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ESSAYS ON BANK EFFICIENCY AND SHADOW BANKING

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Tese apresentada à Escola de Administração de Empresas de São Paulo da Fundação Getulio Vargas, como requisito para a obtenção do título de Doutora em Administração de Empresas.

Campo de conhecimento: Finanças corporativas

Orientador: Prof. Dr. Richard Saito

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Dedicated to the memory of my beloved father Aparecido

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ABSTRACT

Shadow banking refers to credit intermediation activities carried out by non-bank financial institutions. One of the main functions of the shadow banking system is to allow depositary institutions to use securitization instruments to expand their funding sources, limit their exposure to credit risk, and deal with capital requirements. In this sense, by enabling structured finance vehicles, non-bank financial intermediation can be a shock absorption mechanism for risks that develop within the commercial banking system. This thesis aims to understand non-bank financial intermediation in Brazil from three perspectives. We begin by analyzing the macroeconomic trends in shadow banking activities in the Brazilian economy from 2002 to 2020, focusing on structured finance vehicles. We show that the Brazilian shadow banking system complements the banking sector and that the use of structured finance vehicles as a source of external financing in Brazil exhibits a constant increase. Second, we explore the supply side of securitization and analyze the association between the decision to securitize originated loans and bank efficiency using a two-step approach that combines data envelopment analysis and TOBIT panel data regressions. Using data on 53 Brazilian financial conglomerates from June 2001 to December 2012, our findings demonstrate that income from securitization transactions is positively associated with the efficiency in generating interest income but not associated with operational efficiency. Finally, we explore the demand side of securitization and investigate the association between risk retention by originators (the acquisition of first-loss tranches by originators, also known as skin in the game) and the performance of receivables funds. We use data on 85 Brazilian receivable funds with a single originator from January 2013 to December 2020 and find that skin in the game is a buffer against observable risks, in accordance with the buffer hypothesis. Our findings also indicate that the reputation of originators that are financial institutions (measured by delinquency ratios) in the loan market can alleviate moral hazard concerns. However, the opposite holds for funds with fintech originators: risk retention is a signal against the unobservable quality of receivables. Altogether, our findings suggest that the reputation of financial institutions is an essential component to understand the performance of structured finance vehicles and that securitization is a stabilizing mechanism for the financial system in emerging markets because it allows efficient risk transfer to outside investors.

Keywords: shadow banking, banking, securitization, bank financing, efficiency, data envelopment analysis, financial stability, emerging markets

RESUMO

Shadow banking ou sistema bancário paralelo é um termo que se refere às atividades de intermediação de crédito realizadas por instituições financeiras não bancárias. Uma das principais funções desse sistema é permitir que as instituições financeiras depositárias usem instrumentos de securitização para expandir suas fontes de financiamento, limitar sua exposição ao risco de crédito e lidar com os requerimentos de capital. Nesse sentido, ao viabilizar a utilização de veículos de financiamento estruturado, o sistema de intermediação financeira não bancária pode funcionar como um mecanismo de absorção de choques para riscos que se desenvolvem dentro do sistema bancário comercial. Esta tese tem como objetivo compreender a intermediação financeira não bancária no Brasil a partir de três perspectivas. Em primeiro lugar, são analisadas as tendências macroeconômicas das atividades de shadow banking na economia brasileira de 2002 a 2020. Mostramos que o sistema bancário paralelo brasileiro complementa o setor bancário e que o uso de securitização como fonte de financiamento externo no Brasil apresenta um aumento constante. Em segundo lugar, exploramos o lado da oferta da securitização e analisamos a associação entre a decisão de securitizar empréstimos originados e a eficiência dos conglomerados financeiros no Brasil através de uma abordagem de duas etapas que combina análise por envoltória de dados e regressões TOBIT para dados em painel. Usando dados de 53 conglomerados de junho de 2001 a dezembro de 2012, nossos resultados demonstram que a receita de transações de securitização está positivamente associada à eficiência na geração de receita de juros, mas não está associada à eficiência operacional. Por fim, exploramos o lado da demanda da securitização e investigamos a associação entre a retenção de risco por parte dos originadores de crédito (que refere-se a aquisição de cotas subordinadas, também conhecida como skin in the game) e o desempenho dos fundos de investimento em direitos creditórios. Usamos dados de 85 fundos de recebíveis brasileiros com um único originador de janeiro de 2013 a dezembro de 2020 e descobrimos que, de maneira geral a retenção de riscos é um amortecedor contra riscos observáveis. Nossos resultados também indicam que a reputação dos originadores que são instituições financeiras (medida por índices de inadimplência) no mercado de empréstimos pode aliviar as preocupações de risco moral. No entanto, o oposto vale para fundos que têm fintechs como originadores: a retenção de riscos passa a funcionar como um sinal sobre a qualidade não observável dos recebíveis. Em conjunto, nossos resultados sugerem que a reputação das instituições financeiras é um componente essencial para entender o desempenho dos veículos de financiamento estruturado e que a securitização é um mecanismo estabilizador para o sistema financeiro em mercados emergentes, pois permite a transferência eficiente de risco para investidores externos.

Palavras-chave: shadow banking, bancos, securitização, financiamento bancário, eficiência, análise por envoltória de dados, estabilidade financeira, mercados emergentes

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1. An overview of shadow banking activity in Brazil

1.1 Introduction

Shadow banking refers to credit intermediation activities carried out by non-bank financial institutions or non-bank financial intermediation (NBFI). It includes, among other things, the negotiation of securities that generate cash flows to investors according to the tranche in which they invested. While non-bank financial intermediation is a broad measure of all non-bank financial entities, other financial intermediaries (OFIs) are a subset of the NBFI sector, including "investment funds, captive financial institutions and money lenders (CFIMLs), central counterparties (CCPs), broker-dealers, finance companies, trust companies, and structured finance vehicles" (Financial Stability Board – FSB, 2021). Regulators give special attention to those activities because they may engender vulnerabilities through liquidity/maturity transformation or leverage. In this sense, shadow banking can refer to institutions (entities), activities, or financial products. One of the main functions of the shadow banking system is to allow financial institutions to use securitization instruments to expand their funding sources, limit their exposure to credit risk, and deal with capital requirements. In this sense, by enabling the use of structured finance vehicles, the non-bank financial intermediation can be a shock absorption mechanism for risks that develop within the commercial banking system (Culp and Neves, 2018).

According to the Financial Stability Board (FSB, 2011), the main concerns about the shadow banking market relate to procyclicality, its effects on maturity and liquidity transformation, as well as its side effects on credit financing and financial intermediation. Authorities closely monitor those entities that may pose bank-like financial stability risks, including credit intermediation that involves maturity/liquidity transformation, leverage, or imperfect credit risk transfer (FSB, 2021). McCulley (2007) and Cetorelli and Peristiani (2012) argue that financial intermediation has evolved to a securitization-centered system, in which credit is not necessarily financed by bank deposits but rather by separate financing mechanisms, which in turn drive the creation of decentralized intermediation transactions and, thus, fuels the growth of the shadow banking system. The FSB refers to those activities as securitization-based credit intermediation. Securitization is an essential component of shadow banking or non-bank finance because it allows banks to reduce the liquidity risk intrinsic to the banking activity through off-balance-sheet (OBS) operations (Farhi and Prates, 2018). According to Pozsar and Singh (2011), loan securitization and risk transfer outside the banking sector are the core elements that explain the relationship between banks and shadow banks.

Regulatory authorities also closely monitor those institutions that may be involved in regulatory arbitrage. In this sense, regulatory cycles are another component that explains the expansion of shadow banking activities. Some studies emphasize that regulatory arbitrage favors such an

expansion (Pozsar et al., 2010, Jackson, 2013, Buchak, Ari, et al., 2017, Matvos, Piskorski and Seru, 2017, Moreira and Savov, 2017) and that shadow banking activities constitute a core-peripheral structure to the banking system (Priazhkina, 2017, Sun and Jia, 2018). Some authors (Calmés and Théoret, 2009) also argue that the regulatory approach after the 2008 global financial crisis favored the activities of large banking conglomerates and may have fueled the growth of the shadow banking system. In this sense, understanding the shadow banking system or non-bank financing also depends on the comprehension of the changes in banking regulation and the competitive dynamics in the banking industry. Moreover, because shadow banking institutions are not subject to the same regulatory requirements that depositary institutions face, there are also concerns about their impact on financial stability.

Due to this connection between banks and shadow banks, the analysis of shadow banking activities depends on the dynamics of financial institutions' funding instruments. In the Americas, for instance, banks rely more on funding by other financial intermediaries than in other continents, and this link involves investment funds activities but not necessarily balance sheet interconnectivity (Nijs, 2020). In emerging markets, the coronavirus pandemic reinforced the importance of discussing liquidity management in the context of banks, especially for those that engage in off-balance-sheet activities. Li, Xie, and Lin (2020) argue that government capital injections play a crucial role in such a discussion because they can harm the efficiency of shadow banking operations.

The purpose of this chapter is to shed some light on the macroeconomic trends in shadow banking activities in the Brazilian economy from 2002 to 2020, with a particular focus on structured finance vehicles, which are a subset of the NBFI sector. We present an overview of the literature in shadow banking focusing on the key aspects that explain the relationship between shadow banking activity and bank funding mechanisms. Then, we combine several datasets to understand the dynamics of non-bank financing in Brazil, focusing on the critical variables proposed by Moreira and Savov (2017) to understand such a phenomenon: uncertainty, spreads, and asset prices.

Although the size of the shadow banking system in Brazil was historically small, we observed an upward trend in the share of total financial assets by NBFI, from only 5% in 2002 to 47% in 2020. We show that the Brazilian shadow banking system complements the banking sector and that the use of structured finance vehicles in Brazil exhibits a constant increase. Besides, the suggested inverse relationship between shadow banking spreads and asset prices does not always prevail in the Brazilian economy.

1.2 Literature review

Pozsar and Singh (2011) argue that understanding the dynamics of the shadow banking market has to do with the importance of asset managers. On the supply side, asset managers are essential collateral sources for the non-bank intermediation market. On the demand side, these managers need liquid, short-term assets to deal with mandate-related obligations, which means that they transform part of their clients' long-term savings into short-term savings. This reverse maturity transformation creates cash pools that are not intermediated by banks (unlike bank deposits), given that managers use third-party resources such as short-term public debt securities and wholesale asset-backed securities. This interaction between demand and supply of asset managers determines the growth of credit intermediation outside the banking system. As banks need to mediate these collateral mining for financing needs and to obtain superior returns for their clients, levered collateral between banks and resource managers emerges. Large financial conglomerates use traditional and market-based instruments as financing mechanisms, performing bank and shadow bank functions within the financial ecosystem. In other words, bank deposits are not the only source of financing in a financial system, and the sources of financing available to banks include the interbank market and the role of asset managers. Thus, shadow banking is a phenomenon that depends on the interaction between asset managers and banks, often involving off-balance sheet operations.

Moreira and Savov (2017) developed a theoretical model demonstrating that the choice between shadow banking and collateral-intensive funding varies with economic uncertainty, which in turn, has an impact on shadow banking spreads. In their view, shadow banking refers to "the process of creating shadow money" that is fragile-liquid: middle-security tranches are liquid most of the time, having a higher crash exposure than always-liquid securities. In this sense, shadow banking presents a trade-off between stability and growth: during periods of low uncertainty, shadow securities exhibit low spreads compared to always-liquid/money instruments, making it an attractive source of funding, allowing liquidity provision expansion, and causing an increase in asset prices. However, a rise in uncertainty opens up the spread between shadow money and traditional money, making intermediaries switch to money securities and causing a decrease in asset prices, with negative impacts on economic growth.

Much of the discussion about shadow banking relates to the changes in the banking landscape and the increasing importance of banks' off-balance-sheet (OBS) activities. Because these changes have influenced banks' risk-return tradeoff, Calmés and Théoret (2009) argue that the bank's decision to diversify with OBS activities can be endogenous, and the propensity to engage in such operations is higher when banks need extra funding. The 2008 global financial crisis triggered a revision of regulatory frameworks regarding banks' liquidity, on the premise that capital buffers were suboptimal and bank failures could have negative externalities in the financial sector, which led to the Basel III capital requirements (Vazquez and Federico, 2012).

In addition to generating a support system and greater liquidity for the bank credit market, the shadow banking market also takes on two other roles within the financial market: these institutions reduce the information asymmetry about borrowers and have relevant impacts on credit supply. Priazhkina (2017) argues that regulated banks form long-term relationships with the leading players in the shadow banking market, channeling liquidity to these institutions and decreasing the liquidity of peripheral banks. In this sense, financial markets endogenously develop a core-peripheral structure: regulated banks serve as intermediaries of the shadow banking system, rescuing these institutions during crises and channeling the credit risk exposure these institutions face.

Pozsar and Singh (2011) argue that the securitization of loans and the transfer of risks outside the banking system helps to explain the connection between banks and shadow banks. Baur et al. (2016) argue that risk diversification within the banking system increases the level of connection between banks, diminishing the benefits of diversification and transforming the risk transfer outside the banking system into a better alternative. Nevertheless, Gorton and Metrick (2010) argue that this risk reallocation is not the only factor that explains the development of the shadow banking market because shadow entities have a different demand for securitized assets and are willing to pay more for securitized assets than banks. Culp and Neves (2018) argue that banks use the shadow banking system for financing and risk transfer purposes; it functions as a shock absorption mechanism for risks that develop within the commercial banking system. Because of that, regulatory initiatives aimed at increasing the costs to engage in such entities could increase the concentration of risks in the banking sector. In general, these arguments suggest that the risk transfer mechanism is a stabilizing factor because such diversification reduces the exposures to a liquidity shock, increasing banks' efficiency. For instance, Lin, Chen, and Huang (2018) developed an empirical model and demonstrated that securitization has a positive impact on bank efficiency. Despite that, the securitization process has many associated costs that reduce banks' efficiency. Hence, there is no consensus on the stabilizing role of the shadow banking market during liquidity shocks. Chapter 3 is dedicated to a detailed analysis of the association between bank efficiency and engagement in securitization.

In the context of the coronavirus pandemic, Li, Xie, and Lin (2020) developed a theoretical model that compares the effectiveness of credit intermediation by banks with shadow banking operations and banks without such transactions. On the one hand, they demonstrated that the optimal bank interest margin was lower during the pandemic, with a lower effect for institutions that engaged in shadow banking activities and received government capital injections. One of the implications of their model is that government capital injections stimulate bank lending and shadow banking activities. On the other hand, the efficiency of shadow banking operations was lower during the pandemic, mainly because of its impact on banks' earnings.

1.2.1 Shadow banking in Brazil

According to the 2015 Financial Stability Report of the Central Bank of Brazil (BCB), the shadow banking system in Brazil includes the following entities: investment funds, structured finance vehicles or securitization structures (receivables funds - FIDCs, real estate receivables - CRIs, agribusiness receivables certificates – CRAs), real estate investment funds (FII), market intermediaries, financial and capitalization companies, accreditors, and non-bank credit card issuers.

The IMF argues that shadow banking in Brazil is historically small, with bank-led financial conglomerates controlling most financial assets. However, similar to the pattern observed in some developing countries such as China, shadow-banking activities exhibited an upward trend in Brazil. While in 2002 the assets of non-bank institutions represented only 5% of the total financial assets in Brazil, in 2020 they accounted for 47% of the total (**Table *1*** and **Figure *1***). The rapid growth in NBFI assets started in 2006, jumping from 0,02 USD tri in the previous year to 0,30 USD tri. Since the global financial crisis of 2008, the assets of commercial banks in the Brazilian economy represent less than half of the total. In 2020, during the pandemic of the new coronavirus, non-bank financial intermediation reached 47% of total financial assets.

1.2.1.1 The regulatory approach to fintechs in the Brazilian economy

For the general public, fintechs are often known as one of Brazil's main types of shadow banking institutions. Due to the intensive use of financial technology, they were able to lower the barriers of entry in the banking segment, although their ability to effectively challenge the market share of incumbent banks in the credit market is often subject to debate. In terms of regulatory scope, the Securities and Exchange Commission of Brazil (CVM) supervises some financial-technology-intensive startups (fintech) segments, while the Superintendency of Private Insurance (Susep) supervises others. Credit and payment fintechs are in the regulatory scope of BCB. Brazil was the only jurisdiction that introduced a dedicated licensing regime for fintechs (Ehrentraud et al., 2020). Specifically, Resolution 4656/2018 of the National Monetary Council (CMN) concerns direct credit societies (*sociedades de crédito direto* – SCD) and peer-to-peer loan companies (*sociedade de empréstimo entre pessoas* - SEP), considering them new types of financial institutions. An SCD is a "financial institution responsible for carrying out operations of loan, financing, and acquisition of credit rights, exclusively through an electronic platform, operating with its own capital" (Res. 4656/2018, BCB). Regarding prudential financial regulation, SCDs and SEPs are subject to the same laws and regulations imposed on the institutions in segment S5, based on a segmentation that classifies prudential conglomerates depending on their size (as a proportion of Brazilian gross domestic product). According to the regulators, these institutions have a simplified risk profile and, thus, do not pose risks to financial stability.

Due to the challenges in satisfying all of the requirements of Resolution 4656/2018, most of the fintech players in Brazil still operate as correspondents (correspondente bancário), creating a kind of financial services marketplace. Banking correspondents often provide user-friendly platforms that, in practice, offer financial services from large financial conglomerates. The credit granted by such fintechs translates into a bank credit note (cédula de crédito bancário - CCB), which is a security issued by the individual or legal entity that will receive the credit. The approval of Provisional Measure number 897 in October 2019 boosted this market, allowing the issuance of CCBs through an electronic bookkeeping system.

In chapter 3, we analyze structured finance vehicles and discuss the performance of receivables funds, one of the main components of shadow banking in Brazil, comparing those that acquire loans from traditional financial conglomerates to those that acquire loans from fintechs. Because shadow banks can often reduce the information asymmetry about borrowers and have relevant impacts on credit supply, we focus on the signaling and reputation mechanisms in the loans market when observing this new type of technology-intensive financial institution.

1.3 Data

We combined several datasets to understand the dynamics of non-bank financing in Brazil and compare the national scene with the main theoretical findings described in the previous session. We used a descriptive approach to analyze data and explored the relationship between our main variables of interest: total assets of the Brazilian shadow banking system, private credit intermediation, securitization, credit sales, market performance, asset prices, and term-premiums.

We listed all the variables used for this study and its sources in **Table *2***. We use FSB's monitoring dataset to measure the size of the shadow banking market in Brazil. We combined data from the Securities and Exchange Commission of Brazil, the Brazilian Central Bank (BCB), and from the Brazilian Financial and Capital Markets Association to understand the dynamics of the primary structured finance vehicles in Brazil – receivables funds (FIDCs), real estate receivables (CRIs), agribusiness receivables certificates – CRAs, and real estate investment funds (FIIs).

To calculate an alternative measure of shadow banking activities in Brazil, we joined the total assets of the financial institutions described in **Table *3*** with the total assets of receivables funds. We do so to understand the relationship between shadow banking and asset price dynamics in Brazil. To measure asset price dynamics monthly, we combined the Ibovespa, a theoretical index consisting of the most liquid stocks in the São Paulo Stock, Mercantile & Futures Exchange (B3), and the Fipezap, a nationwide indicator that tracks the sale and rental prices of real estate in Brazil, for both commercial and residential buildings. We used the spread on

subordinate quotas (above the Brazilian interbank rate, DI) of Brazilian receivables funds to measure shadow banking spreads. Then, to compare asset price dynamics and shadow banking spreads, we used the average of the last two quarters and compared the spreads with the asset price growth from the next quarter. In chapter 3, we analyze the performance of receivables funds with a single originator in more detail. We will also discuss the related theoretical background for those securitization structures.

1.4 Descriptive statistics

The analysis of the shadow-banking system suggested by Pozsar and Singh (2011) includes the role of asset managers in the national financial system. The growth of credit intermediation by Brazilian non-bank financial institutions and the private credit offered by deposit banks (as a proportion of GDP) exhibited a similar trend from 2002 to 2017 (**Figure *2***). These numbers suggest that shadow banking institutions are not banks' competitors. Instead, they function as a complement, constituting a core-peripheral structure to the banking system (Priazhkina, 2017, Sun and Jia, 2018). Indeed, **Figure *3*** demonstrates that the NBFI sector asset growth and bank/central bank asset growth exhibited similar trends over the years. However, policy interventions during the coronavirus pandemic made the assets of both banks/central banks and shadow banks increase significantly, demonstrating that the support of the flow of credit came from both sources. Moreover, **Figure *1*** and **Figure *2*** suggest that the role of non-bank finance intermediation has been steadily increasing in the Brazilian economy.

We then analyze a subset of the NBFI sector and focus on capital markets because such entities deal with credit intermediation that involves maturity/liquidity transformation, leverage, or imperfect credit risk transfer (FSB, 2021). Since 2015, the volume of transactions by other financial intermediaries in Brazil (stocks, debentures, notes payable, standby letters of credit, real estate receivables, receivables funds, and agribusiness receivables certificates) increased steadily (**Table *4***). From 2018 to 2019, the volume of transactions by other financial intermediaries increased more than 70% (**Figure *4***), and debt securities represented the largest source of external financing for these institutions. From 2014 to 2019, securitization accounted for 19% of external financing, on average, and peaked at 29% in 2016 (**Figure *5***). The number of issues using structured finance vehicles grew steadily since 2016, reaching a peak of 72 billion reais in 2020, in a moment of low record levels of interest rates in response to the pandemic.

In most developed economies, shadow banking is highly procyclical. In Moreira and Savov's (2017) model, shadow money's liquidity cycle drives the macrocycle and economic growth. Thus, the first component to understand shadow-banking dynamics in Brazil refers to cyclicality. To do so, in **Figure *6*** we compare the performance of the Brazilian stock market (yearly) to the volume of issues of structured finance vehicles (SFV), dividing SFVs into receivables funds (FIDCS) and others (CRIs and CRAs). Although the stock market exhibited a deceleration from 2016 to 2018, issues of FIDCs remained relatively strong. During the

pandemic, while the stock market's performance collapsed, issues of receivables funds and other SFVs peaked.

Furthermore, the volume of credit sales boosted during the pandemic, with increases in both credit sales units and liquidation values **Figure *7***). Altogether, these numbers suggest that shadow banking activity in Brazil is not as procyclical as in developed economies. In a moment of market collapse and strong policy response, structured finance vehicles were an essential source of financing in Brazil.

Another component of our analysis is the relationship between shadow banking dynamics and asset prices. Moreira and Savov (2017) argue that during periods of low uncertainty, low spreads in shadow securities expand liquidity provision causing an increase in asset prices. When uncertainty increases, these spreads are higher, and one can observe a decrease in asset prices. Asset price inflation refers to a nominal rise in the prices of assets rather than goods or services. **Figure *8*** suggests that an inverse relationship between shadow banking spreads and asset prices does not always prevail in Brazil. Asset prices and shadow banking spread seem to move together. We will discuss shadow banking spreads in detail in Chapter 3, using severe delinquency ratio as our crucial measure of performance of receivable funds.

We also explore the relationship between shadow banking expansion and banks' funding. On the one hand, credit sales are an essential source of market-based bank funding and, thus, fall within the scope of shadow banking activities. On the other hand, the term premium functions as a proxy of economic uncertainty because higher term premiums usually imply higher economic uncertainty. We analyze the liquidation value of credit sales and the term premium of zero-coupon government bonds (**Figure *9***) to understand the relationship between these variables, using the 10-year minus 1-year spread. We observe two distinct patterns in the Brazilian economy: from 2011 to 2016, there was a sharp decrease in term premiums, but credit sales exhibited a modest upward trend. However, from the third quarter of 2014 until the first quarter of 2020, the liquidation value of credit sales decreased significantly, while the term premium consistently increased. However, after the liquidity shock caused by the pandemic of Covid-19, the volume of credit sales exhibited an exponential increase, and term premiums followed the same pattern. Indeed, from February 2020 to August 2020, the average liquidation value of credit sales almost tripled the average value observed in 2018 and 2019, reaching a peak in May 2020 that is comparable to the levels from December 2014 and June 2015 (**Figure *7***), when Brazil was facing a severe economic crisis.

Finally, we compare credit intermediation by non-bank financial institutions in Brazil to selected economies. As % of GDP, private credit by deposit banks (as % of GDP) grew steadily in emerging economies, while the opposite holds for advanced economies such as Germany and the United States. In Brazil, this proportion grew from 29% in 2002 to 70% in 2020 (**Figure**

10). In emerging economies, credit to the private non-financial sector from non-bank institutions (as % of GDP) also exhibited a steady increase, while in Brazil it remained relatively stable, from 16% in 2002 to 10% in 2020 (**Figure *11***).

1.5 Concluding remarks

Descriptive statistics in this chapter demonstrate that the representation of non-bank institutions in total financial assets in Brasil exhibited a substantial increase, from 5% in 2002 to 47% in 2020. The growth of credit intermediation by Brazilian non-bank financial institutions and the private credit offered by deposit banks exhibited a similar trend, suggesting the Brazilian shadow banking system complements the banking sector that generates more efficiency to the financial market. Structured finance vehicles exhibit a steady growth as a source of external financing, and issues of securitization vehicles do not seem to be strongly correlated to the Brazilian stock market performance. Finally, we observed two distinct patterns: from 2011 to 2016, there was a sharp decrease in term-premiums for Brazilian government bonds, but credit sales exhibited a modest upward trend. However, from the third quarter of 2014 until the first quarter of 2020, the liquidation value of credit sales decreased significantly, while the term premium consistently increased. Nevertheless, after the liquidity shock caused by the pandemic, the volume of credit sales exhibited an exponential increase, and term premiums followed the same pattern.

References

Ari, A., Darracq-Paries, M., Kok, C., Zochowski, D. (2017). Shadow Banking and Market Discipline on Traditional Banks. *IMF Working Paper 17/285*.

Baur, D.G., Cariboni, J., Hallak, I., Petracco, M.G. (2016). Securitization, Connectedness and Shadow Banking" *JRC Technical Reports*.

