institutions, corporate sectors, and their interconnected exposures. We consider the heterogeneity of each economic agent, their specific interconnection patterns, and exposures to exchange rate shock. This detailed approach contrasts with existing research on the effects of exchange rates on the economy, typically conducted at the aggregate level. We apply our model to the Brazilian case. Our empirical analysis reveals while financial institutions typically benefit from positive exchange rate shocks due to their net foreign-denominated assets, nonfinancial firms are more likely to suffer losses, particularly those with significant foreign debt. However, contagion effects matter: even sectors initially better off can incur substantial indirect losses from contagion, underscoring the importance of financial interconnections to drive financial instability. Certain segments, such as development banks and nonbanking financial institutions, have higher vulnerability than the other sectors. However, the system-wide financial stability is robust and supported by sufficient regulatory capital. These insights are vital for policymakers aiming to design targeted interventions to mitigate systemic risks, emphasizing the need to consider network structures in regulatory frameworks and stress-testing methodologies.

We can list some limitations of our study. First, our analysis assumes nonfinancial firms do not hedge their foreign currency exposures, which may not reflect real-world practices. Including data on hedging strategies could provide a more accurate picture of firms' vulnerabilities. Second, the scope of our dataset is limited to Brazil, which may limit the generalization power of our findings to other economies with different structures and levels of financial development, such as more advanced economies. Future research could extend this analysis to other countries to validate the robustness of our conclusions in different economic contexts. We highlight our model is general and could be directly applied to these cases if data are available. Additionally, while our network model captures a wide array of exposures, it does not account for potential behavioral changes by economic agents in response to exchange rate shocks. Incorporating dynamic behavioral models could enhance the predictive power of our framework.

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