Brazilian Central Bank. Resolution 4656 of 2018. https://www.bcb.gov.br/content/financialstability/org_docs/Resolution%204656.pdf

Calmès, C., Théoret, R. (2010). Off-Balance-Sheet Activities and the Shadow Banking System: An Application of the Hausman Test with Higher Moments Instruments. Available at SSRN. http://dx.doi.org/10.2139/ssrn.1676934

Cetorelli, N., Peristiani, S. (2012). The Role of Banks in Asset Securitization. FRBNY

Economic Policy Review, pp. 47-63.

https://www.newyorkfed.org/medialibrary/media/research/epr/2012/eprvol18n2.pdf#page=50

Culp, C.L., Neves, A.M.P. (2018). Shadow Banking, Risk Transfer, and Financial Stability. *Journal of Applied Corporate Finance*, 29, 4, 45-64. https://doi.org/10.1111/jacf.12261

Ehrentraud, J., Ocampo, D.G., Garzoni, L, Piccolo, M. (2020). Policy responses to fintech: a cross-country overview. *Bank for Internation Settlements – FSI Insights on policy implementation No. 23*. https://www.bis.org/fsi/publ/insights23.pdf

Farhi, M., Prates, D.M. (2018). A crise financeira e a evolução do sistema bancário. Texto para

Discussão 2431 – Instituto de Pesquisa Econômica Aplicada. http://repositorio.ipea.gov.br/bitstream/11058/8926/1/td_2431.pdf

Financial Stability Board (2011). Shadow Banking: Strengthening Oversight and Regulation. https://www.fsb.org/wp-content/uploads/r_111027a.pdf?page_moved=1

Gorton, G.B., Metrick, A. (2010). Regulating the Shadow Banking System. *Brookings Papers on Economic Activity*. http://dx.doi.org/10.2139/ssrn.1676947

International Monetary Fund (2018). Brazil: Technical note on stress testing and systemic risk analysis. Financial sector assessment program. IMF Country Report No. 18/344. https://www.imf.org/en/Publications/CR/Issues/2018/11/30/Brazil-Financial-Sector-Assessment-Program-Technical-Note-on-Stress-Testing-and-Systemic-46416

Jackson, P. (2013). Shadow Banking and New Lending Channels – Past and Future. In *50 years of money and finance: Lessons and challenges*, Chapter 11.

Li, X., Xie, Y., Lin, J-H. (2020). COVID-19 outbreak, government capital injections, and shadow banking efficiency. *Applied Economics*. https://doi.org/10.1080/00036846.2020.1808183

Lin, J., Chen, S., Huang, F. (2018). Bank Interest Margin, Multiple Shadow Banking Activities, and Capital Regulation. *International Journal of Financial Studies*, 6, 63, 1-20.

McCulley, P. (2007). Teton Reflections, PIMCO Global Central Bank Focus.

McNamara, C., Metrick, A. (2015). Basel III G: Shadow Banking and Project Finance. *Yale Program on Financial Stability*. Case Study 2014-1G-V1 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2576973

Moreira, A., Savov, A. (2017). The Macroeconomics of Shadow Banking. *The Journal of Finance*, 72, 6, 2381-2432. https://doi.org/10.1111/jofi.12540

Nijs, Luc. (2020). The Handbook of Global Shadow Banking, Volume II. Palgrave McMillan.

Pozsar, Z., Adrian, T., Ashcraft, A.B., Boesky, H. (2010). Shadow Banking. Federal Reserve Bank of New York Staff Report No. 458. http://dx.doi.org/10.2139/ssrn.1645337

Pozsar, Z., Singh, M. (2011). The Non-Bank-Bank Nexus and the Shadow Banking System. International Monetary Fund Working Paper No. 11/289.

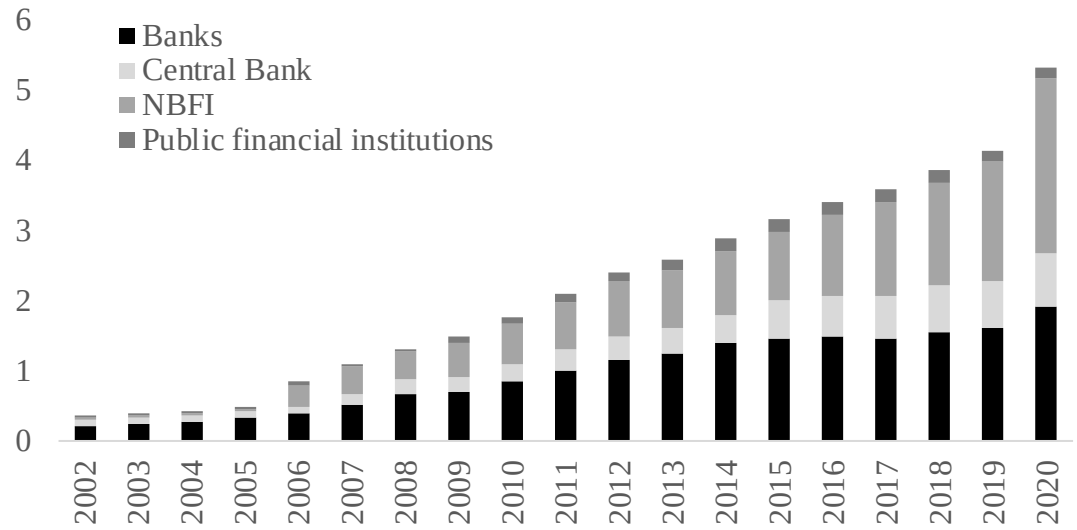
Priazhkina, S. (2017). Liquidity channels and stability of shadow banking. XII Annual Seminar on Risk, Financial Stability and Banking. https://www.bis.org/bcbs/events/rtf_sep2017/priazhkina.pdf

Sun, G., Jia. J. (2018). The definition and Measurement of China's Shadow Banking System from the perspective of Credit Money Creation. Vox China. Available at http://www.voxchina.org/show-55-40.html

Vazquez, F., Federico, P. (2012). Bank Funding Structures and Risk: Evidence from the Global Financial Crisis. International Monetary Fund Working Paper No. 12/29.

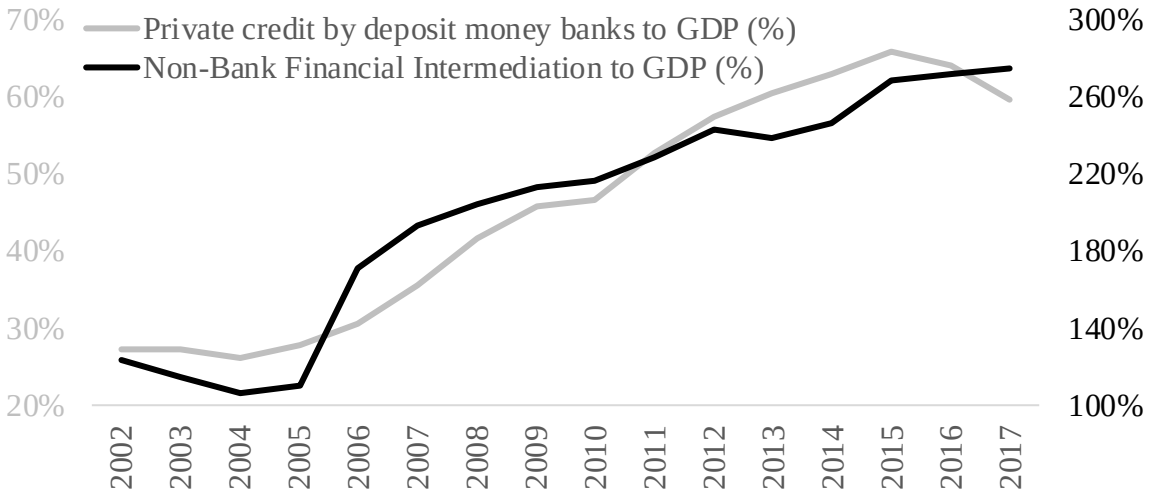
Figures and tables

Figure 1: Total financial assets in Brazil (in USD trillions)



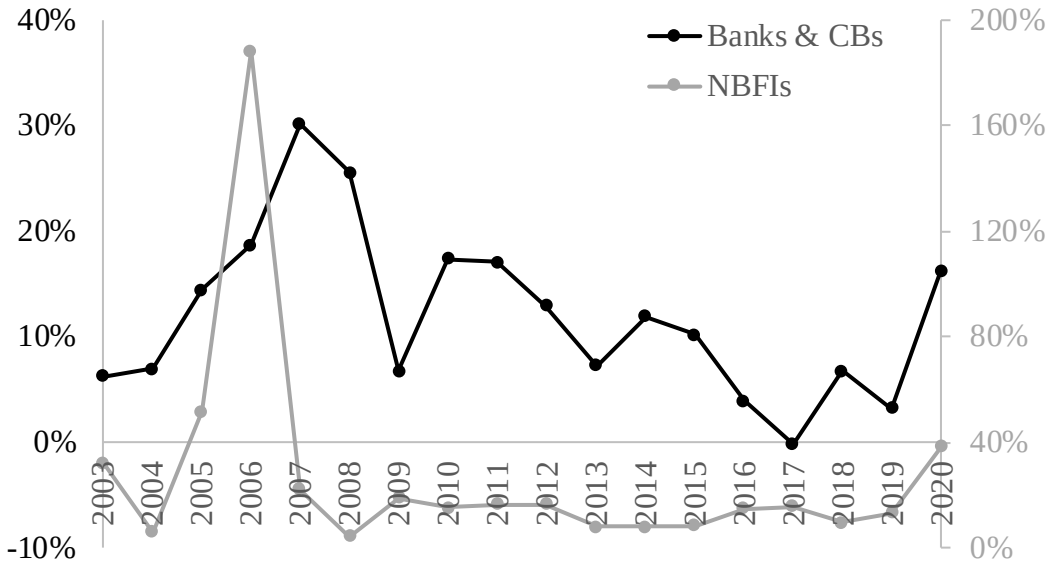
Source: Financial Stability Board. Elaborated by authors.

Figure 2: Credit intermediation in Brazil: banks and non-bank institutions



Sources: Financial Stability Board and World Bank. Elaborated by authors.

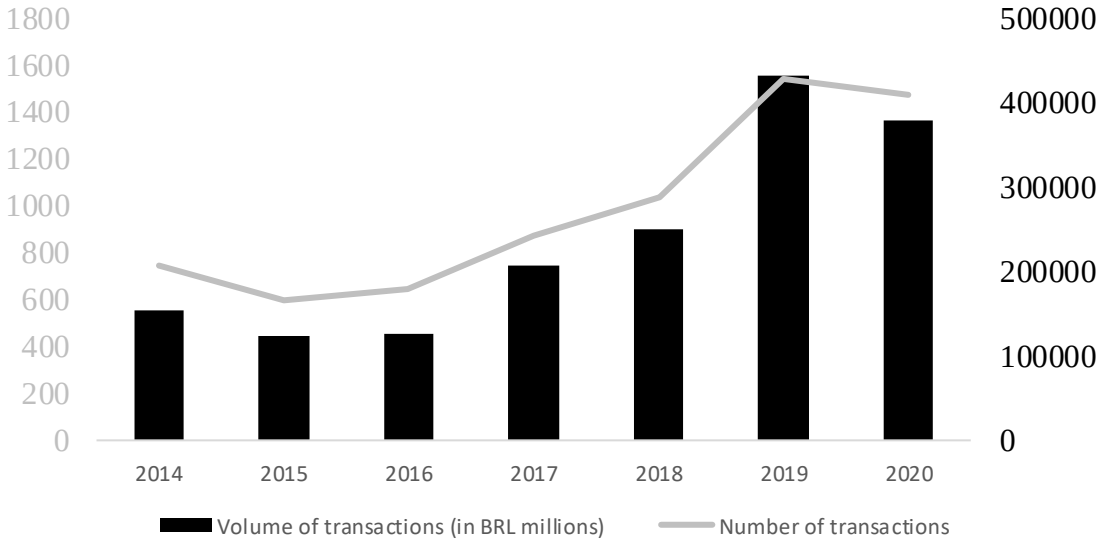
Figure 3: The relationship between NBFI* sector asset growth and bank/central bank asset growth in Brazil



* NBFI includes insurance corporations, pension funds, other financial intermediaries (OFIs) and financial auxiliaries.

Source: Financial Stability Board. Elaborated by authors

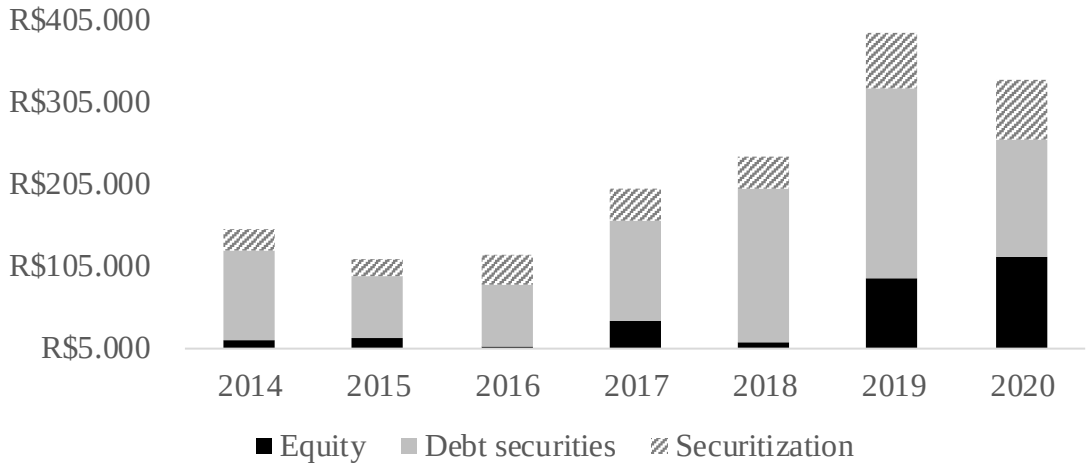
Figure 4: Investment behavior of other financial intermediaries



* Stocks, debentures, notes payable, standby letters of credit, real estate receivables, receivables funds and agribusiness receivables certificates

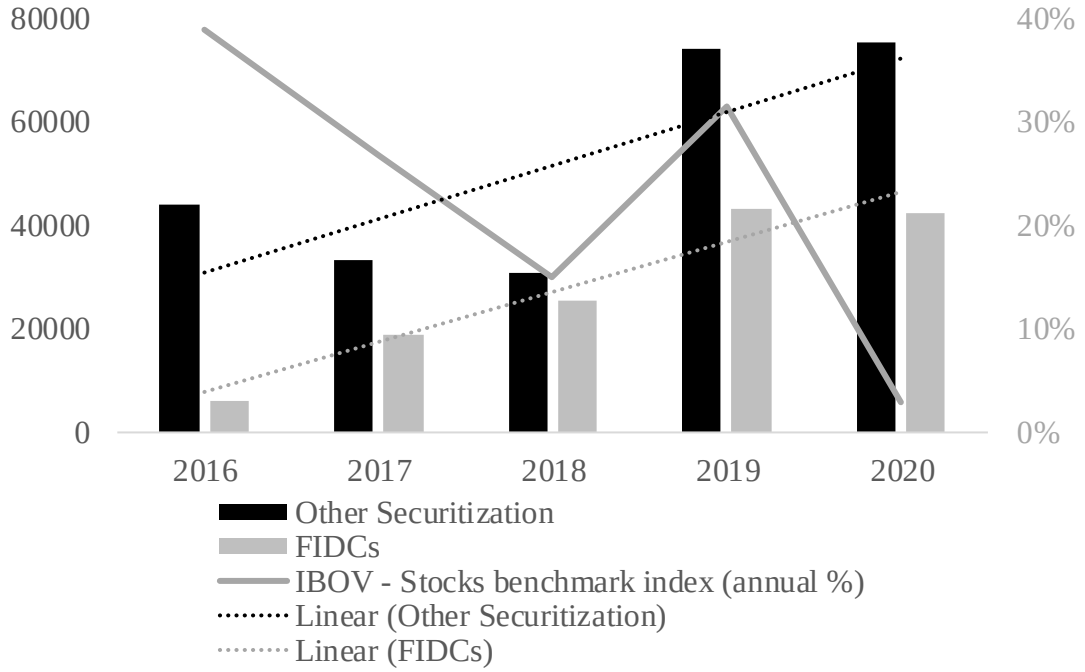
Source: Elaborated by authors

Figure 5: External financing of other financial intermediaries (in BRL millions)



Source: Anbima. Elaborated by authors.

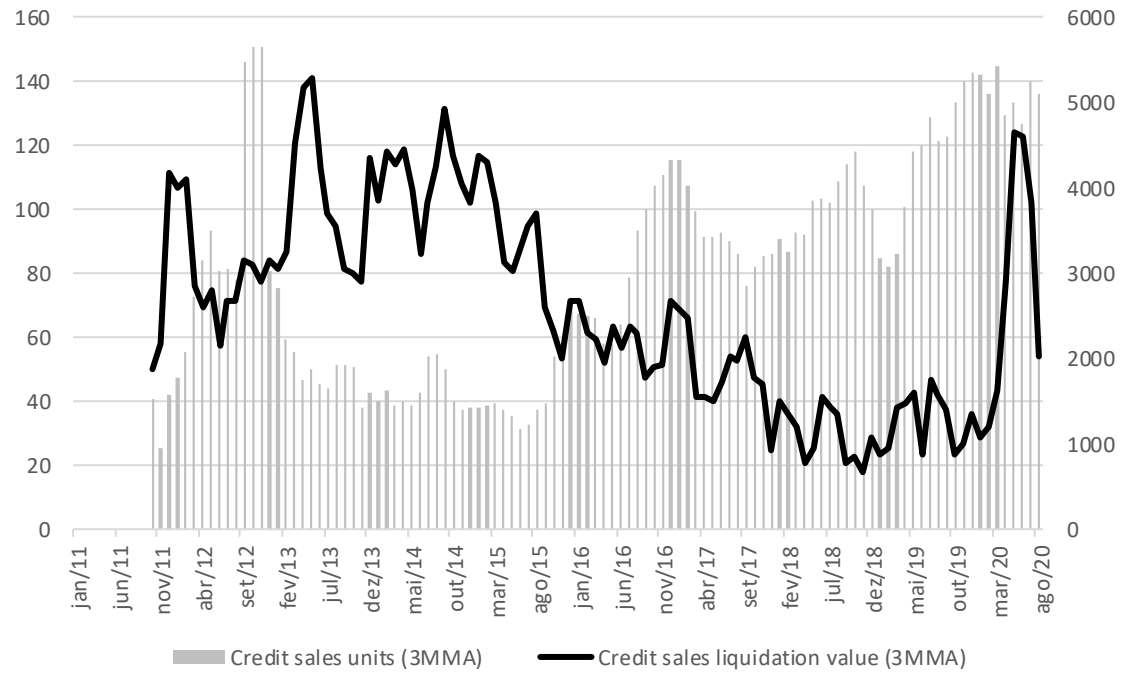
Figure 6: Securitization issues (in BRL millions)* and market performance in Brazil



*Real values (2020 prices, inflated using IPCA). Other securitization includes CRIs and CRAs.

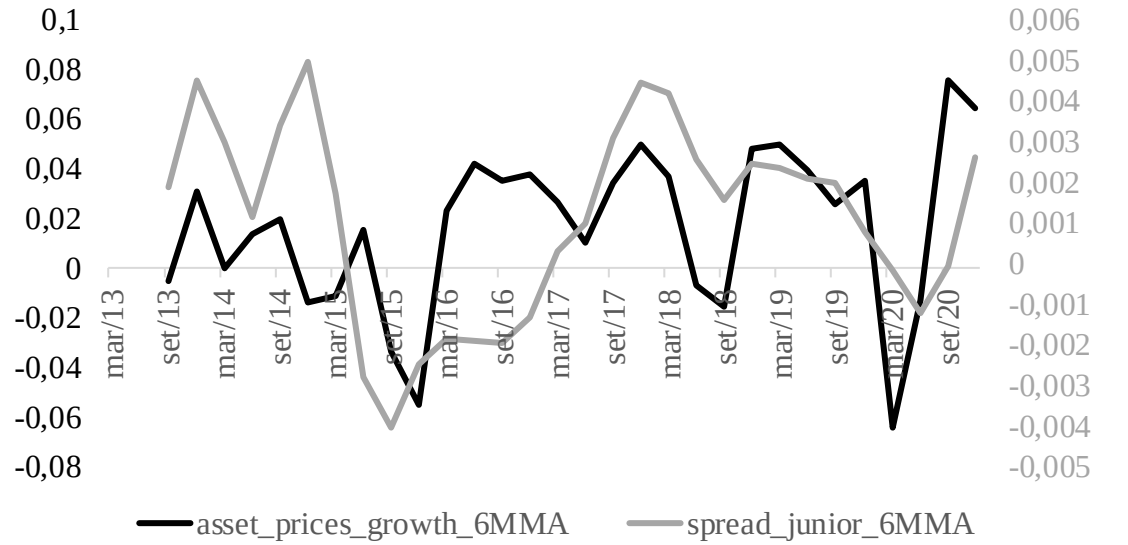
Sources: Anbima, IBGE and B3. Elaborated by authors.

Figure 7: Shadow banking activities in Brazil: credit sales



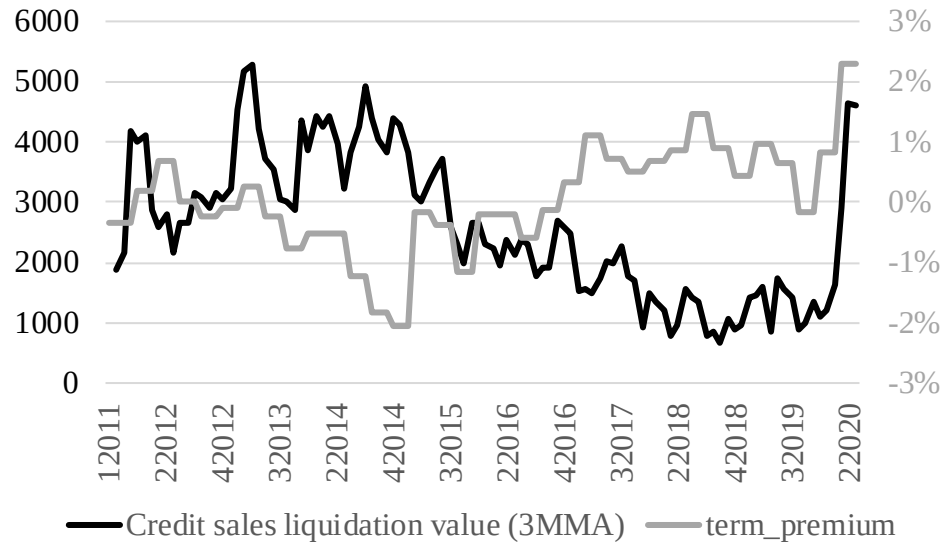
Source: C3. Elaborated by authors.

Figure 8: Asset prices and shadow banking spreads in Brazil



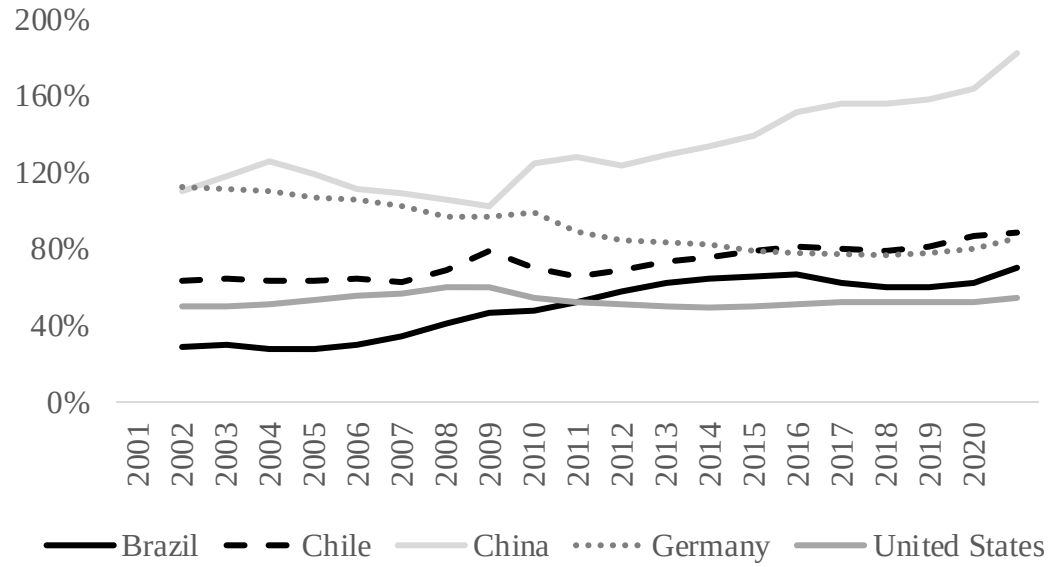
Sources: Securities and Exchange Commission of Brazil, São Paulo Stock, Mercantile & Futures Exchange (B3), Google Finance, Fipe. Elaborated by authors.

Figure 9: The term-premium effect on credit sales



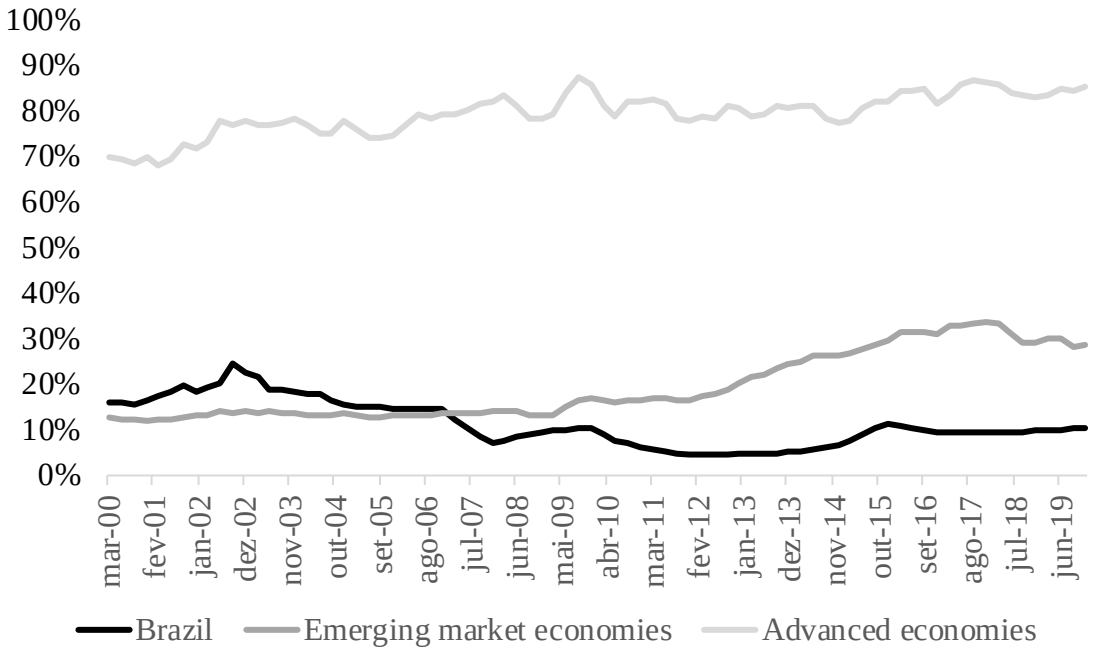
Sources: Anbima and C3. Elaborated by authors.

Figure 10: Private credit by deposit money banks to GDP (%)



Source: Global Financial Development Database. Elaborated by authors.

Figure 11: Credit to private non-financial sector from nonbank institutions at market value (% GDP)



Source: Bank of International Settlements. Elaborated by authors.

Table 1:Development of total assets of financial intermediaries in Brazil (in USD trillions)

Year	2002		2004		2006		2008		2010	
Entity	$	*% total*	$	*% total*	*$*	*% total*	$	*% total*	$	*% total*
Banks	0,221	*61%*	0,261	*63%*	0,392	*46%*	0,666	*50%*	0,855	*48%*
NBFI*	0,019	*5%*	0,028	*7%*	0,308	*37%*	0,400	*30%*	0,563	*32%*
Total	**0,362**		**0,417**		**0,842**		**1,322**		**1,769**	
Year	2012		2014		2016		2018		2020	
Entity	$	*% total*	$	*% total*	$	*% total*	$	*% total*	$	*% total*
Banks	1,141	*47%*	1,388	*48%*	1,492	*44%*	1,547	*40%*	1,924	*36%*
NBFI*	0,780	*32%*	0,916	*32%*	1,153	*34%*	1,481	*38%*	2,480	*47%*
Total	**2,407**		**2,893**		**3,403**		**3,860**		**5,332**	

* NBFI includes insurance corporations, pension funds, other financial intermediaries (OFIs) and financial auxiliaries.

Source: Financial Stability Board. Elaborated by authors.

Table 2: Variables and data sources

Variable	Source	Frequency	Data begins
Financial institutions' total assets	IF Data - Brazilian Central Bank (BCB)	Quarterly	First quarter, 2009
Financial assets by entity	Financial Stability Board	Yearly	2002
Receivables funds' total assets	Securities and Exchange Commission of Brazil (CVM)	Monthly	January 2013
Receivables funds' quotas performance	Securities and Exchange Commission of Brazil (CVM)	Monthly	January 2013
Interbank Rate	São Paulo Stock, Mercantile & Futures Exchange (B3)	Daily	January 02nd, 2009
Credit sales units	C3 Registradora	Monthly	January, 2011
Credit sales liquidation value	C3 Registradora	Monthly	January, 2011
Term structure of interest rates on zero-coupon Brazilian government bonds	Brazilian Financial and Capital Markets Association (Anbima)	Daily	September 21st , 2009
Securitization issues	Brazilian Financial and Capital Markets Association (Anbima)	Daily	Anuary 16th, 2014
Extended National Consumer Price Index (IPCA)	Brazilian Institute of Geography and Statistics (IBGE)	Monthly	January, 2014
Bovespa Index (Ibovespa)	São Paulo Stock, Mercantile & Futures Exchange (B3)		
Fipezap	Institute of Economic Research Foundation (Fipe)	Monthly	January, 2012
Investment funds' net worth	Brazilian Financial and Capital Markets Association (Anbima)	Monthly	December, 2006

Source: Elaborated by authors.

Table 3: Financial institutions included in our shadow banking measure (quarterly data)

Entity	**Proxy – IF Data Institution classification**
Microentrepreneur Credit Society (Sociedade de Crédito ao Microempreendedor)	10
Real Estate Loan Transfer Company (Sociedade de Crédito Imobiliário Repassadora)	31
Leasing Company (Sociedade de Arrendamento Mercantil)	19
Securities brokerage firm (Sociedade corretora de títulos e valores mobiliários)	15
Securities distribution company (Sociedade distribuidora de TVM)	16
Exchange brokerage company (Sociedade corretora de câmbio)	21
Capitalization companies (Sociedades de capitalização)	14
Credit card accreditors (Credenciadoras de cartão de crédito)	41
Non-bank credit card issuers (Emissoras de cartão de crédito não bancário) and Direct credit societies (sociedades de crédito direto)	43

Source: Central Bank of Brazil. Elaborated by authors.

Table 4: Investment behavior of other financial intermediaries*: capital markets

Year	Number of transactions	Volume of transactions (*in BRL millions*)
2014	742	154,331,95
2015	597	122,388,31
2016	646	126,611.34
2017	877	206,020.57
2018	1035	251,186.03
2019	1541	432,978.33
2020	1469	377,981.44

* Stocks, debentures, notes payable, standby letters of credit, real estate receivables, receivables funds and agribusiness receivables certificates

Source: Anbima. Elaborated by authors.

2. Banks' efficiency decomposition, engagement in securitization and productivity gains

This chapter analyzes the relationship between loan securitization and the efficiency of financial conglomerates applying a two-step approach. First, we model a bank's activity using a data envelopment analysis framework with two joint technologies in which loans are an intermediate output. These technologies generate operating and interest income and allow the decomposition of a bank's overall income efficiency by its respective capacity to generate such incomes. Second, we estimate a TOBIT panel data model to analyze a bank's propensity to engage in securitization activities relative to its income inefficiencies and other exogenous indicators. Our dataset contains 53 Brazilian financial conglomerates from June 2001 to December 2012. Our findings suggest that income from securitization transactions is positively associated with efficiency in generating interest income but not associated with operational efficiency.

Keywords: loan sales, data envelopment analysis, bank efficiency, shadow banking, credit risk, emerging markets

JEL Codes: G21, G32, G33, N16, N26

2.1 Introduction

Although the term shadow banking system usually refers to financial intermediation that occurs outside the banking system, banks found new ways to expand their profits and increase their efficiency with such activities, fostering the growth of this system (Ding, Fung, and Jia (2015), Hou et al. (2018), Pozsar et al., 2012). Some of the roots of this codependency are in the originate-to-distribute (OTD) model (Pozsar, 2008), and credit assignments by banks are a prominent example of this practice: financial institutions reduce the retention of originated loans, and nonbank financial intermediaries step in, acquiring credit pools and distributing them to investors with different risk appetites. In this sense, the shadow banking system depends on the banks themselves to perform many essential credit intermediation functions, thus becoming a parallel or "shadow" of the banking system (Sun and Jia, 2018). Some studies argue that bank regulation influences this dynamic because poorly capitalized banks are those that depend on the collection of fees for credit assignment activities to remain in business (Ribeiro and Schiozer (2013) Irani et al. (2018)). Additionally, theoretical and empirical studies suggest a positive relationship between securitization and bank performance (Greenbaum and Thakor (1987), Jiangli, Pritsker and Rapuach (2007), Affinito and Tagliaferri (2010), Wolfe (2010), Li, Sheng and Smallwood (2020), Bayeh et al. (2021)).

Using quarterly financial statements and credit assignment data from June 2001 to December 2012, the purpose of this study is to analyze the relationship between the use of shadow banking instruments by Brazilian banks (loan sales) and their efficiency, offering insights into the relationship between shadow banking and financial stability. By using data from 2001 to 2012, we provide evidence on the association between securitization activity and efficiency for pre- and post-global financial crisis periods. For this analysis, we propose a two-stage approach. Following Boussemart et al. (2019), we first model the bank production process via two joint technologies where loans are intermediate factors while explicitly considering a given level of credit risk. Indeed, each of the two technologies is linked to a specific activity and generates a specific type of revenue: operating income for the first technology and interest income for the second one. Moreover, the latter sub-process uses the distribution of total loans between performing and non-performing loans as an indicator of the bank's credit risk profile. This value-based approach enables us to aggregate the two components of income efficiency into a global efficiency measure, which distinguishes our setting from the one in Boussemart et al (2019). Compared to other estimation strategies (Bayeh et al., 2021), using a non-parametric activity model such as data envelopment analysis (DEA) allows us to estimate the total bank efficiency score and its two components without relying on parametric assumptions.

On a broader basis, the decomposition of efficiency through two different sub-technologies before analyzing the decision to engage in securitization transactions most accurately resembles the decision-making process in a financial institution. Moreover, the combination of two sub-technologies allows for a global benchmark (optimal situation) which is based on two different benchmarks specific to each of the bank's activities: one for operational efficiency and the other for the intermediation activity. The originality of our approach compared to already existing network models such as Boussemart et al. (2019) is at several levels: the objective function is the result of two scores that can be aggregated directly without making the arbitrary choice of exogenous weights. Additionally, we have explicitly introduced a one-quarter lag in the measurement of performing and non-performing loans, because such distinction cannot be

contemporaneous with the amount of loans initiated during a certain quarter. Secondly, in the vein of (Ribeiro and Schiozer (2013), Farruggio and Uhde (2015), Li, Sheng and Smallwood (2020), Bayeh et al. (2021)) we apply a TOBIT model on an unbalanced panel data to investigate whether bank efficiency is associated with the income from securitization transactions among other exogenous balance sheet indicators and control variables. Finally, we also contribute by combining several datasets to analyze the propensity of financial institutions to engage in securitization in an emerging economy and by using a novel approach when evaluating efficiency in the Brazilian financial system.

Our findings suggest that banks that securitize and sell originated loans are more efficient than those that do not. Moreover, income from securitization transactions is positively associated with interest income efficiency but not with operational efficiency. In contrast to international evidence but in line with studies that analyze the Brazilian securitization market (Ribeiro and Schiozer, 2013), we also provide evidence that smaller banks (in terms of asset size) are those that rely more on securitization transactions. Finally, disentangling those effects when analyzing the decision to securitize allows a deeper understanding of the reliance on the originate-to-distribute model.

2.2 Literature

Loan originators usually have more private information about their potential borrowers than the market, so selling these assets in the form of securitization is an insurance mechanism. The ability to transfer risk can reduce a bank's exposure to credit risk and, thus, increase the quality of the loan portfolio (Li, Sheng, and Smallwood, 2020). Parlour and Plantin (2008) offer two explanations for banks relying on the originate-to-distribute (OTD) model. First, it is an efficient risk management tool because it allows the redistribution of capital towards more productive investments. Such risk transfers are also beneficial for society because risks that arise within the commercial banking system are transferred to a more diverse pool and do not remain concentrated in the banking system, making shadow banks (those that acquire the assigned credits) a shock absorber mechanism (Wagner and Marsh (2006), Culp and Neves (2018)). Second, it allows the segregation of balance sheet and customer relationship management.

Banks can sell the loans they issue with or without risk retention. Hartman-Glaser (2017) argues that OTD practices have a signaling component when banks maintain a costly stake in the securities they issue because risk retention is a mechanism to reveal private information about borrowers. In this sense, loan sales can be an insurance mechanism and a signaling mechanism. Because the collection of private information about borrowers is a consequence of the monitoring process, loan sales without risk retention lead to reduced monitoring incentives, which, in turn, can lead to a less informed secondary market, making potential borrowers unaware of the real motivation behind the sale in the first place. In other words, they do not know if the sale occurred because the bank had better loan prospects and wanted to redirect resources to more productive projects or because they did not reveal private information. A secondary loan market will only exist, in equilibrium, if the probability that the bank is disposing of these loans due to private information is sufficiently high. Spreads on such transactions will depend on the reputation of the assigning institutions (Hartman-Glaser, 2017),

on the unconditional probability of default, and on the conditional probability of default given the bank's propensity to distribute originated loans (Parlour and Plantin, 2008). In equilibrium, however, building a reputation through risk retention makes banks more likely to misreport loan quality, which leads to less informative signaling.

Banks have two mechanisms to lay off credit risk: loan sales or loan insurance with the purchase of credit default swaps (CDS) (Thompson, 2008). While in loan sales, the assigning institution transfers both the loan's cash flows and control rights, it transfers only cash flow rights in a CDS. The correlation between the risk of lending opportunities and existing loans is a benign motive for selling off credit risk exposures because in these situations, banks "must either raise additional equity capital or unload the credit risk of the loan." The choice between the two depends on the risk level of borrowers and the bank's cost of equity capital, and loan sales are usually preferable to loan insurance for riskier loans (Parlour and Winton, 2013). Using a theoretical model, Thompson (2008) suggests that banks with a higher cost of capital tend to prefer loan sales rather than loan insurance, even when spreads on assigned loans are high.

According to Cardone-Riportella et al. (2010), the literature suggests three types of motivation to explain a bank's decision to engage in securitization transactions:

a) The search for new sources of financing (funding) or the need for liquidity.
b) Higher-risk banks minimize distress costs and search for increased efficiency.
c) The reduction of capital requirements (regulatory arbitrage).

Indeed, Farruggio and Uhde (2015) argue that banks may engage in securitization transactions to exploit existing regulatory loopholes, and regulatory changes can influence the existence of a secondary loan market. Li, Sheng, and Smallwood (2020) emphasize that regulators reduced the possibility of regulatory arbitrage with the implementation of Basel II, which required some level of capital allocation for all retained securitization tranches. Basel II prevents the possibility of regulatory arbitrage because reductions in capital requirements are associated "both with the quality of the underlying portfolio and with the amount of risk exposure retained by the originating entity" (Cardone-Riportella et al., 2010).

When analyzing several theoretical and empirical literature findings on the relationship between securitization and efficiency, Bayeh et al. (2021) summarize two alternative hypotheses or channels proposed by those studies under investigation. The "monitoring hypothesis" suggests a positive association between securitization and bank efficiency, because of reduced screening and monitoring costs and, consequently, decreased loan quality. The "signaling hypothesis," on the other hand, suggests a negative association between securitization and bank efficiency, because “banks that securitize loans are more prone to sell less risky loans to signal the loan quality to outside investors” (pp. 555).

2.2.1 Evidence on credit assignments

2.2.1.1 Credit assignment in developed markets

Bannier and Hänsel (2008) analyze European banks prior to the global financial crisis (1997-2004) and find that securitization activity is associated with firm-specific characteristics such as bank size, bank liquidity, bank performance, and expected credit risk. They find that the probability of a bank engaging in loan securitization is positively associated with bank size and negatively associated with its liquidity. Moreover, higher-risk banks are more likely to reduce their securitization activity, and well-performing institutions securitize less. Interestingly, they find a "reverse" regulatory arbitrage effect: "banks with low tier 1 capital securitize significantly less than banks with high tier 1 capital." Cardone-Riportella et al. (2010) analyzed the Spanish banking sector from 2000 to 2007 and concluded that the factors associated with the decision to securitize are liquidity and the search for improved performance, not credit risk transfer or regulatory capital arbitrage. Affinito and Tagliaferri (2010) investigate the determinants of bank loan securitization on Italian banks from 2000 to 2006 and demonstrate that the decision to securitize is associated with capital restriction, profitability, liquidity, and increased credit risk.

Irani, Iyer, Meisenzahl, and Peydró (2018) analyze the United States market for syndicated corporate loans and investigate the connections between bank capital regulation and the prevalence of shadow banks. Using surprise features of the U.S. implementation of Basel III as shocks to capital requirements, they find that during these shocks, "less-capitalized banks reduce loan retention, particularly among loans with higher capital requirements and at times when capital is scarce, and nonbanks step in." Bayeh et al. (2021) investigate the relationship between securitization and efficiency for United Stated banks and demonstrate that securitization is positively associated with efficiency, and the reliance on securitization mitigates screening and monitoring efforts. The authors measure efficiency using the cost-to-income ratio and later calculate a proxy for ex-ante screening and monitoring incentives, regressing salary expenses on variables that reflect assets, liabilities, profitability, size, and profit efficiency.

2.2.1.2 Credit assignment in emerging markets

Using data from June 2004 to June 2009, Ribeiro and Schiozer (2013) investigate the relationship between credit assignment and capital constraints for 118 Brazilian banks. Their results suggest a positive association between capital constraints and the expansion of loan sales. Santos and Gartner (2018) studied the relationship between credit assignment practices and the performance of Brazilian banks. Using data from 2004 to 2014 and principal component analysis, the authors argue that operational performance, the composition of non-operating revenues, the types of assets assigned, financing capacity (deposits), liquidity levels, and credit portfolio risk are variables with a higher potential to explain this relationship. They also show that small and medium banks rely heavier on such practices. The authors do not include measures of credit risk when analyzing securitization transactions. Barcelos and Mendonça (2015) investigate the relationship between securitization activities and credit risk-taking into account 60 Brazilian financial institutions from December 2002 to October 2012 and suggest that credit risk is not relevant to explain securitization in Brazil. Their sample includes 32 financial institutions that securitized assets using receivables funds and 28 banks that do not securitize but have similar characteristics (although we do not find mention in their paper to the explicit criteria used to match banks in the sample). Moreover, the empirical strategy of Barcelos and Mendonça (2015) suggests credit risk level depends on the decision to securitize, while some other empirical studies model securitization (be it the decision or the income) as dependent on credit risk (Farruggio and Uhde (2015), Li, Sheng and Smallwood (2020), Bayeh

et al. (2021)). In our methodology, we take into account the credit risk profile of the banks. More discussion about that is included in the next section.

Li, Sheng, and Smallwood (2020) analyzed the determinants of loan securitization using data on 83 Chinese commercial banks and concluded that the typical reasons that drive securitization (liquidity funding, credit risk transfer, or regulatory capital management) do not explain the behavior of these institutions. Instead, they find that banks may be using securitization to mitigate regulatory risk because "as banks approach limits on loan-to-deposits ratios, subsequent securitization activities rise." The authors also note that China introduced loan securitization in 2005 and, after a temporary suspension during the global financial crisis (GFC) in 2008, banks returned to using such instruments since 2012, now being the second-largest securitization market in the world.

2.2.1.3 Credit assignments in Brazil

According to the Brazilian banking regulation, credit assignment transactions can occur with or without risk retention. In the first case, the bank sells the right of a fraction of the loan's cash flow. In case of risk retention, the assigning institution must maintain the appropriate classification of the transaction and proceed with relevant registration criteria. According to Document 3040 of the Central Bank of Brazil (BCB), recourse is one of the types of risk retention that a transferor can assume and refers to the responsibility of paying or replacing the credit assigned in the event of default by the policyholder or other situations provided for in the assignment contract."

The Brazilian National Monetary Council (CMN) has allowed Brazilian financial institutions to assign credits since 2001 (Resolution 2836/2001 of the BCB). The registration of such transactions has been mandatory for financial institutions since July 2011, according to Resolution 3.998/2011 of the CMN. The BCB released public data on credit assignments by financial institutions until the fourth quarter of 2012. Since then, these accounting items have been confidential, registered at the Credit Information System (SCR), followed the rules proposed by BCB Circular Letter 3543/2012, and released at the aggregate level.

The Brazilian Credit Assignment Trade Repository (C3) has released data on monthly credit assignments for the Brazilian economy at the aggregate level since January 2011 (Figure 1). The liquidation value of credit assignments in Brazil reached its peak in May 2013. Since then, the volume of such transactions has steadily declined, reaching a second record level in June 2020 during the COVID-19 pandemic. This steady decline followed the decline of Brazilian interest rates since 2016.

2.2.2 Bank efficiency

2.2.2.1 Theoretical models

Greenbaum and Thakor (1987) develop a theoretical model to analyze a bank's decision to hold or distribute originated loans. In a context of asymmetric information without government

intervention (deposit insurance), banks tend to securitize better quality assets and fund poorer quality assets with deposits. In the presence of deposit insurance, funding through securitization is a low-cost resolution of informational asymmetries but leads to suboptimal risk-sharing. However, the availability of third-party insurance and lower information processing costs (provided by advances in information technology) can alleviate this problem. The authors also suggest that in a context where information costs are low, securitization tends to be a profitable activity, and screening is usually an optimal strategy.

Wolfe (2010) uses a contingent claims model to analyze the effect of securitization on the operational structure of financial institutions. Banks can choose to securitize any proportion of their assets in his setting, depositors are provided with deposit insurance, and banks face capital adequacy requirement constraints. His model suggests that when regulators calculate capital requirements on a risk-adjusted basis, banks tend to securitize their best quality loans while increasing their capital enough to protect them from the increased risks of securitization (due to a higher concentration of poor quality assets held on the balance sheet). In equilibrium, establishing an asset-backed securities pipeline will increase banks' return on capital.

Jiangli, Pritsker, and Rapuach (2007) develop a monitoring-based model to analyze the impact of loan sales and securitization on a bank's funding costs, leverage, risk profile, and solvency. The authors suggest that banks that engage in securitization activity have lower tail risk, and their engagement in such activities depends on the fixed costs of securitizing assets. Because securitization allows reduction of funding costs and to hedge against insolvency risk, securitization is positively associated with profitability.

Staub, Souza, and Tabak (2009) investigate cost, technical and allocative efficiency for Brazilian banks before the financial crisis and demonstrate that foreign banks are less cost-efficient than their domestic counterparts and state-owned banks are more cost-efficient than private banks. Tabak, Craveiro, and Cajueiro (2011) analyze the relationship between non-performing loans and bank efficiency using dynamic panel and panel VAR estimates for Brazilian banks before the financial crisis and demonstrate that variations on bank efficiency precede loan quality deterioration.

2.2.2.2. Empirical findings

Several articles analyze the association between the engagement in securitization and bank performance using accounting ratios, mainly return on equity or cost-to-income ratio, as a proxy for efficiency. Deku, Kara, and Zhou (2019) provide a systematic review of such literature and argue that the implications of securitization on the post-global financial crisis period are still limited. They also point out that empirical findings on corporate loan securitization and bank lending standards are inconclusive for developed markets and relatively non-existent for emerging markets. Michalak and Uhde (2012) analyze European banks from 1997 to 2007 and provide empirical evidence on securitization and financial soundness, using return on assets as the primary performance measure. Casu et al. (2013) analyze U.S. banks from 2001 to 2008 and demonstrate that banks that securitize are more profitable but have higher credit risk exposure and face higher funding costs. To do so, they apply univariate analysis techniques and

evaluate whether the difference between securitizers and non-securitizers is statistically significant, considering only operational performance (return on assets).

Our methodology provides evidence to fill two gaps in this literature. First, we analyze an emerging economy using data on financial conglomerates from 2001 to 2012, allowing a deeper understanding of such association for pre- and post-global financial crisis periods. Second, given the broad definition of bank efficiency, we do not use financial ratios to measure bank efficiency. Instead, we apply data envelopment analysis to capture the entire bank production process, taking into account operational performance and interest income generation, which is crucial to evaluate the decision to securitize and the main component of the intermediation activity.

2.3 Methodology

This study aims to understand the association between the engagement in securitization transactions and the efficiency of financial institutions, using data on Brazilian banks. To do so, we use a two-step approach. First, we use data envelopment analysis (DEA) to estimate a by-technology approach (or a network production technology) with loans as an intermediary factor (see Fukuyama and Matousek (2017)). Without relying on parametric assumptions, we use such a method to see whether banks that sell loans and rely on the originate-to-distribute model are indeed more efficient. We decompose efficiency into two sub-technologies, in line with, Boussemart et al. (2019). However, linking the two sub-technologies (see Figure 2) does not need to rely on an exogenous weighting system. The decomposition of efficiency through two different sub-technologies before analyzing the decision to engage in securitization transactions most accurately resembles the decision-making process in a financial institution. Second, we use the inefficiency scores provided by the DEA approach to estimate a TOBIT panel and understand which factors are associated with the decision to securitize and, specifically, the association between the income from loan sales and balance sheet indicators and individual characteristics, following Farruggio and Uhde (2015).

2.3.1 Data

Using Python programming in July 2019, we first retrieved information on credit assignments using field 7024 in the Quarterly Financial Information report (*Informações Financeiras Trimestrais* - IFT) over the period June 2001 to December 2012, available at the Central Bank of Brazil (BCB)'s website at the time. BCB classified such data into two categories: assignments with/without risk retention and to related/unrelated companies. We collected financial institutions' credit assignments information using their national register of legal entities (Cadastro Nacional de Pessoa jurídica – CNPJ). For institutions that did not belong to any conglomerate, we merged the data using their national register of legal entities (CNPJ).

Second, we retrieved information on non-performing loans (NPL) using monthly balance sheets provided by the Central Bank of Brazil at COSIF System – Consolidated accounting information on the Brazilian national financial system, following Tabak, Craveiro, and Cajueiro

(2011). To classify severe delinquent loans and estimate a proxy for non-performing loans (those that are due more than 90 days), we aggregate the total loan portfolio classified as E, F, G, and H. Data on credit assignments and non-performing loans are available at the individual institution level, so we aggregate that information using the conglomerate codes. Third, we retrieved information on conglomerates' financial statements using IFData, a public database released by the Central Bank of Brazil (BCB) every quarter. All databases provide information in Brazilian reais (BRL).

BCB classifies financial conglomerates into seven major groups (Tipo de conglomerado bancário – TCB): commercial and multipurpose banks with a commercial portfolio and savings banks (b1), multipurpose banks without a commercial portfolio, exchange or investment banks (b2), credit unions (b3s), confederations of credit unions (b3c), development banks (b4), nonbank credit institutions (n1), nonbank capital market institutions (n2) and payment institutions (n4). Because the purpose of the study is to analyze credit assignments by banks, our main specifications include only groups b1, b2, and b4. We discarded those institutions that did not have information on outstanding loans, total assets, and those for which operating expenses were zero.

2.3.1.1 Variable definitions

We present the main variables used in this study, their definition, and calculations in **Table *5***. All inputs and outputs assume a positive value in the sample to apply the DEA procedure, even though expenses are a disbursement. We calculate all the variables using December 2012 values, using the IPCA (Extended National Consumer Price Index). Our initial sample contains 2493 bank-quarter observations. Before proceeding to the outliers treatment, we exclude observations according to the exclusion criteria described in **Table *6***.

2.3.1.2 Outliers treatment

To treat outliers for the data envelopment analysis, we first calculate three ratios using the inputs in the bank production process: Loans to Deposits, Cost-to-income, and implicit interest rates, according to the following (for the definition of each variable, see **Table *5***):

- Loans to Deposits (LD): L/D
- Cost-to-income (CI): (LE+AOE)/NII
- Implicit interest rates (IIL): II/L

Because our sample is very heterogeneous, we exclude each quarter's first and last decile using a dummy: if the observation is an outlier for at least one of the ratios, we exclude it from the dataset. We proceed with such exclusions by quarter because DEA analysis implies that one can observe a different technology set in every period. Moreover, as we need to use L and NPL forwarded, our final sample comprises 23 quarters, from June 2001 to June 2012, and contains 1088 bank-quarter observations. The ex-post analysis of NPLs and PLs includes the production

technology described in the following subsection and on the fact that severe delinquency is only declared 90 days after a loan is issued.

2.3.2 Bank efficiency estimation strategy

We start this section by exposing, for the general banking sector, the methodological aspects of efficiency measures and their calculation with the DEA framework. More specifically, we provide the insights to understand the production technology and its relationship to the subprocesses that may compose it. Then, we go on to introduce the directional distance function which provides a direct way to measure efficiency. .

a) Definition of the production technology

We model the production technology of a bank using an output incomes vector $\mathbf{y} \in \mathbb{R}_+^R$ with $\mathbf{y} = \{y_1, ..., y_r, ..., y_R\}$ that can be produced from an input expenses vector $\mathbf{x} \in \mathbb{R}_+^I$ with $\mathbf{x} = \{x_1, ..., x_i, ..., x_I\}$. We define the production possibility set *T* as follows:

$$T = \left\{ (\mathbf{x}, \mathbf{y}) \in \mathbb{R}_+^I \times \mathbb{R}_+^R : \mathbf{x} \text{ can produce } \mathbf{y} \right\} \quad (1).$$

Or, banks may engage in several activities, which are sometimes linked. Here, we consider that these activities can be divided into two distinct subprocesses T_1 (bank transactions) and T_2 (intermediation), with

$$T = T_1 \bigcap T_2 \quad (2).$$

For this, the output space is divided into two non-overlapping ordered subsets R_1 and R_2, such that $R = R_1 \bigcup R_2$ and $R_1 \bigcap R_2 = \varnothing$. We now define $\mathbf{y}_1 \in \mathbb{R}_+^R$ the output vector related to the first sub-technology and $\mathbf{y}_2 \in \mathbb{R}_+^R$ the output vector corresponding to the second sub-technology. In each of these output vectors, a typical element $y_{k,r_k}, k \in \{1,2\}$ is defined as:

$$y_{k,r_k} = \begin{cases} y_{r_k}, \ r_k \in R_k \\ 0, \text{ otherwise} \end{cases}.$$

Basically, an element in $\mathbf{y}_1$ will include all outputs produced with the first sub-technology, while the outputs produced with the competing technology are set to zero. Conversely, an element in $\mathbf{y}_2$ will include all outputs produced with the second sub-technology while the rest of the outputs are fixed at zero in this sub-technology.

Obviously, the sum of the two ordered vectors will obtain the total output vector: $\mathbf{y} = \mathbf{y}_1 + \mathbf{y}_2$ and the two vectors do not share any common element.

In this respect, in the first subprocess the bank produces two outputs which are the non-interest income (*NII*) and loans (*L*): $\mathbf{y}_1 = (NII, L)$. One component of the second sub-technology is obviously the interest income (*II*). However, the success of this activity largely depends on the quality of the loans granted. In this respect, total loans can be divided into performing loans (*PL*) which are desirable (or 'good') outputs and non-performing loans (NPL), which are non-desirable (or 'bad') outputs. Whereas the distinction between the performing and the non-performing loans is not possible in the first sub-technology (otherwise, the bank would not have granted the non performing loans in the first place), this distinction is possible in the second one (because the bank can check, in the coming quarter, the exact amount of its total loans that have been classified as "delinquent" by the central bank).[1] At this point, we introduce the importance of the time period in which we observe bank activities. So far, we have focused on activities that were contemporaneous. Or, for the second sub-technology, the quality of the loans granted in say, period *t*, will only be evaluated in the coming period, so in *t+1*. Therefore, for this second sub-technology, it would be accurate to say that the output vector corresponds to $\mathbf{y}_{2,t} = (II_t, PL_{t+1}, NPL_{t+1})$ where the sub-script *t* indicates the period in which we observe the specific income component. In this respect, our approach differs from the one developed in Boussemart et al. (20219) in which all components of the production technology were contemporaneous to one another.

In the same way, we partition the input space into two ordered and non-overlapping subsets: $I = I_1 \bigcup I_2$ and $I_1 \bigcap I_2 = \varnothing$. For each of the sub-technologies we define an input-specific vector: $\mathbf{x}_1 \in \mathbb{R}_+^I$ for T_1 and respectively $\mathbf{x}_2 \in \mathbb{R}_+^I$ for T_2 where a specific element $x_{k,i_k}, k \in \{1,2\}$ is defined as:

$$x_{k,i_k} = \begin{cases} x_{i_k}, i_k \in I_k \\ 0, \text{ otherwise} \end{cases}$$

The sum of the two input spaces amounts to the total input and the two sub-spaces are not overlapping. In the first sub-process, the bank uses a vector of three inputs $\mathbf{x}_1 = (D, LE, AOE)$ which stand respectively for deposits collected from lenders, labor-related expenses, and administrative and operational expenses. In the second sub-process, the bank uses a unique type of input which is the loans granted in the first sub-process $\mathbf{x}_2 = (L)$ to generate income.

As mentioned above, many of the bank's activities may be interlinked. To account for that and following Fukuyama and Matousek (2017), we consider a set of intermediary outputs. Thus, the output set $\mathbf{y}_{1,M} \in \mathbb{R}_+^M$, with $M = R_1 \bigcap I_2$ contains some of the outputs produced with technology T_1 that will serve as inputs in the sub-technology T_2. Those inputs used for the second sub-technology are denoted $\mathbf{x}_{2,M} \in \mathbb{R}_+^M$. Thus, one must ensure that in the second sub-technology a bank conglomerate cannot consume more than what it has produced in the former

[1] See the exact definition for non-performing loans in the Data section..

subprocess: $\mathbf{y}_{1,M} = \mathbf{x}_{2,M}$.[2] For the banking sector, the loans collected in the first sub-technology will serve as a basis for generating intermediation income in the second sub-technology. Thus, we consider loans as an intermediary output in this model: $\mathbf{y}_{1,M} = \mathbf{x}_{2,M} = \mathbf{x}_2 = (L)$.

Figure *13* depicts the general operational diagram of a bank conglomerate.

We can formally define each of the sub-technologies as:

$$T_k = \left\{ (\mathbf{x}_k, \mathbf{y}_k) \in \mathbb{R}_+^I \times \mathbb{R}_+^R, \mathbf{x}_k \text{ can produce } \mathbf{y}_k \right\}, \text{for } k \in \{1;2\}$$

Assumptions regarding technology are standard and refer to no free lunch, boundedness, closure, free disposability, and convexity (see Banker et al., 1984). In this frame, the Data Envelopment Analysis approximation of *T* from a set of *N* observed DMUs, under variable returns to scale (VRS) is as follows:

$$T = \left\{ \begin{array}{l} (\mathbf{x}, \mathbf{y}): \\ \quad x_{k,i_k} \geq \sum_{n=1}^{N} \lambda_{k,n} x^k_{k,i_k,n}, \forall i_k = 1,...,I_k; \\ \quad y_{k,r_k} \leq \sum_{n=1}^{N} \lambda_{k,n} y_{k,r_k,n}, \forall r_k = 1,...,R_k; \\ \quad \sum_{n=1}^{N} \lambda_{k,n} = 1; \\ \quad \sum_{n=1}^{N} \lambda_{1,n} y_{1,m,n} = \sum_{n=1}^{N} \lambda_{2,n} x_{2,m,n}, \forall m \in M \\ \quad \lambda_{k,n} \geq 0, \forall n = 1,...,N; k = 1,2 \end{array} \right\} \quad (3).$$

Note that for the given total technology T, one can easily determine the sub-technology T_k, $k \in \{1;2\}$ for each of the bank's sub-process and which is defined by its specific set of activity variables $\boldsymbol{\lambda}_k$. The one before last row in (*3*) explicitly states that, as far as the optimal intermediary outputs are concerned, the bank cannot use in the second technology a higher quantity than the one obtained with the first sub-technology.

b) Efficiency estimation using a directional output distance function

Gaps between observed production plans and the boundaries of the estimated production technology can be measured using a directional distance function. We extend the original function introduced in Chambers, Chung and Färe (1996) to exhaust possible output slacks[3], as proposed by Färe and Lovell (1978) and later on by Briec (2000). Thus, the measure obtained is Pareto efficient in the output space. Specifically, we use a Färe-Lovell directional distance

[2] For a general approach, one must ensure that the intermediary outputs are measured in the same unit measure.
[3] The intermediate factor, which is considered as an output in the first sub-technology is not concerned by this optimization.

function where the vector $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2)$ contains specific components for each sub-technology.

The resulting directional output distance function is defined as:

$$D_T(\mathbf{x}, \mathbf{y}; \mathbf{g}) = \sup_{\beta} \{\boldsymbol{\beta}_1 + \boldsymbol{\beta}_2 : (\mathbf{x}_1, \mathbf{y}_1 + \boldsymbol{\beta}_1 \mathbf{g}) \in T_1, (\mathbf{x}_2, \mathbf{y}_2 + \boldsymbol{\beta}_2 \mathbf{g}) \in T_2;\ \mathbf{g} \geq 0\} \qquad (4).$$

The direction is common to both sub-technologies, consequently, we can easily interpret the result obtained, i.e. the value of $D_T = \boldsymbol{\beta}_1 + \boldsymbol{\beta}_2$, as the necessary percentage income increases to reach the optimal benchmark of the banking technology in the direction given by the mapping vector **g**. For this analysis, the unique direction for the two sub-technologies is given by the conglomerate's total income (*TI*) defined as the sum of two incomes:

$$TI = NII + II \qquad (5).$$

The value of the directional distance function can be interpreted as an inefficiency score, where a null value for one of its components signals zero inefficiency in that output activity. If a conglomerate obtains a null score in each output dimension, that the conglomerate is deemed as overall efficient.

The following linear program (*LP*) provides a practical way to obtain the necessary increases in each type of income activity for any bank conglomerate *o*. In this *LP*, one must keep in mind that in the second sub-technology, non-performing loans (*NLP*) is an undesirable (or bad) output and thus must not increase, hence the sign for this constraint.

$$D_T(\mathbf{x}_o\mathbf{y}_o;\mathbf{g}_o) = \underset{\beta_1,\beta_2,\lambda_1,\lambda_2}{Max} \quad \beta_1 + \beta_2$$

$$\begin{aligned}
s.t. \quad & \sum_{n=1}^{N} \lambda_{1,n} NII_{n,t} \geq NII_{o,t} + \beta_1 TI_{o,t} \\
& \sum_{n=1}^{N} \lambda_{1,n} L_{n,t} \geq L_{o,t} \\
& \sum_{n=1}^{N} \lambda_{1,n} D_{n,t} \leq D_{o,t} \\
& \sum_{n=1}^{N} \lambda_{1,n} LE_{n,t} \leq LE_{o,t} \\
& \sum_{n=1}^{N} \lambda_{1,n} AOE_{n,t} \leq AOE_{o,t} \\
& \sum_{n=1}^{N} \lambda_{1,n} = 1 \\
& \sum_{n=1}^{N} \lambda_{2,n} II_{n,t} \geq II_{o,t} + \beta_2 TI_{o,t} \\
& \sum_{n=1}^{N} \lambda_{2,n} PL_{n,t+1} \geq PL_{o,t+1} \\
& \sum_{n=1}^{N} \lambda_{2,n} NPL_{n,t+1} \leq NPL_{o,t+1} \\
& \sum_{n=1}^{N} \lambda_{2,n} = 1 \\
& \sum_{n=1}^{N} \lambda_{1,n} L_{n,t} = \sum_{n=1}^{N} \lambda_{2,n} L_{n,t} \\
& \lambda_{1,n} \geq 0 \quad \forall n = 1, \ldots, N \\
& \lambda_{2,n} \geq 0 \quad \forall n = 1, \ldots, N
\end{aligned} \qquad \textit{(LP 1)}.$$

On this basis, we can readily define the evaluated bank's inefficiency score in relation to each of its sub-processes. The inefficiency score measures the potential income increase in each sub-technology in percentage of the total income. Thus, the sub-technology specific inefficiency can be read directly from the inefficiency score in *LP 1*:

$$Ineff_{1,o,t} = \frac{\left(NII_{o,t} + \beta_{1,o,t} TI_{o,t}\right) - NII_{o,t}}{TI_{o,t}} = \beta_{1,o,t}$$

(6) and (7)

$$Ineff_{2,o,t} = \frac{\left(II_{o,t} + \beta_{2,o,t} TI_{o,t}\right) - II_{o,t}}{TI_{o,t}} = \beta_{2,o,t}$$

For any period *t*, the bank's total inefficiency (defined as the potential total income increase by the observed total income) is then simply the sum of the two previously defined sub-technology inefficiency scores. Moreover, one notes that this amounts to the value of the directional distance function estimated with (*LP 1*).

(8) $Ineff_{o,t} = Ineff_{1,o,t} + Ineff_{2,o,t} = \beta_{1,o,t} + \beta_{2,o,t}$

This is a noteworthy difference between our approach and the one followed in Boussemart et al. (2019) where the different score of the objective function had to be aggregated by an exogenous and arbitrary system of weights. By using a common direction, which is the bank's total income, we avoid this issue.

In the Appendix, we consolidate this method by applying a subsampling approach to obtain robust inefficiency scores, in the vein of Politis and Romano (1994; 1999) and Kneip, Simar, and Wilson (2008).

2.3.3 TOBIT panel data model

The second step of our empirical analysis provides evidence on bank-specific characteristics associated with loan securitizations. When analyzing how much each bank securitizes, the sample contains many zeros, indicating that such a decision does not equalize among banks included in the sample. In this sense, the TOBIT framework allows us to account for the constrained range of the dependent variable, and such an econometric choice provides consistent estimates for regression coefficients (Minton et al., (2004), Affinito and Tagliaferri (2010), Farruggio and Uhde (2015)). When using TOBIT analysis, one cannot distinguish between the marginal effects of each coefficient separately. In this sense, when analyzing the estimates, the focus is on the coefficients' sign and whether they have statistical significance to explain the dependent variable. Second, TOBIT models depart from the assumption that the underlying residuals are normally distributed. To see if this is the case in the estimates, one has to check the p-value of the entire model. In all of our specifications, Chi2 tests are all below 1%. The panel data approach allows for between and within variation in the data and unobservable heterogeneity across banks. Following Farruggio and Uhde (2015), we employ a random-effects TOBIT regression model on panel data, which "allows for both between and within variation in the data as well as unobservable heterogeneity across banks." Following their approach, we also include quarter dummies to control for time-specific effects in all model specifications, and bank-specific regressors are lagged by one period to avoid potential endogeneity problems.

Our sample includes securitizing and non-securitizing Brazilian financial conglomerates (henceforth referred to as "banks"). The sample contains 194 banks considering all the quarters. Of those, 53.6% engaged in securitization transactions at least once. The dependent (latent) variable (S_t^*) corresponds to the total income from loan sales relative to total assets per quarter for each bank. We specify the regression model in Equation (8):

$$S_{o,t} = \eta Ineff_{o,t-1} + Z'_{o,t-1}\theta + \delta_o + \gamma_t + \mu_{o,t}, \text{where } S_{o,t} = S^*_{o,t} \text{if } S^*_{o,t} > 0 \text{ and } 0 \text{ otherwise} \quad (9)$$

In Equation (9), η is the coefficient related to the overall inefficiency score we estimated using the DEA approach for bank o at period t-1. θ is a vector of parameters associated with regressor vector *Z* that includes the exogenous balance sheet ratios described in Table 1 – Part II as well as individual characteristics of financial conglomerates. In this respect we employ two alternative liquidity measures in our specifications, following the studies described in Table 5. δ_o refers to the individual bank effects, γ_t refers to the quarter dummies, and $\mu_{0,t}$ $\mu_{i,t}$ is the error term. Our set of estimates includes two approaches: estimates 1 to 4 in Tables 3 and 4 use the overall score as our measure of bank efficiency, while estimates 5 to 8 use the individual scores on interest and non-interest income to decompose efficiency in the two technologies (equation 10).

$$S_{o,t} = \eta_1 Ineff_{1,o,t-1} + \eta_2 Ineff_{2,o,t-1} + Z'_{o,t-1}\theta + \delta_o + \gamma_t + \mu_{o,t}, \text{ where } S_{o,t} = S^*_{o,t} \text{ if } S^*_{o,t} > 0 \text{ and 0 otherwise} \quad (10)$$

2.4 Descriptive statistics

Among the 104 securitizing banks (of 194), ten banks issued 25% of securitization transactions over the entire sample period of 12 years, 46% of the banks in our sample did not issue any securitization transaction and 7% issued a single transaction. Moreover, only 4% of the banks in our sample are responsible for 71% of the total securitization volume over the entire sample period. Securitization recurrence is not necessarily higher for larger banks: **Figure *14*** displays the financial conglomerates that account for 50% of the total number of transactions for the entire sample and demonstrates that, from the top 10 securitizers by the number of transactions, only one is a large bank (Itaú). **Figure *15*** shows that, from the top 8 securitizers by volume (those that account for 71% of the securitization volume for the entire sample period), only three are large banks (Itaú, BB, and Bradesco). **Figure *16*** displays the percentage of sample banks engaged in securitization per quarter. The lowest and highest percentages occurred in December 2011 and June 2008 (one quarter before the financial crisis). We observe two distinct patterns when analyzing the proportion of income from loan sales to total loans: prior to the global financial crisis (GFC), there is an upward trend in such ratio, while the opposite occurs after the GFC. In the first quarter after the beginning of the GFC, the ratio reached a peak and, afterward, reached its lower level in June 2012.

Regarding external funding necessity, banks that engage in loan sales and lay off credit risk in our sample exhibited lower loan-to-deposit ratio than those that do not, and the difference is statistically significant (t = 2.44), even though those that securitize exhibited larger loan portfolios (t = -2.97). After the global financial crisis, banks in our sample exhibited larger loan portfolios (t = -5.29) and lower loan-to-deposit ratio (t = 3.46), demonstrating that the dependence on external funding increased after 2008. Indeed, Agostino and Mazzuca (2009) analyze Italian banks and establish that securitization works as an alternative funding channel. In our sample, banks that securitize also exhibited lower Tier 1 capital ratios (for definitions, see **Table *5***) than those that do not, and the difference is also statistically significant (t = 5.32). Altogether, these statistics suggest that either the funding hypothesis (by which banks securitize to gain alternative funding channels) or the regulatory capital arbitrage hypothesis (banks

securitize to reduce the equity capital) can hold in our sample. However, our methodology allows decomposing credit risk and operational efficiency before evaluating such hypotheses (we discuss this when evaluating estimates for our empirical model).

Our sample includes 505 securitization transactions and 1087 bank-quarter observations. On average, Brazilian banks made 22 transactions by quarter. On average, 40% of those transactions include some form of risk retention. While recourse provision by risk retention is often a mechanism to signal loan credit quality, we observe a downward trend in the proportion of risk retention over the sample period. While in January 2001, 86% of securitization activity involved risk retention by bank originators, one year after the global financial crisis (December 2009), this proportion decreased to 18% and reached 67% in December 2011.

Banks in our sample exhibit an average 20% Tier1 capital ratio, with a standard deviation of 16.741%. This ratio is the amount of Tier 1 Capital as a proportion of risk-weighted assets (RWA). The first liquidity ratio, which refers to the ratio between money lent to other banks to money borrowed from other banks, is 2,2 on average, with a standard deviation of 1,7. The second liquidity ratio, which refers to total liquid assets to deposits and short-term funding, averages 1,2 with a standard deviation of 1,93. Finally, banks with foreign control represent 18% of the sample. We observe the lowest and highest proportion of banks with foreign control in June 2006 and June 2009.

2.5 Results

2.5.1 Bank efficiency

In what follows, we restrict the presentation to the original inefficiency estimation based on the technology defined in equation (3) and its corresponding linear program (*LP 1*) where the production set includes all the banks observed. Concerned readers may consult the Appendix, which contains the subsampling robust approach to efficiency.

In this industry level analysis, for each period *t*, total income efficiency ($Ineff_{t\,t}$) and its two components, namely non-interest income inefficiency ($Ineff_{1,t}$) and interest income inefficiency ($Ineff_{2,t}$) are obtained from equations (6) and (7) by replacing bank level incomes with their aggregate, group level ones.

$$Ineff_{1,t} = \frac{\sum_{o=1}^{N} \beta_{1,o,t} TI_{o,t}}{\sum_{o=1}^{N} TI_{o,t}}, Ineff_{2,t} = \frac{\sum_{o=1}^{N} \beta_{2,o,t} TI_{o,t}}{\sum_{o=1}^{N} TI_{o,t}} \text{ and } Ineff_{t} = \frac{\sum_{o=1}^{N} \left(\beta_{1,o,t} + \beta_{2,o,t}\right) TI_{o,t}}{\sum_{o=1}^{N} TI_{o,t}} - 1$$

We present the industry inefficiency scores along the dimension of securitization. Thus, *Secur = 1* refers to the inefficiency scores of the subindustry formed by banks that engage in securitization and *Secur = 0* refers to those that do not. The evolution of the total income inefficiency (**Figure *17***) indicates two patterns. First, the inefficiency score for the group of banks that engage in securitization is less volatile than the same score for the banks that do not (the standard deviation for the former group is 2% whereas it is 8% for the second one). For the former group, the inefficiency level is generally stable while for the latter, we even notice an increase in both inefficiency level and volatility that starts with the global financial crisis in 2008. Second, the group formed by the banks that securitize clearly observed a lower inefficiency level throughout the entire period studied than their counterparts that do not securitize (the entire period mean inefficiency score is 6% for the former group and 16% for the second one).

In **Figure *18*** and **Figure *19*** we look more in depth into the evolutions of the two components of inefficiency (non-interest income and interest income). We can thus notice that the evolution perceived in total income inefficiency is mainly due to banks' performance relative to their income-generating intermediation activities (**Figure *19***). Indeed, for both groups of banks, interest income inefficiency accounts for a large share in the total income (an average of 66% of the total income inefficiency for the groups that securitize vs. 74% for the banks that do not). The patterns of evolution between the two inefficiency indicators, namely total and interest income, also demonstrate a very high degree of similarity. For example, we observe that the banks that securitize have lower levels of interest income inefficiency and lower volatility for this measure than the group of banks that do not.

Concerning the inefficiency score relative to non-interest income, we note in Figure 7 that both groups' period inefficiency levels are highly volatile, without being able to identify a clear evolution. However, their levels are relatively low, and they count to a small extent in the total income inefficiency.

Finally, we compare delinquency ratio gaps between the two groups of banks. We compute this indicator as the difference between the optimal delinquency ratio (calculated from the optimal levels observed by the benchmark[4]) and the observed ones (**Figure *20***). This gap thus informs us of the necessary efforts, by each group of banks, to align with their respective benchmark in terms of total income efficiency. A negative sign for this indicator suggests that banks are below their optimal level in terms of delinquency ratio. If the indicator is null, then it means that the banks have reached the optimal level of delinquency ratio. We notice that the evolution of this indicator exhibits two distinct patterns for the two groups. At the beginning of the sample period, we observe comparable gap levels for both groups. However, for the banks that securitize, this indicator rapidly evolves towards 0 (except for one incident in the last quarter of 2011), showing the success of the group as a whole to align with the best observed practices.

[4] Notice that the optimal delinquency ratio is not necessarily null in this case, as it relies on the observed delinquency ratios of the best practices that compose the bank's benchmark.

For the group of banks that do not engage in securitization activities, this indicator is very rapidly declining, reaching its minimum during the turmoil of the global financial crisis.[5]

2.5.2 Efficiency and engagement in securitization

Table *7* displays baseline results from Tobit regressions and includes the entire sample period. Baseline estimates indicate that Brazilian banks with lower overall inefficiency scores (those that are more efficient according to the DEA methodology) have a higher propensity to engage in securitization transactions. More precisely, when we decompose overall inefficiency score lagged by one period ($Ineff_{o,t-1}$) into operational and interest income components ($Ineff_{1,o,t-1}$ and $Ineff_{2,o,t-1}$, respectively), results indicate that interest income efficiency in the previous period is the main driver to explain current securitization activity $S_{o,t}$, while operational inefficiency has no explanatory power over a bank's propensity to engage in such activities. In other words, our findings suggest a positive association between efficiency and engagement in securitization activity.

Our estimates indicate that smaller banks are more prone to engage in loan sales, in contrast to international studies (Bannier and Hänsel (2008), Cardone-Riportella et al. (2010), Faruggio and Uhde (2015), Li, Sheng and Smallwood (2020), Bayeh et al. (2021)) but in line with a study that analyzes securitization in Brazil (Ribeiro and Schiozer, 2013). In all of our estimations, liquidity ratios and capital restrictions are not statistically significant to explain engagement in securitization, in line with Bayeh et al. (2021). Finally, our specifications show that banks with foreign control have a lower propensity to securitize. To visualize the comparison of our results to those studies, see **Table *8***.

2.5.3 Discussion on empirical estimations

A decrease in interest income efficiency over time suggests that banks may profit from productivity gains in screening activities, which is the ability to select borrowers with a higher willingness to pay. Altogether, our findings suggest that the decrease in interest income inefficiency is not a byproduct of lower screening (operating) costs, because banks that securitize become more efficient over time in both dimensions. Moreover, our analysis demonstrates that securitization is a stabilizing mechanism for the financial system in emerging markets because it allows efficient risk transfer to outside investors.

Second, several studies argue that securitizing only riskier loans could hurt a financial institution's reputation in capital markets and, thus, make outside investors less likely to purchase assigned loans in the future (Gorton and Pennacchi, 1995). Indeed, Parlour and Winton (2013) develop a theoretical model in a context of repeated lending and in which a bank's decision to unload credit risk involves reputation concerns. In their setting, when market

[5] Curiously, for the last period in the analysis, this indicator is null, but we cannot conclude that this virtuous behavior has been definitely adopted by this group of banks.

participants use loan defaults (non-performing loans) as a noisy signal of lack of monitoring, loan sales support better monitoring activity and allow efficient risk-sharing. In this sense, "the shadow banking system works as both a source of commercial bank financing and a shock absorber for risks arising from commercial bank lending activities" (Culp and Neves, 2018, p. 47). In line with these studies, our findings suggest that increased efficiency does not come at the expense of loan portfolio quality because banks that securitize, on average, exhibit lower delinquency gaps – optimal vs. observed (**Figure *20***). Indeed, from 2006 to 2010, the gap in best practices when comparing both groups increases significantly.

Third, Cardone-Riportella et al. (2010) argue that only relatively large banks can set up a securitization program due to high fixed costs. In Brazil, however, receivable funds – fundos de investimento em direitos creditórios – are among the main instruments used for securitization. FIDCs do not require the creation of a special purpose entity, are technically similar to mutual funds, and usually offer tax advantages. In line with Ribeiro and Schiozer (2013), our findings show that smaller Brazilian banks are more likely to securitize and, thus, may perceive higher benefits from increased reputation in capital markets.

Finally, Bannier and Hänsel (2008) demonstrate that regulatory capital arbitrage does not appear to have driven the loan securitization market for European banks, in line with our findings.

2.6 Concluding remarks

The purpose of this study was to provide an empirical analysis about the relationship between loan securitization and bank efficiency, using data envelopment analysis (DEA) and TOBIT panel data estimations. Our methodology provides evidence to fill two gaps in this literature. First, we analyze an emerging economy using data on 53 Brazilian financial conglomerates from June 2001 to December 2012, allowing a deeper understanding of such association for pre-and post-global financial crisis periods. To do so, we combine information available at three public datasets on Brazilian banks provided by the Central Bank of Brazil. Second, given the broad definition of bank efficiency, we do not use financial ratios to measure bank efficiency. Instead, we apply data envelopment analysis to capture the entire bank production process. We contribute by modeling the income generating process in a bank without relying on parametric assumptions and using such estimates to analyze the decision to securitize while taking into account the credit risk of a loan portfolio.

Our findings suggest that banks that securitize and sell originated loans are more efficient than those that do not. Moreover, income from securitization transactions is positively associated with interest income efficiency but not with operational efficiency. Moreover, our results indicate that smaller banks are those more likely to engage in securitization and that capital ratio is not necessarily the main driver to explain securitization activity. By using DEA, we find that banks that securitize exhibit productivity gains in generating interest income over time, which implies that the decision to securitize is dynamic and that increased efficiency does not come from decreased monitoring costs. Finally, we also demonstrate that banks that engage in

securitization activity are those with lower delinquency gaps (the difference between optimal and observed values) and that securitization is a stabilizing component because it allows efficient risk transfer.

Although several empirical findings on securitization suggest that such activities increase the overall risk of a financial institution and may lead to suboptimal risk sharing, most of those studies evaluate the period prior to the global financial crisis. Given the efforts made by regulators to improve capital requirements and the overall financial soundness after 2008, our results suggest two points. First, securitization is an effective funding mechanism that does not negatively affect financial stability. Second, banks that engage in securitization are, on average, those with better loan portfolio quality and those that exhibit higher productivity gains over time.

References

Affinito, M., Tagliaferri, E. (2010). Why do (or did?) banks securitize their loans? Evidence from Italy. Banca D'Italia Working Paper N. 741.

Akerlof, G.A. (1970). "The Market for "Lemons": Quality Uncertainty and the Market Mechanism". *The Quarterly Journal of Economics*, 84, 3, 488-500.

Banker, R. D., Charnes, A., Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*, 9, 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Bannier, C.E., Hänsel, D.N. (2008). Determinants of European banks' engagement in loan securitization. Discussion Paper Series 2: Banking and Financial Studies No 10/2008. Deutsche Bundesbank.

Barcelos, V.I., Mendonça, H.F. (2015). Securitization and credit risk: Empirical evidence from an emerging economy. The North American Journal of Economics and Finance. https://doi.org/10.1016/j.najef.2015.01.002

Baur, D.G., Cariboni, J., Hallak, I., Petracco, M.G. (2016). "Securitization, Connectedness and Shadow Banking" *JRC Technical Reports*, 1-26. http://publications.europa.eu/resource/cellar/f4d38cec-bc4c-11e6-a237-01aa75ed71a1.0001.01/DOC_1

Bayeh, A., Bitar, M., Burlacu, R., Walker, T. (2021). Competition, securitization, and efficiency in US banks. *The Quarterly Review of Economics and Finance*, 80, 553-576. https://doi.org/10.1016/j.qref.2021.04.004

Boussemart, J.P., Leleu, H., Shen, Z., Vardanyan, M., Zhu, N. (2019). Decomposing banking performance into economic and credit risk efficiencies. *European Journal of Operational Research*, 277, 2, 719-726. https://doi.org/10.1016/j.ejor.2019.03.006

Briec, W. (2000). An extended Fare-Lovell technical efficiency measure. *International Journal of Production Economics*, 65, 2, 191-199. https://doi.org/10.1016/S0925-5273(99)00019-5

Cardone-Riportella, C., Samaniego-Medina,R., Trujillo-Ponce, A. (2010). What drives bank securitisation? The Spanish experience. *Journal of Banking & Finance*, 34, 11, 2639-2651. https://doi.org/10.1016/j.jbankfin.2010.05.003

Carneiro, M., Salgado Junior, A.P., Macoris, L.S. (2016). Avaliação da eficiência bancária por meio da abordagem de intermediação: uma análise comparativa de instituições financeiras brasileiras. *Revista Eletrônica de Administração*. http://www.scielo.br/pdf/read/v22n3/1413-2311-read-22-3-0336.pdf

Casu, B., Clare, A., Sarkysian, A., Thomas, S. (2013). Securitization and Bank Performance. Journal of Money, Credit and Banking, 45, 8, 1617-1658. https://doi.org/10.1111/jmcb.12064

Chambers, R. G., Chung, Y., & Färe, R. (1996). Benefit and distance functions. *Journal of Economic Theory*, 70, 2, 407–419. https://doi.org/10.1006/jeth.1996.0096

Culp, C.L., Neves, A.M.P. (2018). Shadow Banking, Risk Transfer and Financial Stability. *Journal of Applied Corporate Finance*, 29, 4, 45-64.

Deku, S.Y., Kara, A., Zhou, Y. (2019). Securitization, bank behaviour and financial stability: A systematic review of the recent empirical literature. International review of Financial Analysis, 61, 245-254. https://doi.org/10.1016/j.irfa.2018.11.013

Ding, N., Fung, H.G., Jia, J. (2015). "What Drives Cost Efficiency of Banks in China?" *China & World Economy*. https://doi.org/10.1111/cwe.12107

Färe, R., & Lovell, C. A. K. (1978). Measuring the technical efficiency of production. *Journal of Economic Theory*, *19*, 1, 150–162. https://doi.org/10.1016/0022-0531(78)90060-1

Farruggio, C., Uhde, A. (2015). Determinants of loan securitization in European banking. *Journal of Banking & Finance*, 56, 12-27. https://doi.org/10.1016/j.jbankfin.2015.01.015

Fukuyama, H., Matousek, R. (2017). Modelling bank performance: a network DEA approach. *European Journal of Operational Research*, 259(2), 721-732. https://doi.org/10.1016/j.ejor.2016.10.044

Gorton, G., Pennacchi, G. (1995). Banks and loan sales: marketing nonmarketable assets. *Journal of Monetary Economics*, 35, 389-411.

Greenbaum, S.I., Thakor A.V. (1987). Bank funding modes: securitization versus deposits. *Journal of Banking and Finance*, 11, 3, 379-401. https://doi.org/10.1016/0378-4266(87)90040-9

Hartman-Glaser, B. (2017). Reputation and signaling in asset sales. *Journal of Financial Economics*, 125, 2, 245-265. https://doi.org/10.1016/j.jfineco.2017.05.009

Irani, R.M., Iyer, R., Meisenzahl, R.R., Peydró, J.L. (2018). "The Rise of Shadow Banking: Evidence from Capital Regulation" *FEDS Working Paper* No. 2018-039. https://www.bis.org/events/confresearchnetwork1809/peydro.pdf

Jiangli, W., Pritsker, M., Raupach, P. (2007). Banking and Securitization. SSRN Electronic Journal. http://dx.doi.org/10.2139/ssrn.967895

Kneip, A., Simar, L., and Wilson, P. W., (2008). Asymptotics and consistent bootstraps for DEA estimators in non-parametric frontier models. *Econometric Theory*, 24, 6, 1663–1697. https://doi.org/10.1017/S0266466608080651

Li, J., Sheng, Z., Smallwood, A.D. (2020). Determinants of credit loan securitization in Chinese banking. *Pacific Economic Review*. https://doi.org/10.1111/1468-0106.12343

Michalak, T.C., Uhde, A. (2012). Credit risk securitization and bank soundness in Europe. The Quarterly Review of Economics and Finance, 52, 3, 272-285. https://doi.org/10.1016/j.qref.2012.04.008

Minton, B.A., Sanders, A., Strahan, P. (2004). Securitization by banks and finance companies: Efficient financial contracting or regulatory arbitrage? Working Paper, Ohio State University

Neves Júnior, I.J., Ribeiro, F.S., Mendes, F., Cunha, M.A. (2007). Eficiência operacional: uma análise exploratória dos 50 maiores bancos brasileiros pelo ranking Bacen. *USP International Conference in Accounting*. https://congressousp.fipecafi.org/anais/artigos72007/54.pdf

Parlour, C.A., Plantin, G. (2008). Loan Sales and Relationship Banking. *The Journal of Finance*, 63, 3, 1291-1314.

Parlour, C.A., Winton, A. (2013). Laying off credit risk: Loan sales versus credit default swaps. *Journal of Financial Economics*, 107, 1, 25-45. https://doi.org/10.1016/j.jfineco.2012.08.004

Peleias, I.R., Andrade, P.R.M., Alencar, L.B., Weffort, E.F.J. (2012). Banco Panamericano - um problema de governança corporativa*? Revista Gestão Organizacional*, 5, 1, 117-129.

Périco, A.E., Rebelatto, D.A.N. Santana, N.B. (2008). Eficiência bancária: os maiores bancos são os mais eficientes? Uma análise por envoltória de dados. *Gestão e Produção*, 15(2), 421-431. http://www.scielo.br/scielo.php?pid=S0104-530X2008000200016&script=sci_abstract&tlng=pt

Politis D.N., Romano J.P., 1994. Large Sample Confidence Regions Based on Subsamples under Minimal Assumtions. Annals of Statistics, 22, 4, 2031–2050. https://doi.org/10.1214/aos/1176325770

Politis D.N., Romano J.P., 1999. Subsampling. Springer, New York.

Pozsar, Z. (2008). "The Rise and Fall of the Shadow Banking System". *Regional Financial Review*, pp. 13-82. https://www.economy.com/sbs

Pozsar, Z., Adrian, T., Ashcraft, A., Boesky, H. (2012). Shadow Banking. Federal *Reserve Bank of New York Staff Reports*. https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr458.pdf

Ribeiro, F.V.F., Schiozer, R.F. (2013). "Cessão de crédito e restrição de capital: um estudo com bancos brasileiros". *Revista de Administração de Empresas*, 54, 5, 521-536. https://rae.fgv.br/rae/vol54-num5-2014/cessao-credito-restricao-capital-estudo-com-bancos-brasileiros

Santos, A.L., Gartner, I.R. (2018). Cessões de direitos creditórios dos bancos brasileiros: análise exploratória do impacto no desempenho operacional e financeiro. *Revista Contemporânea de Contabilidade*, 15, 35, 142-160. https://doi.org/10.5007/2175-8069.2018v15n35p142

Schinasi, G.J. (2004) Defining Financial Stability. IMF Working Paper 187, 1-19. Disponível em https://www.imf.org/external/pubs/ft/wp/2004/wp04187.pdf

Souza, J.A., Mendonça, D.J., Benedicto, G.C., Carvalho, F.M., Campos, R.S. (2016). Análise do desempenho das maiores instituições bancárias brasileiras: Um estudo com a análise

envoltória de dados aplicada a indicadores econômico-financeiros. *Revista Espacios*, 38, 6. https://www.revistaespacios.com/a17v38n06/a17v38n06p19.pdf

Staub, R.S., Souza, G., Tabak, B.M. (2009). Evolution of Bank Efficiency in Brazil: A DEA Approach. *Central Bank of Brazil Working Paper Series* no. 200, 1-48.

Sun, G., Jia, J. (2018). "The Definition and Measurement of China's Shadow Banking System from the Perspective of Credit Money Creation" *Vox China.*

Tabak, B.M., Craveiro, G.L., Cajueiro, D. O. (2011). Bank Efficiency and Default in Brazil:

Causality Tests. *Central Bank of Brazil Working Paper Series* no. 253, 1-29.

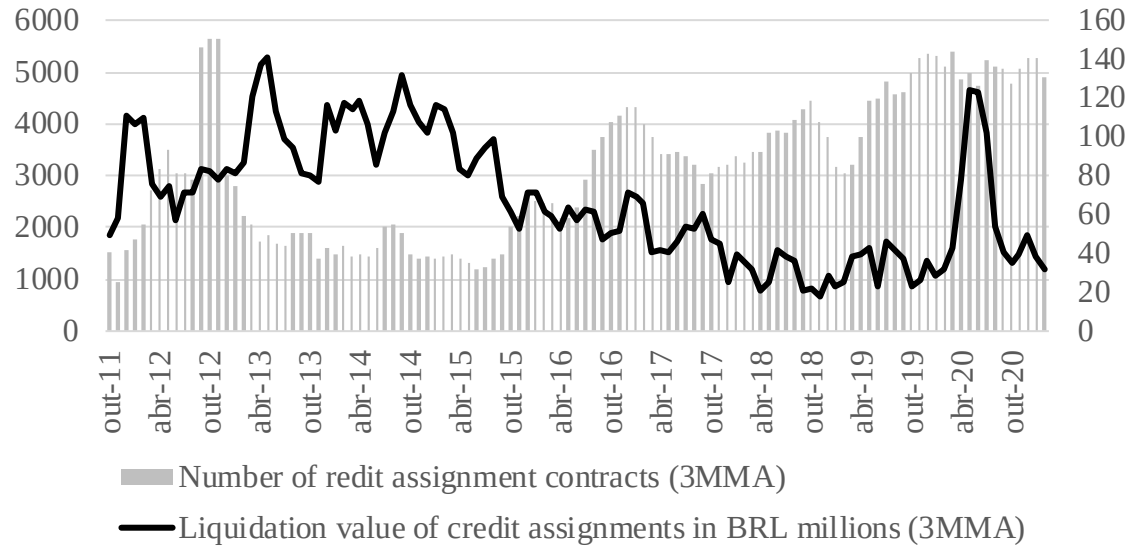
Thompson, J.R. (2008). Credit Risk Transfer: To Sell or to Insure. http://dx.doi.org/10.2139/ssrn.1278087

Wagner, W., Marsh, I.W. (2006). Credit risk transfer and financial sector stability. *Journal of Financial Stability*, 2, 2, 173-193. https://doi.org/10.1016/j.jfs.2005.11.001

Wolfe, S. (2010). Structural effects of asset-backed securitization. The European Journal of Finance, 6, 4, 353-369. https://doi.org/10.1080/13518470050195119

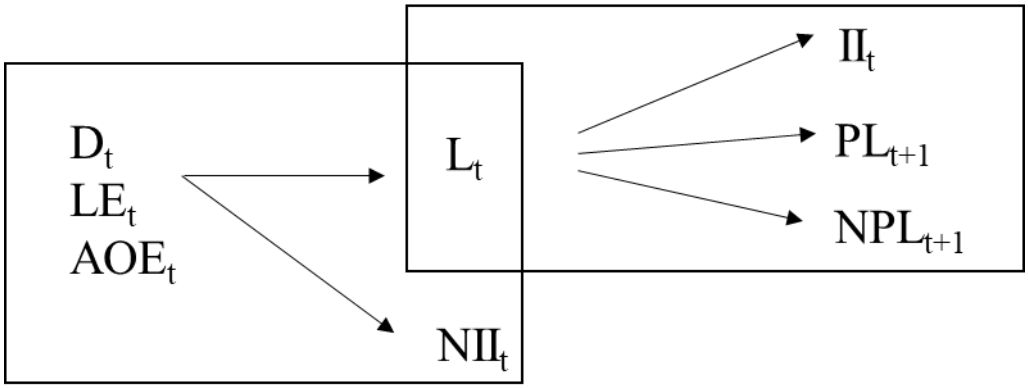
Figures and tables

Figure 12: Credit assignments in Brazil



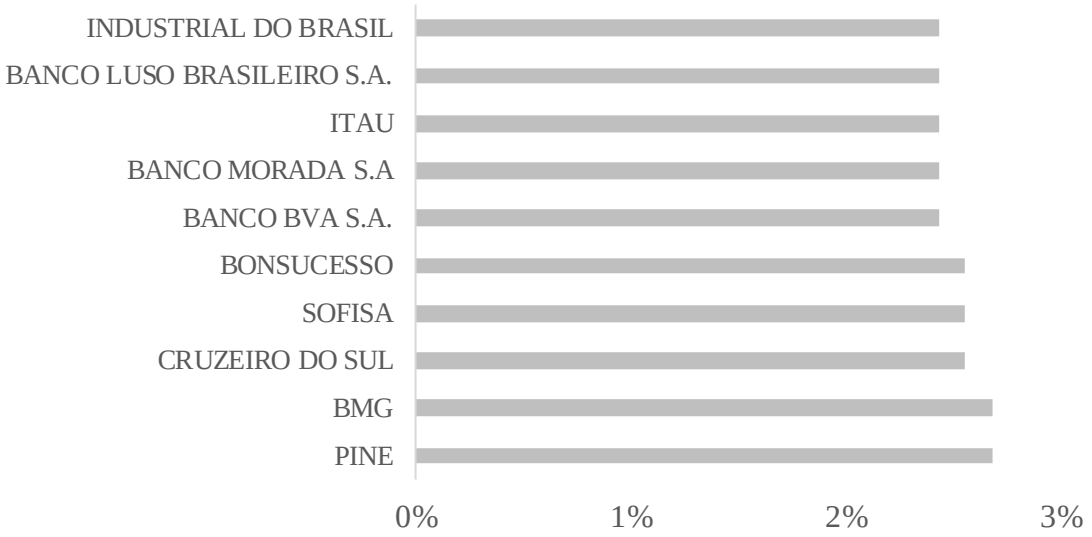
Source: Brazilian Credit Assignment Trade Repository (C3)

Figure 13: Banking production process



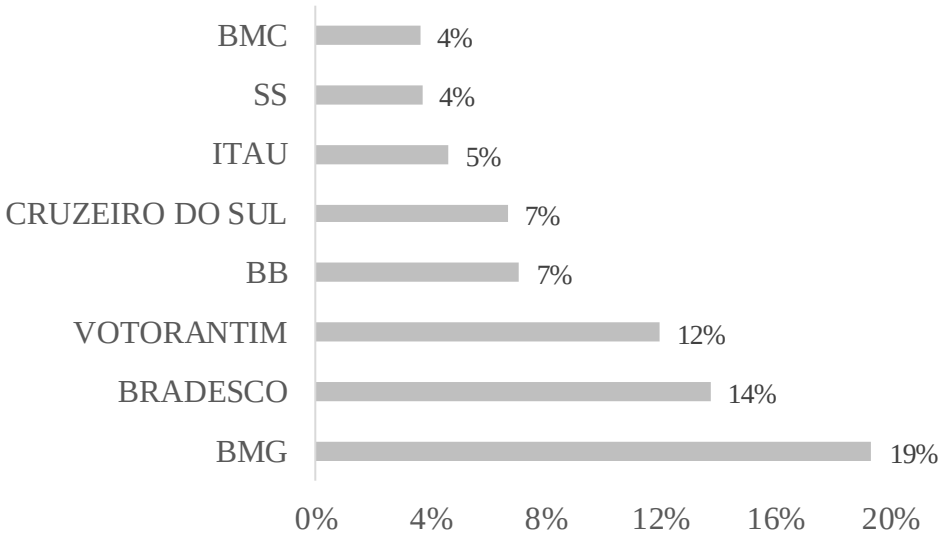
Source: Elaborated by authors

Figure 14: Frequent securitizers by number of transactions (as % of total transactions over the entire sample period)



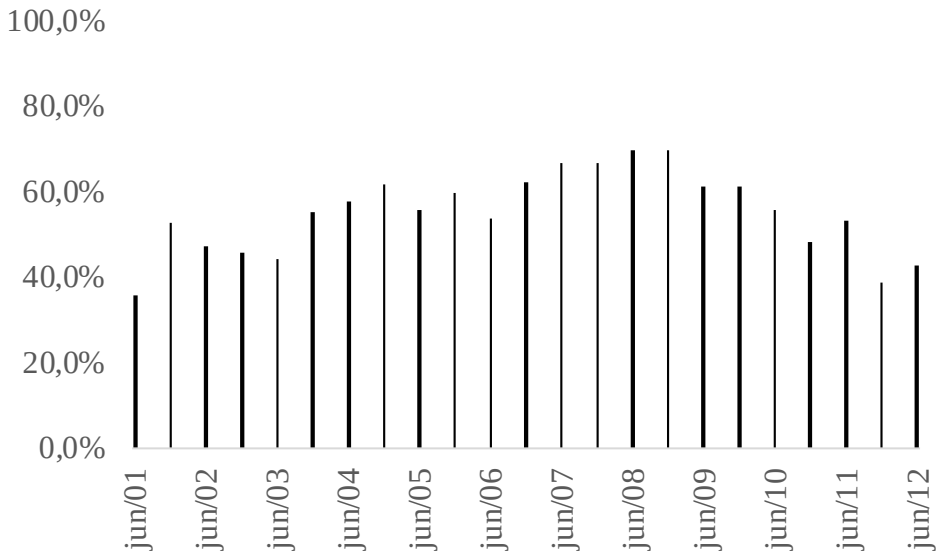
Source: Elaborated by authors.

Figure 15: Frequent securitizers by transaction volume



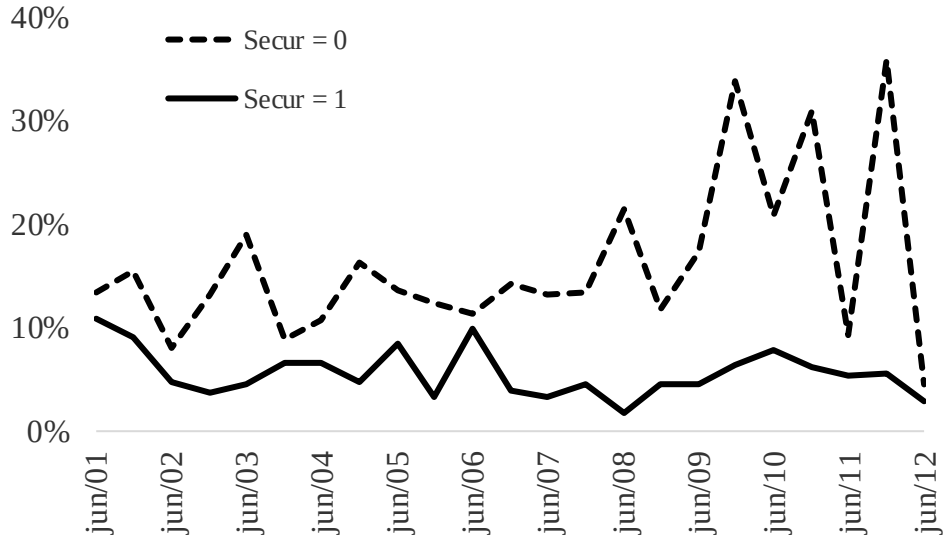
Source: Elaborated by authors.

Figure 16: Distribution of securitization activity over time



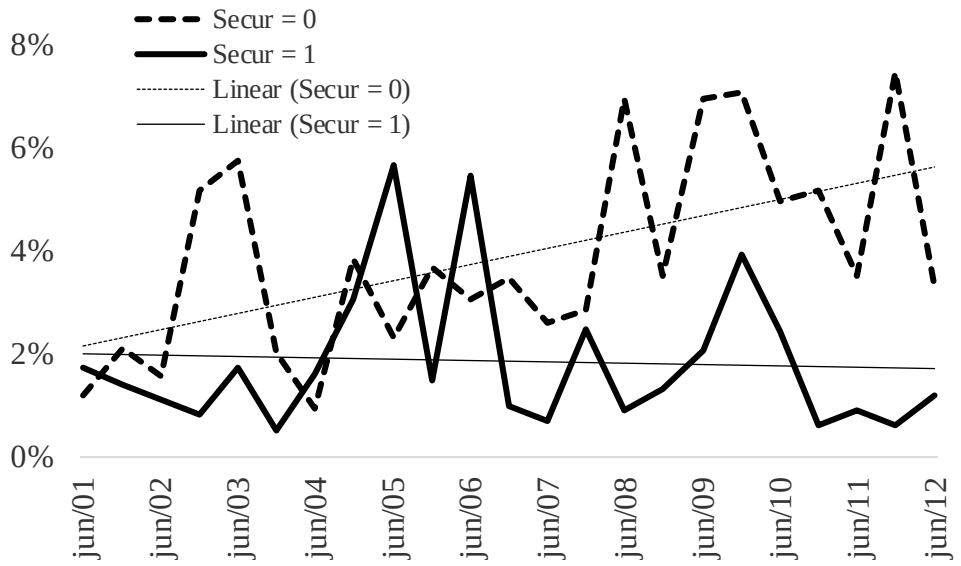
Source: Elaborated by authors.

Figure 17: Total inefficiency



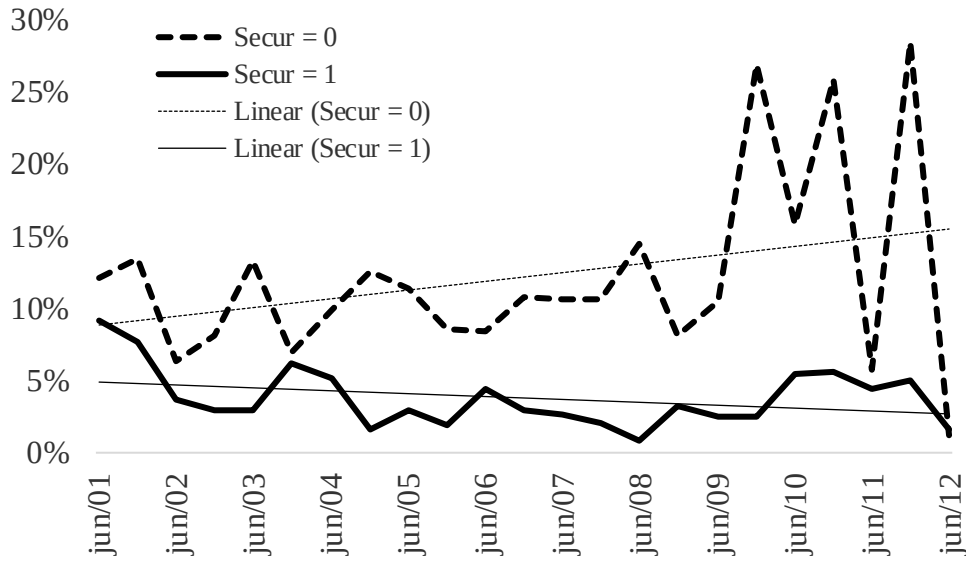
Source: Elaborated by authors

Figure 18: Non-interest income inefficiency



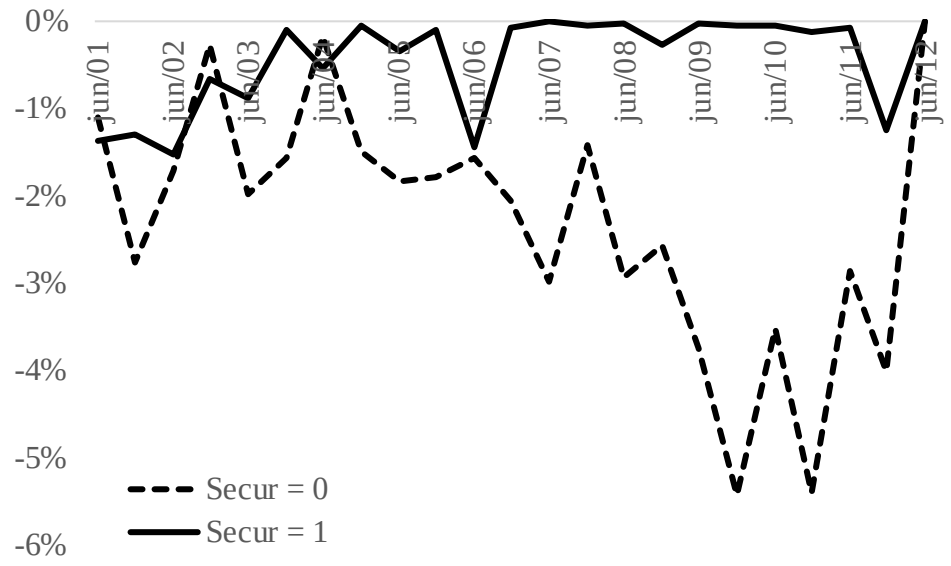
Source: Elaborated by authors

Figure 19: Interest income inefficiency



Source: Elaborated by authors

Figure 20: Delinquency gaps: optimal vs. observed



Source: Elaborated by authors.

Table 5: Variable definitions

Variable	Description	Calculation[1]	Source
Part I: Data envelopment analysis (DEA)			
Inputs			
D	Total deposits	Liabilities - a	IFData
LE	Labor expenses	Income statement (d3)	IFData
AOE	Administrative and operational expenses	Income statement (d4 + d8)	IFData
Intermediary outputs			
L	Loans	Assets (d1)	IFData
Outputs			
NII	Non-interest income	Income statement (d1 + d2 + d7)	IFData
II	Interest-income	Income statement (a1)	IFData
NPL	Non-performing loans	Loans with risk levels E (31600008), F (31700001), G (31800004) and H (31900007)	COSIF
PL	Performing loans	L – NPL	Calculation
Part II: TOBIT panel data			
Latent (dependent) variable			
ILS_assets	Loan sales to total assets	Loan sales (IFT) and Assets (k)	IFT and IFData
Explanatory variables			
Tier1	Tier 1 Capital/RWA	Capital (c/i)	IFData
Assets	Total Assets	Assets (k)	IFData
Liquid1	Liquidity ratio 1: money lent to other banks to money borrowed from other banks	Ln (1+(Assets (b) / Liabilities (a3)))	IFData
Liquid2	Liquidity ratio 2: liquid assets to deposits and short-term funding	Ln (1+(Assets (a+b) / Liabilities (e)))	IFData
Foreign	Dummy indicating whether a bank is controlled by a foreign institution (TCB column)		IFData

All data are provided by the Central Bank of Brazil (BCB).

[1]Letters and numbers in parentheses indicate the codes used by the BCB.

Source: Elaborated by authors

Table 6: Exclusion criteria for data envelopment analysis

Initial sample: 2492 observations	
Exclusion criteria	# of exclusions
D = 0	25
LE <= 0	16
AOE <= 0	2
L = 0	93
II <= 0	93
IE <= 0	36
NPL = 0	236
PL <= 0	18

Source: Elaborated by authors

Table 7: TOBIT panel data results: baseline estimates

Dependent variable: $S_{o,t}$	Overall inefficiency scores				Income specific inefficiency scores			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ineff_{o,t-1}$	-0.0334*	-0.0344**	-0.0332*	-0.0345**				
	(0.0171)	(0.0170)	(0.0171)	(0.0170)				
$Ineff_{1,o,t-1}$					0.0352	0.0295	0.0376	0.0316
					(0.0404)	(0.0404)	(0.0409)	(0.0409)
$Ineff_{2,o,t-1}$					-0.0469**	-0.0468**	-0.0475**	-0.0478***
					(0.0185)	(0.0184)	(0.0186)	(0.0185)
$Ln(Assets_{o,t-1})$	-0.0272***	-0.0259***	-0.0269***	-0.0258***	-0.0259***	-0.0247***	-0.0257***	-0.0247***
	(0.00554)	(0.00542)	(0.00548)	(0.00536)	(0.00563)	(0.00551)	(0.00557)	(0.00547)
Foreign		-0.0648**		-0.0665**		-0.0624**		-0.0642**
		(0.0293)		(0.0301)		(0.0297)		(0.0306)
$Liquid1_{0,t-1}$	-0.00443	-0.00502			-0.00443	-0.00502		
	(0.00492)	(0.00488)			(0.00491)	(0.00488)		
$Liquid2_{0,t-1}$			-0.00129	-0.00121			-0.00153	-0.00144
			(0.00344)	(0.00343)			(0.00342)	(0.00342)
$Tier1_{o,t-1}$	-0.105	-0.125	-0.0462	-0.0660	-0.105	-0.124	-0.0472	-0.0659
	(0.0836)	(0.0828)	(0.0815)	(0.0808)	(0.0837)	(0.0830)	(0.0817)	(0.0810)
Constant	0.513***	0.505***	0.481***	0.476***	0.482***	0.477***	0.456***	0.452***
	(0.0949)	(0.0926)	(0.0951)	(0.0931)	(0.0969)	(0.0947)	(0.0969)	(0.0950)
Observations	443	443	451	451	443	443	451	451
Number of instit	63	63	67	67	63	63	67	67

Standard errors in parentheses. Method: Standard TOBIT panel data model with random effects. All regressions include time fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Comparison of regression results with existing literature

Authors	Our study	Ribeiro and Schiozer (2013)	Barcelos and Mendonça (2015)	Li, Sheng and Smallwood (2020)	Bayeh et. al (2021)	Bannier and Hänsel (2008)	Cardone-Riportella et. al (2010)	Affinito and Tagliaferri (2010)	Faruggio and Uhde (2015)
1. Data									
Sample	Brazil	Brazil	Brazil	China	United States	Europe	Spain	Italy	Europe
Start date	2001	2004	2002	2012	2001	1997	2000	2000	1997
End date	2012	2009	2012	2018	2019	2004	2007	2006	2010
2. Independent variable									
Efficiency[1]	(-)*		(-)	(-)*	(-)*	(-)	(-)	(-)*	(-)
3. Controls									
Credit risk	[2]		N.S.	(+)	(-)*	(+)*	(+)	(+)*	(-)*
Total assets	(-)*	(-)*		(+)*	(+)*	(+)*	(+)		(+)*
Liquidity 1[3]	N.S.					(-)*	(-)*		
Liquidity 2[3]	N.S.	N.S.	(+)		(-)		(+)		(-)*
Tier 1 Capital	N.S.	(-)*		(-) / (+)	(-)*	(-)	(-)	(-)*	(-)
4. Regression Type									
TOBIT		X		X	X				X
PROBIT								X	
LOGIT				X		X	X	X	
GMM		X	X						
PSM					X				

[1] Signals displayed according to the measure chosen by the authors (ROE(+) or cost-to-income ratio (-)).

[2] We include a proxy for non-performing loans in the DEA methodology.

[3] For definitions, see Table 1.

[*]All signals indicated with (*) in this table indicate the measure is statistically significant either at the 1%, 5% or 10% level.

Appendix: A subsampling DEA approach to income inefficiency

The output directional distance function and the production set defined in equations (*11*) and (*12*) prompt to a potential empirical issue, because inefficiency scores compare observed and optimal performances positioned on the relevant production frontier. Or, the true frontier is unknown and in Equation (12) we estimate an empirical benchmark using the DEA technique for a multi-input, multi-output setting (Charnes, Cooper, and Rhodes, 1978). Thanks to its nonparametric nature, this linear programming method allows us to avoid misspecification effects that result from an arbitrary choice of functional technology form[6]. However, one may in turn regret that the main drawback of DEA (fundamentally, an enveloping technique), is the absence of a robust computation of the efficiency score, as in the usual econometric methods. To overcome this drawback, it is possible to apply the notion of subsampling frontiers by estimating successive partial frontiers, rather than the usual full-frontier approach (Politis and Romano, 1994; 1999). Therefore, robust estimators of the efficiency measures can be derived (Kneip, Simar, and Wilson, 2008).

The computational algorithm is as follows. For all evaluated DMUs, *B* Monte-Carlo replications compute a distribution of subsampling output directional distance functions. First, for each replication ($b = 1, ..., B$), we generate a random sample of size $J(b)$ independently, uniformly, and with replacement from the initial sample of the observed banks. The associated production set is denoted by $\hat{T}^{J(b)}$:

$$\hat{T}^{J(b)} = \left\{ \begin{array}{l} (\mathbf{x}_1, L, NII, II, PL, NPL): \\ x_{1,i_1} \geq \sum_{j=1}^{J(b)} \lambda_{1,j} x_{1,i_1,j}, \forall i_1 = 1,..,3,\ L \leq \sum_{j=1}^{J(b)} \lambda_{1,j} L_j, NII \leq \sum_{j=1}^{J(b)} \lambda_{1,j} NII_j, \sum_{j=1}^{J(b)} \lambda_{1,j} = 1; \lambda_{1,j} \geq 0, \forall j = 1,..., J(b); \\ L \geq \sum_{j=1}^{J(b)} \lambda_{2,j} L_j, II \leq \sum_{j=1}^{J(b)} \lambda_{2,j} II_j,\ PL \leq \sum_{j=1}^{J(b)} \lambda_{2,j} PL_j, NPL \geq \sum_{j=1}^{J(b)} \lambda_{2,j} NPL_j, \sum_{j=1}^{J(b)} \lambda_{2,j} = 1; \lambda_{2,j} \geq 0, \forall j = 1,..., J(b); \\ \sum_{j=1}^{J(b)} \lambda_{1,j} L_j = \sum_{j=1}^{J(b)} \lambda_{2,j} L_j \end{array} \right\}$$

(11).

Compared to the traditional deterministic model, in which all *N* observed banks are included in equation (*7*), a subsample of size *J* defines the subsample technology (equation *6*). Notice here that same subsample is used for both subprocesses $\left(\hat{T}_1^{J(b)} \text{ and } \hat{T}_2^{J(b)}\right)$[7].

Second, for every production plan $(\mathbf{x}, \mathbf{y})$ in the population *N* of observed banks, the corresponding Färe-Lovell output directional distance function relative to subsample *b* is given by:

6 These problems can indeed arise in stochastic frontier analysis, based on Cobb-Douglas or translog production functions.

7 These two subsample activity-specific sub-technologies can be easily inferred from (*6*) where essentially the second line deals with the first subprocess and the third line deals with the second subprocess.

$$\hat{D}_T^b(\mathbf{x},\mathbf{y};\mathbf{g}) = \sup_{\boldsymbol{\beta}} \left\{ \boldsymbol{\beta}_1^b + \boldsymbol{\beta}_2^b : \left(\mathbf{x}_1, \mathbf{y}_1 + \boldsymbol{\beta}_1^b \mathbf{g}\right) \in T_1, \left(\mathbf{x}_2, \mathbf{y}_2 + \boldsymbol{\beta}_2^b \mathbf{g}\right) \in T_2;\ \mathbf{g} \geq 0 \right\} \quad (12).$$

We adapt the linear program *LP*1 to obtain the subsampling directional distance function defined in (*11*), for each observed bank $o \in \{1,...,N\}$ in the sample and for each replication $b \in \{1,...,B\}$:

$$\hat{D}_T^b(\mathbf{x},\mathbf{y};\mathbf{g}) = \underset{\beta_1^b, \beta_1^b, \lambda_1^b, \lambda_2^b}{Max} \quad \beta_1^b + \beta_2^b$$

$$s.t. \quad \sum_{j=1}^{J(B)} \lambda_{1,j}^b NII_{j,t} \geq NII_{o,t} + \beta_1^b TI_{o,t}$$

$$\sum_{j=1}^{J(B)} \lambda_{1,j}^b L_{j,t} \geq L_{o,t}$$

$$\sum_{j=1}^{J(B)} \lambda_{1,j}^b D_{j,t} \leq D_{o,t}$$

$$\sum_{j=1}^{J(B)} \lambda_{1,j}^b LE_{j,t} \leq LE_{j,t}$$

$$\sum_{j=1}^{J(B)} \lambda_{1,j}^b AOE_{j,t} \leq AOE_{o,t}$$

$$\sum_{j=1}^{J(B)} \lambda_{1,j}^b AOE_{j,t} \leq AOE_{j,t}$$

$$\sum_{j=1}^{J(B)} \lambda_{1,j}^b = 1$$

$$\sum_{j=1}^{J(B)} \lambda_{2,j}^b II_{j,t} \geq II_{o,t} + \beta_2^b TI_{o,t}$$

$$\sum_{j=1}^{J(B)} \lambda_{2,j}^b PL_{j,t+1} \geq PL_{o,t+1}$$

$$\sum_{j=1}^{J(B)} \lambda_{2,j}^b NPL_{j,t+1} \leq NPL_{o,t+1}$$

$$\sum_{j=1}^{J(B)} \lambda_{2,j}^b L_{j,t+1} \leq L_{o,t+1}$$

$$\sum_{j=1}^{J(B)} \lambda_{2,j}^b = 1$$

$$\sum_{j=1}^{J(B)} \lambda_{1,j}^b L_{j,t} = \sum_{j=1}^{J(B)} \lambda_{2,j}^b L_{j,t+1}$$

$$\lambda_{1,j}^b \geq 0 \quad \forall j = 1,...,J(B) \text{ with } J(B) \subset N$$

$$\lambda_{1,j}^b \geq 0 \quad \forall j = 1,...,J(B) \text{ with } J(B) \subset N \quad (LP\ 2).$$

The robust inefficiency score for each bank *o* in the sample, i.e. $\bar{\boldsymbol{\beta}}_o = \left(\bar{\beta}_{1,o}, \bar{\beta}_{2,o}\right)$ is obtained as the average, over the *B* replications of the subsampling efficiency scores.

$$\bar{\beta}_{k,o} = \frac{1}{B} \sum_{b=1}^{B} \beta_{k,o}^b, \text{for } k \in \{1,2\} \quad (13).$$

We conclude this presentation on efficiency estimation method with an important remark. In a deterministic approach as outlined in (*11*) the evaluated bank always belongs to the production set, and thus, its total income efficiency equal to zero (if the bank is 'efficient') or greater than zero (if the bank is 'inefficient'). Conversely, in the subsampling approach, the sampling process used on the production set does not guarantee that the evaluated production plan is included in the referent technology.

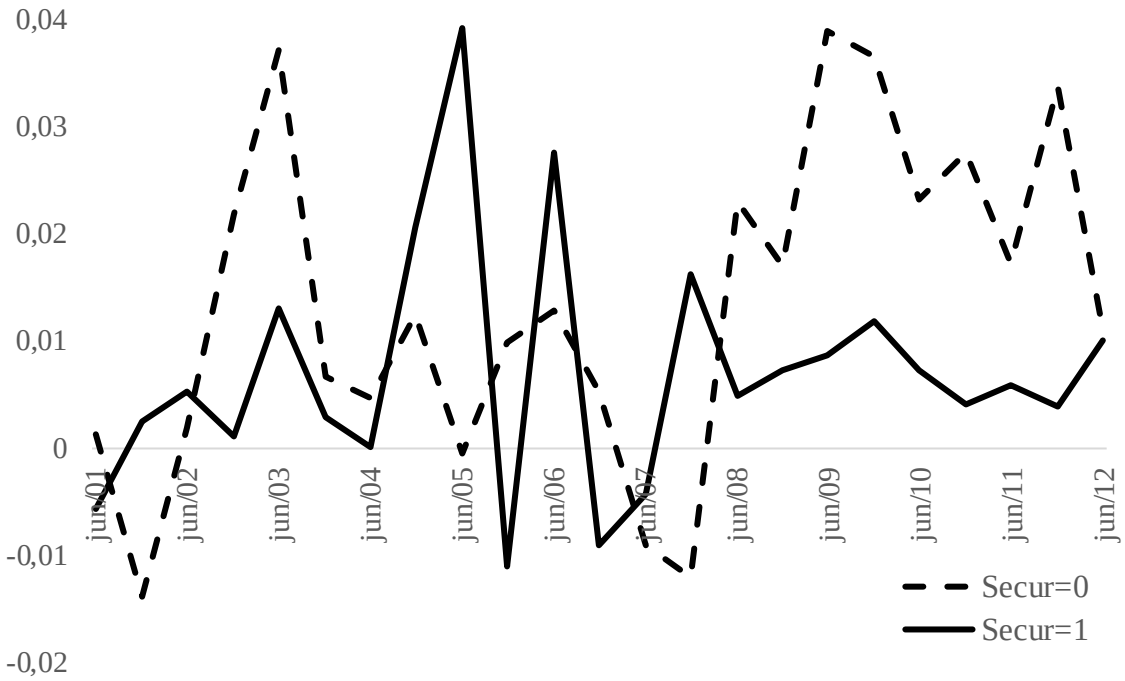
As a result, its efficiency score can even be strictly negative. In this case, this bank is above the selected benchmark, and is defined as being super-efficient.

Next, we present the results on inefficiency scores computed with the subsampling approach.

Figure 21: Total inefficiency (subsampling approach)

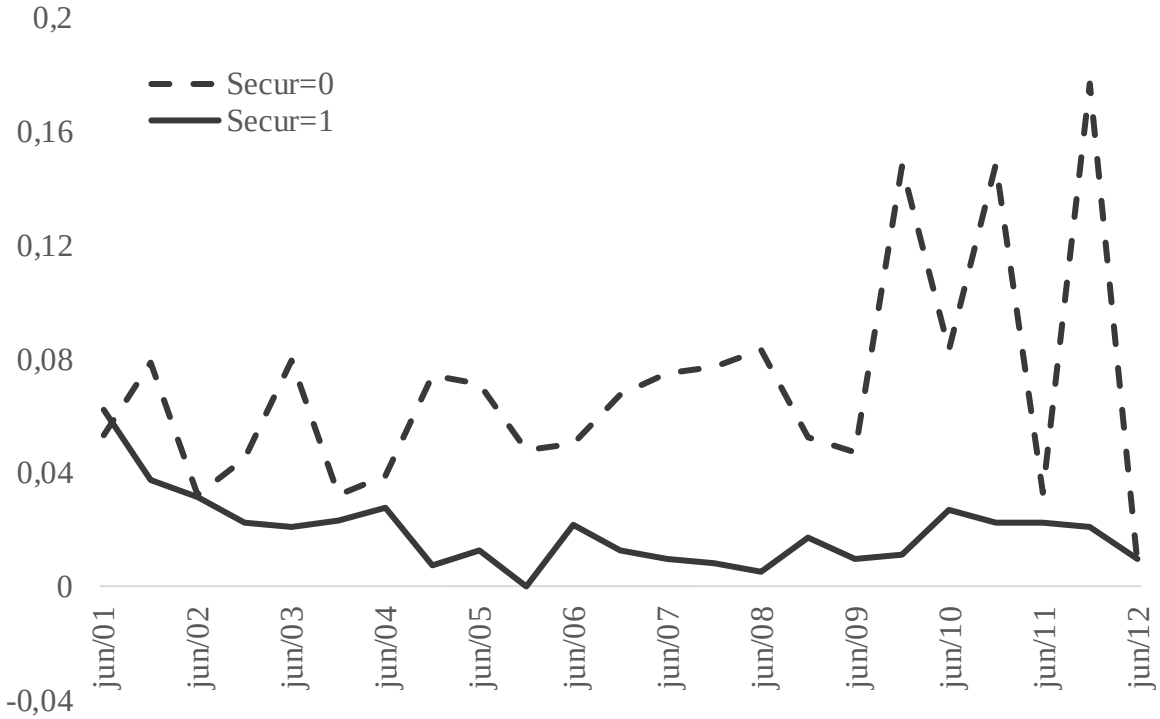
Source: Elaborated by authors.

Figure 22: Non-interest income inefficiency (subsampling approach)



Source: Elaborated by authors.

Figure 23: Interest income inefficiency (subsampling approach)



Source: Elaborated by authors.

Table 9: TOBIT panel data results: robust estimates

Dependent variable: $S_{o,t}$	Overall inefficiency scores				Income specific inefficiency scores			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ineff_{o,t-1}$	-0.0241	-0.0275	-0.0215	-0.0255				
	(0.0246)	(0.0246)	(0.0246)	(0.0246)				
$Ineff_{1,o,t-1}$					0.0856	0.0770	0.102*	0.0924*
					(0.0546)	(0.0546)	(0.0559)	(0.0559)
$Ineff_{2,o,t-1}$					-0.0560**	-0.0576**	-0.0577**	-0.0598**
					(0.0283)	(0.0282)	(0.0286)	(0.0285)
$Liquid1_{0,t-1}$	-0.00449	-0.00509			-0.00440	-0.00499		
	(0.00494)	(0.00490)			(0.00491)	(0.00488)		
$Tier1_{o,t-1}$	-0.116	-0.137	-0.0532	-0.0740	-0.0887	-0.110	-0.0268	-0.0473
	(0.0844)	(0.0836)	(0.0823)	(0.0816)	(0.0848)	(0.0842)	(0.0826)	(0.0821)
$Ln(Assets_{o,t-1})$	-0.0260***	-0.0246***	-0.0256***	-0.0245***	-0.0250***	-0.0238***	-0.0246***	-0.0236***
	(0.00554)	(0.00540)	(0.00548)	(0.00536)	(0.00553)	(0.00541)	(0.00549)	(0.00538)
Foreign		-0.0656**		-0.0670**		-0.0623**		-0.0635**
		(0.0296)		(0.0304)		(0.0295)		(0.0305)
$Liquid2_{0,t-1}$			-0.00156	-0.00149			-0.00179	-0.00171
			(0.00345)	(0.00344)			(0.00342)	(0.00342)
Constant	0.485***	0.478***	0.452***	0.447***	0.456***	0.451***	0.426***	0.422***
	(0.0946)	(0.0922)	(0.0948)	(0.0926)	(0.0951)	(0.0928)	(0.0953)	(0.0933)
Observations	443	443	451	451	443	443	451	451
Number of instit	63	63	67	67	63	63	67	67

Standard errors in parentheses. Method: Standard TOBIT panel data model with random effects. All regressions include time fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

3. Skin in the game and credible signaling in securitization: are fintechs different?

This chapter explores the association between risk retention by originators (*skin in the game)* and the performance of securitized assets. We combine hand-collected and publicly available data on 85 Brazilian receivable funds with a single originator from January 2013 to December 2020. We find that *skin in the game* is a buffer against observable risks, in accordance with the buffer hypothesis, although the reputation of originators that are financial institutions in the loan market can alleviate moral hazard concerns. For funds with *fintech* originators, the opposite holds: enhancements are indeed a signal against the unobservable quality of receivables.

Keywords: FIDC, receivable funds, skin in the game, securitization, delinquency rate, credible signaling, Brazil, emerging markets

JEL Codes: D53, G21, G23, G32, N26

3.1 Introduction

Market-based financing mechanisms are an increasingly important tool for firms in emerging markets to obtain financing. Securitization is one of those mechanisms that allows companies to bypass high-cost intermediaries and to access financing tools that would otherwise not be feasible (Schwarz, 2010). In Brazil, receivable funds (*fundos de investimento em direitos creditórios* or FIDCs) are one of the most common forms of securitization. FIDCs are structures for creating asset-backed securities (ABS) that invest in private credit issued by Brazilian companies and financial institutions in which investors can acquire senior or junior (first loss) tranches. The share of FIDC operations and issues in the Brazilian capital markets more than doubled from 2015 to 2020, with the volume of issues jumping from R$5.8 bn to R$33.9 bn. In 2020, the receivable market reached an important milestone, with more than 1,000 funds in operation. Regulators are also working on new rules that aim to reshape the structural aspects of those instruments.

Securitization decisions by originators depend on informational asymmetries among originators, outside investors and credit rating agencies. The essence of such decisions lies in the signaling benefits of retaining ownership of securitized assets, or risk retention, because outside investors often attach a higher value to firms that engage in securitization (Iacobucci and Winter, 2005). Risk retention is often referred to as skin in the game, a mechanism for alignment of incentives that mitigates moral hazard on the issuer's side. It consists of an implicit guarantee used to convey private information about the quality of receivables. (Gorton and Pennachi (1995), Iacobucci and Winter (2005), Sarkisian and Casu (20130), Ozerturk (2017)). Such retentions are common practice in Brazilian receivable funds (Peppe and Wellichen, 2013). Sarkisian and Casu (2013) demonstrate that the strength of the signal depends on the size and scale of originators and on the recurrence of such operations. Kuncl (2019) argues that when risk retention takes the form of first-loss tranche retention by the originator (horizontal retention), the signaling effect can be even stronger and that the efficiency of such signals in Europe depends on the stage of the business cycle.

Although the signaling hypothesis is the most common explanation for the practice of risk retention by originators in the academic literature, some authors highlight that a concurring explanation, the buffer hypothesis, can play a relevant role in such risk retention decisions (Berger and Udell (1990), Ashcraft, Vickery, and Goldsmith-Pinkham (2010)). Mandel, Morgan and Wei (2012) argue that while the signaling hypothesis suggests that credit enhancements (risk retention being one of those) function as a signal against unobservable quality, the buffer hypothesis implies that the use of credit enhancements is actually a buffer against observable risk. They investigate the relationship between total enhancements provided by banks and the performance of securitized assets (severe delinquency ratios). The authors find evidence consistent with the buffer hypothesis: by keeping "skin in the game", banks offer a buffer against observable risk, and even though the signaling component may be at play depending on the riskiness of the securitizes assets, that role is dwarfed by the buffering role.

Empirical studies about securitization in the Brazilian economy focus on the relationship between engagement in such operations and credit risk levels for financial institutions (de Mendonça and Barcelos, 2015, Catão et al., 2009) or on the level of risk faced by investors that

acquire first-loss tranches (Pinheiro and Savoia, 2009). We did not find empirical studies concerned with the role of skin in the game (retention of first-loss tranches by originators) as a credible signal about the quality of receivables in emerging markets or evidence evaluating whether risk retention in Brazil is indeed a signal or merely a buffer. Our methodology allows us to analyze a novel dataset on securitization activity in an emerging economy where shadow banking activity is expanding quickly: in 2020, for the first time, non-bank financial institutions represented a larger percentage of total financial assets than that of traditional institutions. With our empirical findings, we also contribute by presenting evidence on local securitization activity in an emerging economy.

Second, several studies suggest that the innovative and cost-effective approach to lending used by fintechs and their technology and portfolio differences have significant impacts on their pricing strategies and that their funding supply differs significantly from traditional financial institutions (Buchak et al. (2018), Odinet (2018), Tsang (2019), Odinet (2020), Di Maggion and Yao (2021)). These aspects, in turn, are essential to understand whether skin in the game is a buffer or a signal depending on the type of financial originator. Third, we did not find studies that combine data on several types of originators (both financial and nonfinancial) or empirical analyses that evaluate not only the role of enhancements but also recurrence to understand the performance of securitized assets.

In this sense, our primary research question is the following: what is the association between risk retention by originators and the performance (severe delinquency ratios) of securitization instruments in Brazil? Second, we investigate whether such an association changes or intensifies depending on the type of originator (financial vs. nonfinancial, traditional financial institutions vs. fintechs). To answer such questions, we analyze monthly data on 85 FIDCs with a single originator between January 2013 and December 2020. To perform our analysis, we combined hand-collected data on risk retention levels by originators and cessation rates with public datasets from the Securities and Exchange Comission of Brasil (CMV) and used panel data with fixed effects and clustered standard errors by fund. Following Mandel, Morgan and Wei (2012), our main dependent variable is the monthly severe delinquency ratio (lower ratios imply a higher performance).

Similar to the pattern in developed markets, we observe that ABS issues (FIDC offerings) in Brazil are relatilvely cyclical. We also note that from 2013 to 2018, the cost of bank financing exceeded the cost of securitization. In 2020, because of artificial levels of the policy rate in response to the pandemic of the new coronavirus, the opposite occurred. In our sample, there is an upward trend in the proportion of enhancements (skin in the game) offered by originators until the end of 2016, while the opposite holds after 2017. Our descriptive statistics suggest that the relationship between delinquency ratios and enhancements provided by originators depends on factors such as recurrence and the total asset size of funds.

Our main specification demonstrates that enhancements by originators (skin in the game) are positive and statistically significant to explain delinquency ratios, in accordance with the buffer hypothesis: for the whole sample, we observe that enhancements are a buffer against observable risk (Ashcraft, Vickery, and Goldsmith-Pinkham (2010), Mandel, Morgan, and Wei (2012)).

When we consider only receivable funds with fintechs as originators, however, the opposite holds, and enhancements turn out to be a signal against unobservable quality (Gorton and Pennachi (1995), Iacobucci and Winter (2005), Uzerturk (2017)). Because fintechs are new entrants and compete directly with incunbent banks in the loan market, recourse can be a tool to build reputation. The use of skin in the game as a signal for fintechs can be attributable to three components: differences in funding supply and regulatory requirements, screening technology differences and loan pricing strategies and, finally, their loan supply approach (relationship banking vs. convenience approach). Although our main findings suggest that recourse provision by financial originators is not a mechanism to alleviate moral hazard, we investigate whether the reputation of a financial institution in the loans market can be a signal of unobserved quality of receivables. Indeed, our findings demonstrate that receivable funds with financial institutions (FIs) with lower reputations in the loan market as originators exhibit higher delinquency ratios (Winton and Yerramilli (2021), Deku, Kara and Marques-Ibanez (2021)), regardless of how these FIs respond to loan demand. We also find that recurrence is positively associated with delinquency ratios in all specifications, which suggests that as time passes by, revolving funds may use their good reputation (acquisition of assets with lower risk levels) to change their portfolio characteristics. For funds with financial institutions as originators, however, the level of enhancements provided by originators is not significant in explaining delinquency ratios. We contribute by demonstrating that the role of credit enhancements can vary depending on the type of originator and that recurrence may function as a reputation mechanism in the securitization market.

3.2 Literature review

3.2.1 The signaling hypothesis

Market-based financing mechanisms are an increasingly important tool for emerging market (EM) firms to obtain financing. Securitization falls under the umbrella of shadow banking activities (Qanas and Raza, 2018) and is a mechanism that allows companies to bypass high-cost intermediaries and to access financing tools that would otherwise not be feasible (Schwarz, 2010). The securitization of receivables helps companies mitigate the underinvestment problem (Myers, 1977) and access cheaper sources of capital, especially when the company's credit quality is inferior to the credit quality of its clients (Katz and Blatt, 2008). Iacobucci and Winter (2005) categorize theories of asset securitization into two classes of informational asymmetries (the set of informational differences). The first relates to hidden information to investors at the time securities are issued, and the second relates to the different sets of informational managers and investors that are "realized during the period between security issues and the date of security maturity" (p. 163), which is known as the agency problem. Another hidden-information problem is the asymmetry among different classes of outside investors and arises not because of uncertainties about the assets of the issuing firms but because of uncertainties about the securitized assets.

This disintermediation approach allows firms to raise funds and improve their liquidity position without increasing their balance-sheet liabilities (Benea and Duma, 2013). In developed economies such as the United States, the conversion of illiquid assets into tradable debt and equity obligations occurs when the originator sells the assets to a special purpose vehicle (SPV), which takes the legal title of the assets. Once securities are issued by the SPV, the transferred assets increase in value because they are worth more outside the company than within it (Benea

and Duma, 2013). Although securitization is often beneficial for the originator and can provide economic value to nonfinancial firms (Korgaonkar, 2009), the originate-to-distribute model might create moral hazard, which refers to the possibility of postcontractual opportunism of the agent.

In the context of securitization, moral hazard arises from originators' ability to securitize and then sell credits. It is a problem of incentives between the originator and the investor not being sufficiently aligned (Adrian, 2011). Sopranzetti (1999) argues that the securitization of receivables is more likely to occur for tranches of lower risk and higher credit quality, given reputation concerns about such transactions. Firms prefer securitization instead of the issue of secured debt because while the first only depends on the collateral value of the portfolio, the second depends on the firm's actual debt capacity (Smith and Schnuker (1994), Roever and Fabozzi (2003)).

Because originators typically have better information about loan quality than buyers of ABS securities, signaling by recourse provision is key to address the issue of asymmetric information (Kuncl, 2019). Issuers use two signals of security quality in an attempt to achieve a separating equilibrium in securities markets: implicit and explicit recourses. Implicit, moral or relational recourses involve reputational mechanisms or arrangements that circumvent the difficulties of formally contracting (Gorton and Souleles (2006), Kuncl (2019)). Retaining a portion of the loan – risk retention – functions as an implicit recourse because it is a signal that the originator is willing to evaluate and monitor the borrower (Gorton and Pennachi, 1995). Explicit recourses, on the other hand, usually take the form of overcollateralization, which is the provision of excess collateral to protect ABS buyers from default on the underlying loans and represents the difference between the total asset backing and the total value of quotas (Anbima (2015), Kuncl (2019). The role of risk retention as a signal of security quality varies depending on the moment of the business cycle. Despite the fact that the provision of implicit guarantees increases the occurrence of separating equilibria, in the boom stage of the business cycle, there are only pooling equilibria in which the information about the quality of loans remains private and the allocation of investment is inefficient (Kuncl, 2019).

Iacobucci and Winter (2005) argue that "the essence of securitization under the informational assumptions […] is it use by insiders as a means of retaining ownership" of assets abouth which they have private information. The signaling benefit thus occurs because outside investors attach a higher value to firms that engage in securitization. For FIDCs, risk retention is a positive signal about the quality of the receivables in the portfolio because it demonstrates that the originator is willing to absorb losses and share risks with other investors.

Ozerturk (2017) argues that risk retention is a mechanism for the alignment of incentives by which sellers of high-quality assets can credibly signal their private information. Because risk retention is a form of credit support, it works as a mechanism that mitigates moral hazard on the issuer's side and has three basic functions. First, it is "an incentive device for issuers to exert costly monitoring effort and improve the asset payoff after the sale". Second, it is useful for investors because they can "exert pre-sale screening effort to improve asset quality during the

loan origination stage". Third, it is "a credible signal of quality when the issuers have private information on the asset's quality". Buchanan (2016) argues that the enforcement of risk retention and regulatory initiatives in this regard can be useful to restore market confidence after periods of economic crises.

Adrian (2011) argues that the menu approach to risk retention includes vertical and horizontal retention. “Vertical retention refers to holding a portion of all tranches, while under horizontal retention, the securitizer retains a first-loss tranche restricted to receive only scheduled principal”. The author also explains that the incentives to monitor will vary according to the choice of risk retention and that vertical retention usually provides stronger incentives. Kuncl (2019), on the other hand, argues that when risk retention requirements take the form of first-loss tranche retention by the originator, the signaling effect may be stronger. In Brazil, the originator of the fund usually retains a significant portion of first-loss tranches (Peppe and Wellichen, 2013), which means that horizontal retention is common practice.

Empirical studies that focus on the relationship between the likelihood of securitizing assets with risk retention and firm-level characteristics highlight the importance of taking into account the firm’s internal cost of financing, its bankruptcy probability, the credit quality of its portfolio (drawees’ credit quality) and its sector (Sopranzetti (1998), Palia and Sopranzetti (2004)). Sarkisyan and Casu (2013) observe data for the banking industry and demonstrate that total retained interests and guarantees offered to own securitisation structures have distinct impacts depending on the size of securitisers: “for “large-scale” securitisers retained interests increase overall risk, while having a risk-reducing effect for “small-scale” and/or first-time securitisers”. They find that structures with higher proportions of first-loss tranches have a greater impact on a bank’s default risk.

3.2.2 The buffer hypothesis

The signaling hypothesis implies that the provision of enhancements by originators has a positive relationship with the performance of securitized assets. In other words, by keeping skin in the game, originators offer investors a signal against unobservable quality, and such a signal leads to separating equilibria, as it allows investors to distinguish between riskier and safer borrowers. In this sense, the higher the level of enhancements on a deal, the lower its delinquency ratio.

The buffer hypothesis, however, offers an alternative explanation: enhancements are actually used as a buffer against observable risk and not as a discriminating mechanism (Mandel, Morgan and Wei, 2012). Because of the mechanic nature of the use of enhancements as a buffer to achieve a given rating due to the estimated loss function on the underlying collateral, one should expect to observe a negative relationship between the level of enhancements and the performance of securitized assets or a positive relationship between the level of enhancements and delinquency ratios. The buffer hypothesis has to do with the literature on collateral pledges in the context of asymmetric information. Evidence on this topic is provided by Berger and Udell (1990), Ashcraft, Vickery, and Goldsmith-Pinkham (2010) and Mandel, Morgan and Wei

(2012). The first demonstrated that collateral was associated with riskier borrowers and loans, the second that delinquency on subprime securitized assets is positively associated with the amount of subordination and the third that by keeping "skin in the game", banks offer a buffer against observable risk, although the signaling component may be at play depending on the riskiness of the securitizes assets.

Although risk retention by the originator is an important signaling mechanism and can provide informational content about the quality of receivables, it also has potential drawbacks. First, after the global financial crisis, regulators in the United States discussed possible solutions to minimize the moral hazard problem in the context of securitization, which included the Dodd-Frank requirements that originators retain some risk of loss and the regulation of loan underwriting standards. Arner et al. (2019) argued that this response ignored that the retention of substantial risk on underlying loans was always common practice for sponsors of securitizations. In this sense, the assumption that the high rate of defaults resulted from moral hazard inadvertedly created a novel information failure: a mutual misinformation problem caused by complexity. Mutual misinformation implies that requirements of risk retention can affect cessation rates charged by funds, making it difficult to identify good-quality credits, which adds a layer of opacity to the securitization market.

3.2.3 Receivables funds in Brazil

In Brazil, the most common forms of securitization are receivable funds (*fundos de investimento em direitos creditórios* or FIDCs) and factorings. FIDCs are shadow banking entities that generate a support system and greater liquidity for the bank credit market and help reduce the asymmetry of information about borrowers. FIDCs are common structures for creating asset-backed securities (ABS) that invest in private credit of Brazilian companies and financial institutions. FIDCs take the legal form of joint ownership and function like an ABS but are technically similar to mutual funds in the sense that investors buy quotas that pay dividends if the private credits of the portfolio are not in default. Quotas are similar to tranches in the American market. The difference is that quotas are amortizing structures that have a target return, not a legally binding interest rate. The structure resembles a simple cash waterfall (Budinger, 2012). FIDCs do not require the creation of a special purpose entity (SPE) because these funds do not constitute a legal personality. The Securities and Exchange Comission of Brazil (Comissão de Valores Mobiliários – CVM) first regulated FIDCs according to Instruction CVM n. 356/01. Because such regulation was not specific about the role and responsibilities of the fund manager, custodian and administrator, it ended up generating some governance concerns. To alleviate them, CVM issued Instruction number 531/13. In terms of risk mitigation, CVM demands that FIDCs only use derivatives for protection purposes, concentration limits by originator and that the originator should not be bound to the fund manager, custodian or to the consulting agent. Additionally, FIDCs are not subject to Brazilian bankruptcy law.

The constitution of an FIDC can include six mechanisms for mitigating credit risk or credit enhancements: the subordination level, overcollateralization, recourse provision, excess spreads, credit insurance, and excess warranties (Anbima, 2015). Subordination levels, overcollateralization, co-obligation – the three types of risk retention – and excess spreads refer

to the quality of internal credit reinforcements because they constitute the fund's operational structure. Subordination levels are not the only internal credit risk mitigation mechanism because in the event of cash flow fluctuations due to the receivable portfolio, the fund may suffer losses (Anbima, 2015). Credit insurance and excess warranties constitute external credit reinforcements because they are usually provided by originators or by third parties (Austin Rating, 2017).

FIDCs are usually assigned a rating by a credit rating agency, although some funds are not required to do so according to Article 23-A in ICVM 356. Brazilian regulators classify receivables in an FIDC portfolio into two categories: receivables with acquisition of risks and benefits ("*com aquisição substancial de riscos e benefícios*", which implies no risk retention, and receivables without acquisition of risks and benefits ("*sem aquisição substancial de riscos e benefícios*"), which are receivables with risk retention. According to a CVM study from 2014, the purpose of risk retention is to prevent the originate-to-distribute model from comprising fragile lending practices. In this sense, risk retention seeks to address both moral hazard and adverse selection problems. For FIDCs, the decision to acquire credit rights without risk retention by the originator depends on the exposure level of the fund to expected cash flow variations of the receivables (Anbima, 2015). In the case of a significant level of exposure, the FIDC acquires credit rights without risk retention by the originator. Acquisitions of credit rights with risk retention occur when the originator acquires enough junior/first-loss tranches to guarantee the coverage of certain expected losses on receivables. Transactions without risk retention by the originator are also known as nonrecourse transfers of receivables or true sales, which implies that the originator is not liable in case of default by the debtor. According to the Brazilian tax regime, true sales are not subject to the tax on financial transactions (IOF), although the rates were reduced to zero between April and July of 2020 as part of the government's response to the COVID-19 pandemic (Assis et al., 2020).

The Securities and Exchange Commission of Brazil does not impose a minimum level of risk retention by originators. Despite the IOSCO guidelines released in 2011 suggesting that securitization activities should require at least 5% risk retention to avoid information asymmetry problems and potential negative effects induced by moral hazard, Brazilian regulators concluded that the measure had no contribution to the Brazilian securitization market. Using a regulatory impact analysis approach, a study proposed by CVM in 2014 argues that the requirements of public disclosure of information and the tools that reinforce the independence of the administrator make fragile practices in credit concession less detrimental. Moreover, because originators in Brazil often retain more than 5% of the risks in securitization products, adopting such a requirement in Brazil would consist of an unnecessary regulatory burden and could even lead to higher risks in the securitization industry.

An important regulatory milestone for credit fintechs in Brazil was provisional measure (MP) number 897 of 2019, which authorizes the electronic issue of Cédulas de Crédito Bancário (CCBs), which consists of legal authorization for an electronic bookkeeping system. Since October 2019, the Central Bank of Brazil has regulated the exercise of these electronic bookkeeping activities. Credit fintechs benefited from such measures because these electronic issues can now be considered extrajudicial executive titles by Brazilian courts. This means that in the case of a bankruptcy procedure, the riskiness of securitized assets is no longer connected

to the riskiness of the issuer (the fintech), which makes securitization through receivable funds (FIDCs) a relatively safe tool from the point of view of investors – especially those that acquire junior tranches (Odinet, 2020).

Most of the evidence about securitization in the Brazilian economy relates to the use of suck instruments and risk taking on traditional financial institutions. De Mendonça and Barcelos (2015) analyze securitization transactions from 60 financial institutions (FIs) from October 2002 to September 2012 and find that the use of securitization transactions increases the credit risk of these FIs. In line with their results, Catão, Rodrigues, Libonati and Lagioia (2009) analyze 10 banks and 12 FIDC public offers and demonstrate that securitization transactions decrease the credit quality of banks' portfolios, decrease leverage ratios and increase liquidity ratios. Pinheiro and Savoia (2009) use a stochastic model to simulate risk and return for quotaholders of FIDCs and find that the probability of a return below the risk-free interest rate is very low due to the spreads charged from originators.

Several studies suggest that the innovative and cost-effective approach to lending used by fintechs and their technology and portfolio differences have significant impacts on the determination of loan interest rates and pricing strategies (Buchak et al. (2018), Odinet (2018), Tsang (2019), Odinet (2020), Di Maggion and Yao (2021)). Moreover, in contrast to traditional financial institutions that can rely on government funds and deposits, securitization is one of the main sources of funding for fintechs. Acharya, Schnabl and Suarez (2013) demonstrate that banks can use conduits for regulatory arbitrage, not necessarily to transfer risks to outside investors, and that banks rely much more on explicit than implicit guarantees. These aspects, in turn, are essential to understand whether skin in the game is a buffer or a signal depending on the type of financial originator. In this sense, our empirical analysis is dedicated to such evaluation.

3.3 Data

We identified 850 FIDC issues between January 2013 and December 2020 in the Brazilian Financial and Capital Markets Association's (Associação Brasileira das Entidades dos Mercados Financeiro e de Capitais – Anbima) Capital Markets Monthly Report. For the purpose of this study, we will consider only FIDCs issued through Instruction CVM 476, by which companies are exempt from presenting a prospectus. Our sample begins in 2013 because CVM worked on Instruction n. 531/13 to avoid potential conflicts of interest in the management of these funds and to mitigate concerns about the reliance of Brazilian investors on the strength of the issuer to evaluate an ABS (Budinger, 2012). In this sense, including issues from previous years in our sample would make our comparisons unrealistic.

We excluded all FIDCs with multiple originators (*"multicedentes"*) because it is not possible to identify all of the originators in the credit reports and bylaws, making it impossible to measure the level of risk retention on such funds, our main topics of interest. Moreover, we excluded funds that are nonstandardized (*"não padronizados"*) because risk retention by the originator of nonstandardized FIDCs not only does not make sense but is also not feasible due

to the very nature of the portfolio of credits, which is more complex and involves specific risks (according to ICVM 444/06). Finally, we also excluded those FIDCs intended for the acquisition of credit rights derived from public sector entities. Our final sample consists of 85 FIDCs with a single originator (*"monocedentes"*). To avoid survivorship bias, our sample includes both active and extinct FIDCs. Extinct funds represent 24.705% of our sample (21 FIDCs).

We hand-collected information for each FIDC using CVM monthly reports, quarterly credit reports and bylaws. We manually collected information that was not previously available in CVM's public datasets because some of them are disclosed in quarterly credit reports or in the credit rating agency's report, as Brazilian regulators do not require the disclosure of such information on a monthly, structured basis. Cessation rates for credit rights are one of those.

Finally, authors argue that the securitization of receivables helps companies mitigate the underinvestment problem and access cheaper sources of capital (Myers (1977), Katz and Blatt (2008)). To see if this is the case for Brazilian firms, we use monthly data from January 2013 to December 2020 and compare the Brazilian benchmark rate (SelicOver) to three sources of external funding: banks' discount rate on receivables (bank financing), bond yields that use DI as a benchmark at issue date (capital markets) and FIDCs monthly average cessation rates (securitization). We do so to analyze the cost of external funding for Brazilian firms and provide an overview of financing costs faced by Brazilian firms, combining data from the Central Bank of Brazil, Ipeadata, CVM, B3 and Anbima. We also use DI (the average rate of interbank transactions carried out through interbank certificates of deposits in Brazil) as our risk-free rate because most of the FIDCs in our sample use DI plus a premium to determine their benchmarks. Benchmarks were usually percentages of the Brazilian Interbank deposit rate (DI) or of the Broad National Consumer Index (IPCA).

3.4 Methodology

3.4.1 Independent variables

In securitization transactions, signals of security quality can be internal (structural) or external. Internal credit reinforcements refer to risk retention or excess spreads, while external reinforcements refer to credit insurance or excess warranties. This study has a focus on risk retention or recourse provision, which can be implicit (signaling or reputational) or explicit. While subordination levels and co-obligation mechanisms are the main forms of implicit signals, overcollateralization is the main form of explicit recourse provision (Gorton and Pennachi (1995), Gorton and Souleles (2006), Anbima (2015), Kuncl (2019)). We offer a visual representation of such mechanisms in **Figure *24***. The main purpose of this study is to understand whether implicit recourses function as a signal against unobservable quality or a buffer against observable risk – which is, whether the acquisition of first-loss tranches by originators is associated with lower delinquency ratios. We evaluate whether the role of skin in the game (as a signal or as a buffer) is stronger depending on the type of originator (financial vs. nonfinancial) and on recurrence. Our measures of internal credit enhancements are summarized in **Table *10***.

To identify whether FIDC originators are willing to share losses with investors, we use the methodology proposed by a CVM report from December 2014 entitled "Risk Retention in Securitization". Since CVM Instruction n. 489/11, FIDCs are required to report risk retention levels. When an FIDC classifies its portfolio as "without substantial acquisition of risks and benefits", we considered it to be evidence of risk sharing. According to CVM requirements, funds must report the proportions of first-loss tranches acquired by originators that are higher than 10%. We use these data to measure co-obligation or skin in the game, our main variable of interest. Because our sample includes only funds with a single originator, we sum all of the values reported in the monthly reports so we can define the total share of risk retention by the originator. We then calculate our main independent variable (*Enhance*) by multiplying this share for the total value of assets with risk retention and calculate a ratio, considering the total value of securitized assets (total value of assets acquired with and without substantial acquisition of risks and benefits), in accordance with Mandel, Morgan and Wei (2012).

We also use the proportion of risk retention to net worth to measure the level of risk retention in a certain fund (*Risk_ret_nw*). As an alternative measure of skin in the game, we use a categorical variable indicating whether originators hold at least 10% of the junior tranches (*Skin*), which is the mere existence of co-obligation. Altogether, these three variables (*Enhance*, *Risk_ret_nw* and *Skin*) offer different ways to measure implicit signals.

To measure explicit recourse and improve our descriptive statistics, we calculated two variables for overcollateralization: one categorical variable (*Overcoll*) and the overcollateralization ratio using the methodology proposed by Kuncl (2019), Anbima (2015) and Austin Rating (2017). Anbima (2015) states that overcollateralization refers to the balance of underlying assets (such as cash, performing loans and investments in securities) that exceeds the value of issued quotas. To calculate the monthly value of asset coverage, we use the following variales available at CVM balace sheets: cash (*disponibilidades*), performing loans with and without risk retention (*créditos existentes a vencer e adimplentes*) and securities (fixed income (corporate and public bonds and bank deposit certificates) and shares), subtracting the total value of senior and junior tranches. Finally, to complete the range of variables for internal credit enhancements, we measure excess spreads using the value of cessation rates (*Cess_rate*) available in some quarterly reports. Arner et al. (2019) argue that requirements of risk retention can affect cessation rates charged by funds, which suggests some level of connection between the main forms of implicit signals, recourse provision and excess spreads.

3.4.2 Dependent variable

Following Mandel, Morgan and Wei (2012), our main dependent variable is the severe delinquency rate for each FIDC (*Severe_delinq*). It consists of the sum of securitized assets ninety or more days past due and written off (more than 1080 days), divided by total securitized assets outstanding at each fund in each month.

To improve our descriptive statistics and analyze whether the performance of first-loss tranches of FIDCs with a single originator is superior to their benchmarks, we collected the monthly series of DI and IPCA using B[3] (Brazil securities exchange) and National Statistics Bureau (IBGE) statistics, respectively. We then calculate *Spread_sub*, which is the return on first-loss tranches above the risk-free interest rate. Although this variable could be an alternative dependent variable, other assets in a fund's portfolio also influence the performance of first-loss tranches.

3.4.3 Controls, outliers and filters

Our main controls are described in **Table *11***. To treat the outliers, we use the following criteria: for cessation rates, subordination to net worth and spread over DI, we discard values that are above the mean plus two standard deviations. For delinquency ratios, risk retention to net worth ratio and risk retention above 10%, we discard the values that are above 100%. For our main dependent variable (*Enhance*), we discarded all the proportions above 100% (101 observations).

3.4.4 Empirical strategy

Our null hypothesis (H_0) assumes that there is a positive relationship between co-obligation (*Enhance*) and the delinquency ratios of securitized assets (*Severe_delinq*). In other words, we assume that skin in the game by originators is a buffer against observable risk and go under the null that there is a positive relationship between enhancements and delinquency ratios: higher levels of enhancements should be required for securities with a higher likelihood of delinquency. In case we find a negative relationship between the level of enhancements and delinquency ratios, however, there will be evidence indicating that enhancements are actually a signal against unobservable quality, confirming the signaling hypothesis that higher levels of enhancements provided by originators function as a distinction mechanism from riskier borrowers (H_1). We use panel data with fixed effects and clustered standard errors by fund. Our main specification is defined in ***Equation 14***.

Because the effects of enhancements on the performance (delinquency ratio) of securitized assets can be distinct for bank originators (Sarkisyan and Casu (2013), Daley, Green, and Vanasco (2019)), we include two subsamples: one for originators that are financial institutions and another for originators that are fintechs. We make this distinction between types of financial institutions because both reputational and buffering effects could be distinct for new entrants.

Kuncl (2019) demonstrates that the effect of enhancements can vary depending on the moment of the business cycle. Although measurements of the business cycle are beyond the scope of this study, we also include a subsample considering market conditions: we classified each

month as a bull or bear market. A bull market is defined when Ibovespa (market index) increases in comparison to the previous month, and a bear market is defined when the opposite happens.

Finally, we also consider an alternative measure for enhancements: to see if the mere acquisition of first-loss tranches by originators (skin in the game), regardless of the amount, can explain the performance of securitized assets, we substitute *Enhance* by *Skin*, according to ***Equation 15***.

$$Severe_delinq_{i,t} = \beta_0 + \beta_1 Enhance_{i,t} + \beta_2 Enhance * prime_{i,t} + \beta_3 Tot_asset_ln_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 Subord_nw_{i,t} + \beta_6 Recurr_{i,t} + u_{i,t} \quad (14)$$

$$Severe_delinq_{i,t} = \beta_0 + \beta_1 Skin_{i,t} + \beta_2 Enhance * prime_{i,t} + \beta_3 Tot_asset_ln_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 Subord_nw_{i,t} + \beta_6 Recurr_{i,t} + u_{i,t} \quad (15)$$

3.4.5 Limitations and suggestions for future research

Although controlling for the cost structure of funds could be useful, we could not identify structured information about this in the reports we analyze. Practitioners argue that FIDCs are often more cost effective than banks because they directly connect investors and companies and have a structure exempt from intermediate taxes. The efficiency of such a structure depends on the relationship between the volume of credit sales and maintenance costs because, on average, a fund's annual maintenance costs revolve around R$200-300 thousand Brazilian reais", and for funds with a single originator, the securitization structure only pays off when the funding value is higher than R$30 million Brazilian reais (R7, Sep. 2015). Although we did not collect information on such a topic, future research could include FIDCs' cost structures in the analysis.

Second, empirical studies that analyze the relationship between asset securitization and firm-level characteristics highlight the importance of taking the originator's internal cost of financing and the credit quality of its portfolio into account (Sopranzetti (1998) and Palia and Sopranzetti (2004)). We could not gather data on originators' cost of capital or on the average rating of their portfolios because most of these companies do not release such information on a structured public basis. However, one-third of the FIDCs in our sample (28 of 85) have financial institutions as originators, and data on their quarterly financial statements are available at the Central Bank of Brazil website. In this sense, future research could also make use of such information to expand the analysis of securitization with risk retention and originators' characteristics.

Finally, recent studies demonstrate that the role of risk retention as a signaling mechanism depends on the stage of the business cycle. Using data for European asset-backed securities, Kunl (2019) demonstrates that implicit guarantees play a lesser role in signaling the actual quality of loans in the boom stage of the business cycle. A possible extension of this study could focus on the strength of risk retention as a signlaing mechanism depending on the stage of the

business cycle. Krznar and Matheson (2017) present a range of statistical methods to estimate cycles for the Brazilian economy and can be useful in this regard.

3.5 Descriptive statistics

3.5.1 Brazil: an overview of the receivables funds market and the cost of external financing

The volume of FIDC issues has grown from 2015 to 2020. FIDCs represented 4.784% of the total issues in Brazilian capital markets in 2015 and jumped to 9.100% in 2020. Historically, debentures (fixed income instruments) accounted for more than half of the volume of issues in Brazilian capital markets. In 2020, however, the proportion of such issues decreased to 32.575%. The share of FIDC operations in the Brazilian capital market more than doubled: while in 2015, it represented only 10.420% of operations, in 2020, it inceased to 21.764% (**Figure *25***).

Similar to the pattern in developed markets, ABS issues (FIDC offerings in Brazil) are relatilvely cyclical (**Figure *26***). A higher performance of the Brazilian stock exchange (Ibovespa index) is usually followed by an increase in FIDC offerings. The majority of these offerings had restricted placement efforts pursuant to CVM Instruction 476. Indeed, offerings via ICVM 476 grew steadily since 2016. In 2018, The Brazilian Securities and Exchange Comission (CVM) issued CVM Instruction 601, amending CVM Instructions 400 and 476.

Authors argue that the securitization of receivables allows companies to access cheaper sources of capital (Katz and Blatt (2008)). To see if this is the case for Brazilian firms, we use monthly data and compare the Brazilian benchmark rate (SelicOver) to three sources of external funding: bank financing, issue of bonds in local capital markets and FIDC monthly average cessation rates using hand-collected data for FIDCs with a single originator (**Figure *27***). Using yearly average rates, we observe that from 2013 to 2018, the cost of bank financing exceeds the cost of securitization. In 2020, because of artificial levels of the policy rate in response to the pandemic of the new coronavirus, the opposite occurs. For even years in our sample (except 2020 due to unavailable data), rates (measured at the date of issue) for local bonds are much lower than those for other sources of external funding because these companies can often rely on cheaper sources of funding due to their higher credit ratings.

When we compare the performance of FIDCs with a single originator in our sample with the entire FIDC industry using a 6-month moving average performance, we observe that the funds in our sample tend to exhibit higher spreads over the risk-free interest rate for first-loss tranches, despite the higher volatility (**Figure *28***). While the average monthly Sharpe ratio (the average return earned in excess of the risk-free rate per unit of volatility or total risk) is actually negative for all the tranches, regardless of the sample, it reaches the less negative value for the first-loss tranches of FIDCs with a single originator.

3.5.2 An overview of receivables funds with a single originator

We classified the originators in our sample into 11 categories according to their main sector of activity (**Table *12***). The majority of funds are in the consumer credit, credit cards, financial assets and payroll loans sector (44.705%). Of those, 28 (73.684%) are banks or financial institutions that release public financial statements, and 18 (47.368%) are FIDCs that have fintechs as originators. Those fintechs are (in alphabetic order): *Acqio Adquirência, Bizcapital, Blu Pagamentos, Credz, Fortbrasil, Listo Tecnologia, Mercado Pago, Money Plus* (2 funds), *Nubank, Pagseguro, Sorocred, Stone* (5 funds) and *Tradepay*. An important regulatory milestone for credit fintechs in Brazil was Provisional Measure number 897 of 2019, which consists of legal authorization for an electronic bookkeeping system. In some cases, however, although the origin of the receivables is classified in a specific sector, the originator itself is a financial institution. The identification of each of the funds and its originators is available upon request.

Summary statistics for our main variables of interest are reported in **Table *12***. Funds with originators involved in consumer credit, credit cards, financial assets and payroll loans (mostly financial institutions) exhibit the highest monthly average delinquency ratios (5.929%), followed by those with originators involved in vehicle financing. When comparing individuals with similar characteristics, Di Maggio and Yao (2021) suggest that fintech borrowers are more likely to default than those from traditional financial institutions. Although our data do not allow any type of matching procedure, a test on the equality of means indicates that the monthly average delinquency ratio for receivable funds with financial institution originators is equal to the ratio for receivable funds with fintech originators (0.056, t = -0.0344). Funds with originators involved in cellulose and printing and infrastructure and sanitation exhibit the highest levels of credit enhancement provided by originators (acquisition of first-loss tranches).

Internal mechanisms of credit enhancement in receivable funds include risk retention and excess spreads. Risk retention can be implicit, in the form of subordination or co-obligation (acquisition of first-loss tranches by originators), or explicit, in the form of overcollateralization. Funds in our sample exhibit a small negative linear correlation between the level of subordination and skin in the game (-2.06%) and a small positive correlation between the level of subordination and the overcollateralization ratio (5.26%). Higher levels of risk retention by the originators (*Enhance*) also have a small negative correlation with overcollateralization ratios (-2.13%). Altogether, these findings suggest that although internal credit enhancements are usual and may be seen as best practice for most receivable fund structures in Brazil, their signaling power can be less effective.

Figure *29* demonstrates an upward trend in the proportion of enhancements (skin in the game) by originators until the end of 2016, although FIs exhibited lower proportions. Since 2017, however, the proportion of enhancements exhibited a sharp decrease for funds with both FI and no FI originators. After the beginning of the COVID-19 pandemic, funds with FI originators exhibited even lower levels of skin in the game, reaching less than 5% at the end of 2020. In comparison to originators who are financial institutions, receivable funds with fintech originators exhibited higher levels of skin in the game during 2020, although one can observe

a downward trend for both types of funds (**Figure *30***). While fintechs often rely on securitization because they do not have privileged access to government funding or to customer deposits, banks can use conduits for regulatory arbitrage (especially those that are more capital-constrained) and not to transfer risks to asset-backed commercial paper investors (Acharya, Schnabl and Suarez (2013), Odinet (2020)). In this sense, these levels in our sample suggest that recourse provision in securitization may have different purposes when we compare receivable funds with traditional financial institution originators with those that have fintechs as originators. We will explore this topic in the results session.

In Brazil, practitioners in the receivable funds industry argue that the main purpose of smaller institutions to use FIDCs has not to do with signaling purposes but rather with financing needs (capital release), which is in accordance with the buffer hypothesis. Indeed, Sarkisian and Casu (2013) argue that the strength of the signal depends on the scale/size of originators and recurrence: the signaling benefits of risk retention are stronger for larger originators and for institutions that use in on a revolving basis. Altogether, this suggests that the asset size of originators can have a moderating effect on the relationship between skin in the game and performance and that larger originators would need less to incur less risk retention (or less skin in the game) for their signal to be effective. In our sample, the correlation between the proportion of risk retention by originators (*Enhance*) and the asset size (*Tot_asset_ln*) is 12.96% for non-FI originators and 9.55% for FI originators. **Figure *31*** and **Figure *32*** depict this relationship (asset size is in the y-axis). We highlight some large FIs in the panel and verify that fintechs such as *Nubank, Pagseguro and Stone Payments* have much less skin in the game than the other FIs. The same occurs for large payment institutions such as *Cielo*, actually the largest in asset size for FIs in our sample.

Regarding recurrence, the originators with the largest number of FIDCs in our sample are *CHG Meridian* with 10 funds and Stone Payments with 5 funds, and both are financial institutions. *Stone* is one of the largest fintechs in Brazil, and *CHG Meridian* is a company that executes and finances individual technology infrastructures. Because Sarkisian and Casu (2013) argue that the strength of risk retention as a credible signal also depends on recurrence, we analyze for how long receivable funds exist in the Brazilian market by type of originator. While funds with non-FI originators have an average existence of 41 months, funds with FI originators exist for 40 months, on average. The two funds with the longest existence in our sample (109 months) have a financial institution (*Policard Systems and Services*) and a public fund ("*Fundo de Compensação de variações salariais*") as originators.

Figure *33* depicts the relationship between enhancements and delinquency ratios, our main variables of interest (delinquency ratios in the y-axis). In a quarter of our sample (22 funds), originators acquired more than 50% of the first-loss tranches. In those cases, monthly delinquency ratios are only 2%, on average. Two outliers have delinquency ratios of 9% and 11%, and both have Sabemi as their originator. The fund with the highest level of enhancements and lowest delinquency ratios has *Companhia Pernambucana de Saneamento* as the originator, a Brazilian sanitation company. The fund with the highest average delinquency ratio has *Credsystem* as the originator (33.036%), followed by the one with *Mercado Pago* as its originator (25.690%), one of the largest Brazilian fintechs. For the entire sample, the correlation between the acquisition of first-loss tranches by originators and severe delinquency ratios is

small and negative (-9.440%), which suggests that the understanding of such a relationship is moderated by other factors.

Table *13* emphasizes the relationship between the main variables of internal credit enhancements (for definitions, see **Table *10***). As previously mentioned, *Enhance* is our measure of risk retention by the originator (the amount of first-loss tranches they hold) and, thus, skin in the game. Table 4 demonstrates that while cessation rates have a strong positive correlation with the level of subordination (43.63%), they are negatively correlated with the proportion of skin in the game (-7.640%). This suggests that for funds in which the originator is more committed to the credibility signal via retention of first-loss tranches, cessation rates are slightly lower, which in turn implies that the funds acquire their credit portfolios with lower discounts. In sum, our data suggest that the proportion of skin in the game exhibits lower negative correlations with the main mechanisms of risk retention (subordination, overcollateralization and cessation rates).

3.6 Results

We report our regression results in **Table *14***. In our main regression (Column 1), the point estimate on enhancements (*Enhance*) is positive and statistically significant with a 99% confidence level as well as in our specification that considers only bull markets. This evidence is in accordance with the buffer hypothesis, which suggests that enhancements are a buffer against observable risk and not a signal of unobserved quality (Ashcraft, Vickery, and Goldsmith-Pinkham (2010), Mandel, Morgan, and Wei (2012)). This evidence complies with that of Adrian (2011), who suggests that vertical retention (holding a portion of all tranches) usually provides stronger monitoring incentives than horizontal retention (retention of first loss tranches). When we consider only receivable funds with fintechs as originators (Column 3), however, the estimate on credit enhancements is negative and statistically significant at the 99% level, and its relationship with delinquency ratios is even stronger than what we observe in our main specification (0.0482 vs. -0.0892). This suggests that, for the latter, enhancements do have a signaling effect, and skin in the game (acquisition of first-loss tranches by originators) is indeed a signal against unobservable quality, in accordance with theoretical models of sinalization in securitization (Gorton and Pennachi (1995), Iacobucci and Winter (2005), Uzerturk (2017)). Because fintechs are new entrants and compete directly with incunbent banks in the credit market, co-obligation can be a tool to build reputation. Moreover, Mandel, Morgan and Wei (2012) suggest that, for banks, the signaling component may be at play depending on the riskiness of the securitized assets. Because the loan portfolio of fintechs is riskier than the portfolio of traditional FIs, the signaling effect actually occurs. More precisely, the general estimation indicates that a 100 basis point increase in the level of enhancements is followed by a 4.82% increase in severe delinquency ratios (4.82 basis points). For fintechs, however, estimates indicate that the same increase in enhancements is followed by an 8.92% decrease in delinquency ratios.

The contrasting findings for the use of skin in the game as a buffer or a signal depending on the type of originator are in accordance with several studies suggesting that the innovative and cost-effective approach to lending used by fintechs and their technology differences have significant

impacts on loan pricing strategies (Buchak et al. (2018), Odinet (2018), Tsang (2019), Odinet (2020), Di Maggion and Yao (2021)). This, in turn, can impact the use of skin in the game (or recourse provision) by originators, given the portfolio differences and funding demand between fintech and traditional financial institution originators. First, banks often use conduits for regulatory arbitrage, not necessarily to transfer risks to asset-backed commercial paper investors and rely much more on explicit guarantees (Acharya, Schnabl and Suarez, 2013). Second, the improved underwriting models used by fintechs can capture the risk profile of consumers otherwise overlooked in traditional score models (Odinet (2018), Odinet (2020). Although some fintech lenders focus on the lower end of the credit spectrum (unique challenges, difficulties in assessing complex risk profiles), they have better pricing strategies because the interest rate they charge correlates with the loan default probability (Di Maggio and Yao, 2021). Even though fintech lenders can sometimes focus on low credit score borrowers, they also seem to be better at addressing credit demand: Wang (2020) demonstrates that their portfolios do not exhibit higher credit risk conditional on observable characteristics required by the underwriting process. There is also an important dynamic component at play: as time passes, the quality of their pool of borrowers significantly improves, and they rely more on soft information (Di Maggio and Yao, 2021). Third, while traditional financial institutions rely more on relationship banking, online origination technology allows fintechs to have a convenience-based loan supply or a cream-skimming approach through the use of sophisticated algorithms and big data, and the origination of loans with greater convenience for borrowers allows them to charge an interest rate premium for their services (Buchak et al., 2018). In sum, these findings suggest that fintech originators differ significantly from traditional financial institutions in three dimensions: a) funding supply and regulatory requirements, b) screening technology differences and loan pricing strategies and c) loan supply approach (relationship banking vs. convenience approach).

In all of the specifications, recurrence (*recurrence*) is positive and statistically significant with a 99% confidence level, suggesting that an increase in recurrence is followed by an increase in delinquency ratios that varies from 0.176% to 0.713%. Although its effect is significant, its magnitude is much lower than the estimates on enhancements. A test on the equality of means comparing the average recurrence of funds that have fintechs and financial institutions as originators indicates that the first group is in effect less recurrent (23.130 vs 29.664, $t = 5.963$). However, it is important to mention that the establishment of fintechs in Brazil as a new type of financial institution dates back to 2018, a relatively short period considering that our sample ends in December 2020. In general, these findings suggest that as time passes by, revolving funds may use their good reputation of acquiring assets with lower risk levels to change their portfolio characteristics, which in turn leads to higher delinquency ratios. In this sense, even though signaling components might be at play, they have a dynamic component. Sopranzetti (1999), for instance, argues that the securitization of receivables is more likely to occur for tranches with lower risk and higher credit quality. The estimates on recurrence, however, suggest that this motivation may change. In sum, even though we find no general evidence suggesting that the signaling hypothesis actually prevails, the signaling benefits of recurrence can also be taken into account.

Sarkisyan and Casu (2013) demonstrate that for large-scale securitizers, retained interest increases overall risk. The specifications in which the size of a fund is significant to explain its delinquency ratio are (2) and (3), indicating that those funds exhibit lower average delinquency

ratios, probably due to the quality of the portfolios of the underlying FIs. In sum, when considering funds with FI and fintech originators, large funds tend to exhibit lower delinquency ratios. However, we note that our findings analyze the size of the receivable fund itself and not the asset size of the originator. Indeed, Besanko and Thakor (1987) use a theoretical model to demonstrate that when a bank acts as a price-setting monopolist in the loan market, its credit policy discourages high-risk borrowers from applying for credit (higher loan interest rates). Interestingly, the level of enhancements is not significant in explaining the level of delinquency ratios of such funds. In fact, for funds with FIs as originators, the effect of size, in module, has almost the same magnitude effect of enhancements when we compare it to the general specification (-0.0389 vs. 0.0482).

In accordance with Ashcraft, Vickery, and Goldsmith-Pinkham (2010), we also find that delinquency is positively associated with the amount of subordination when we consider the subsample that only includes funds with fintechs as originators. Contrary to our expectations, market conditions do not seem to have an impact on the estimates because the coefficient on enhancements remains relatively unchanged (0.0482 vs. 0.0498).

3.6.1 Robustness checks

Some studies suggest that a deeper understanding of the relationship between securitization performance and enhancements depends on the reputation of financial institutions in the loan market. Winton and Yerramilli (2021) develop a theoretical model of repeated lending in which loan default history is a noisy measure of past monitoring activity and, thus, a reputation mechanism to incentivize monitoring. The authors suggest that if risk retention is a credible commitment, higher reputation banks monitor more intensively, which implies less risk retention in the future. Conversely, the negative reputation effect of past defaults is offset by more risk retention in the present. In their model, reputation is a sanctioning mechanism, not a learning process about banks' hidden characteristics. The extent to which a bank provides recourse (risk retention) depends on loan demand and on the riskiness of the loan portfolio. One of the empirical implications of their model is that when banks provide some level of recourse, in equilibrium, banks that suffer more default subsequently increase loan retention. During periods of high loan demand, banks can accommodate by increasing loan volume or not. In case they do, this strategy can lead to less monitoring, especially for low-reputation banks. Deku, Kara and Marques-Ibanez (2021) analyze the link between issuer bank reputation and the performance of mortgage-backed securities in the European market and demonstrate that securitization by banks with higher reputations leads to lower delinquency ratios. However, during booms (characterized by declining credit standards), banks tend to offer lower-quality collaterals. Using data on US banks in mortgage securitizations, Scholz (2013) demonstrates that recourse demand is lower for high-reputation banks.

Our main findings indicate that for receivable funds that have financial institutions as originators, enhancements are a buffer against observable risk and not a signal against unobservable quality, in contrast to the idea that recourse provision is a mechanism to alleviate moral hazard concerns. To see if the reputation of a financial institution has any impact on the relationship between the performance of securitized assets and recourse provision, we analyze quarterly data on 17 financial institutions for which public information is available. In other

words, we analyze whether the reputation of a Brazilian financial institution in the loans market is a mechanism to reduce moral hazard in securitization activities. We measure reputation by a dummy (*Reputation*) that equals 1 if, in the previous quarter, there was an increase in the severe delinquency ratio of the financial institutions' loan portfolio in comparison to the previous quarter. In this sense, in each quarter, financial institutions with low reputation will receive a value of 1, and high reputation institutions will receive a value of 0. To do so, we use data on the total loan portfolio that is classified as delinquent (more than 90 days) provided by the COSIF (*Consolidado Contábil do Sistema Financeiro Nacional*) system of the Central Bank of Brazil as a proportion of the total loan portfolio (data available at IFData, another public datasource from the Central Bank of Brazil). We also use a relative measure of reputation (Reputation2): we compare the percentage change in the delinquency ratio of a financial institution to the national quarterly percentage change in the delinquency ratio. If the FI exhibited a higher percentage change in delinquency than the observed national average, we classified it as a low-reputation institution, and *Reputation2* = 1. If reputation in the loans market is indeed a signal of unobserved quality of receivables, we should observe a positive relationship between the performance of securitized assets (*Delinq_fidc*) and *Reputation*, which implies that receivable funds of originators that are financial institutions with lower reputation (*Reputation* =1) would have higher delinquency ratios. For this second analysis, then, our null hypothesis (H_0) assumes that there is a negative relationship between reputation (*Reputation*) and the delinquency ratios of securitized assets (*Delinq_fidc*).

We also measure a bank's response to loan demand with another dummy (*Response*): the Central Bank of Brazil conducts a quarterly credit conditions survey and provides an index that ranges from 2 to -2, indicating increases or decreases in observed loan demand. We use data on loan demand for large and middle-sized companies as well as on private consumption. In case at least two of those three indexes increased in the previous quarter (in comparison to the previous one), a support dummy assumes the value of 1 (otherwise zero). We then compare the response of the financial institutions to such demand: in case the financial institution followed maket demand, *Response* equals 0. In case it had a contrarian movement and i) increased loan supply when there was a lower market demand or ii) decreased loan supply when there was a higher market demand, *Response* equals 1. We analyze the response of financial institutions by calculating the percentage change in the loan portfolio. We also control for the size of a financial institution in natural logarithm (*Ln_assets*), which also functions as a proxy for the riskiness of loans (large institutions have lower risk portfolios).

We use panel data with fixed effects and clustered standard errors by financial institution. Although our main database contains information on 38 receivable funds with financial institutions (FIs) as originators, we could only gather all the data we needed for this second analysis for 17 FIs. Our specification is defined in Equation 16.

$$Delinq_fidc_{i,t} = \beta_0 + \beta_1 Enhance_{i,t-1} + \beta_2 Reputation_{i,t-1} + \beta_3 Response_{i,t-1} + \beta_4 Ln_assets_{i,t} + u_{i,t} \quad (16)$$

Results are reported in **Table 15**. Our findings indicate that receivable funds with financial institutions (FIs) with lower reputations as originators exhibit higher delinquency ratios,

regardless of how these FIs respond to loan demand. The coefficient on reputation is statistically significant at the 99% level of confidence, suggesting that having an originator with lower reputation increases the delinquency ratio of receivables by 1.34%. Although our main findings suggest that recourse provision by a financial institution does not necessarily have a signaling component in securitization activities (see **Table *14***), its reputation in the loans market can be a mechanism to reduce moral hazard, in accordance with Winton and Yerramilli (2021) and Deku, Kara and Marques-Ibanez (2021). Our alternative measure of reputation (*Reputation2*) is also significant at the 90% confidence level (although with a much lower economic significance). **Figure *34*** depicts the average quarterly delinquency rate of receivable funds in comparison to the delinquency rate of receivable funds with financial institutions as originators. In almost the entire sample, the observed delinquency of rates of securitized assets is lower than the delinquency rate of the FIs, indicating that the securitization of receivables is more likely to occur for tranches of lower risk and higher credit quality, given reputation concerns about such transactions (Sopranzetti, 1999). In all of the specifications in **Table 15**, a financial institution's response to loan demand is not significant in explaining the delinquency ratios observed in the receivables it sells in capital markets. In this sense, our findings demonstrate that the extent to which a bank responds with increases or decreases in subsequent risk retention is not associated with previous loan demand. We emphasize that our sample size consists of only 17 FIs, and further investigation on the topic could provide additional insights.

3.7 Concluding remarks

The purpose of this study was to present empirical evidence on the relationship between risk retention by originators and the performance of securitized assets. Our descriptives combine different measures of internal credit enhancements (both implicit and explicit), and our empirical analyses include not only measures of credit enhancements but also for recurrence, using data on receivable funds with different types of originators that are both financial and nonfinancial institutions. Specifically, we analyze the relationship between the acquisition of first-loss tranches by originators – co-obligation, our measure for skin in the game and a type of credit enhancement – and severe delinquency ratios. Our dataset consists of 85 Brazilian receivable funds (FIDCs) with a single originator from January 2013 to December 2020. We combined hand-collected data on risk retention levels by originators and cessation rates with public datasets from the Securities and Exchange Comission of Brasil (CMV) and used panel data with fixed effects and clustered standard errors by fund.

The academic literature suggests two possible hypotheses for the relationship between such variables. The signaling hypothesis suggests that enhancements provided by originators are a signal against the unobservable quality of receivables and, in this case, one should observe a positive relationship between enhancements and performance or, alternatively, a negative relationship between the level of enhancements and delinquency ratios (Gorton and Pennachi (2005), Iacobucci and Winter (2005), Ozerturk (2017), Buchanan (2016), Kuncl (2019)). In contrast, the buffer hypothesis indicates that enhancements are actually a buffer against observable risk. In this sense, one should expect to find a negative relationship between enhancements and performance or, alternatively, a positive relationship between the level of enhancements and delinquency ratios (Besanko and Thakor (1987), Berger and Udell (1990), Ashcraft, Vickery, and Goldsmith-Pinkham (2010), Mandel, Morgan and Wei (2012)).

Our results present evidence in accordance with the buffer hypothesis, which suggests that enhancements are a buffer against observable risk. When we consider funds with financial institutions as originators, we observe that the size of the fund has a much larger role in explaining delinquency ratios than the level of skin in the game by the originator. For funds with fintechs as originators, however, the opposite holds: enhancements do have a signaling effect, and skin in the game is indeed a signal against unobservable quality. We compare our findings to the literature and observe that the use of skin in the game as a signal for fintechs can be attributable to three components: differences in funding supply and regulatory requirements, screening technology differences and loan pricing strategies and, finally, their loan suplly approach (relationship banking vs. convenience approach). Although our findings suggest that recourse provision by financial institutions does not alleviate moral hazard concerns for securitized assets, our robustness checks demonstrate that receivable funds with financial institutions (FIs) with lower reputations in the loan market as originators exhibit higher delinquency ratios, regardless of how these FIs respond to loan demand. This demonstrates that reputation (which is a dynamic component in our specification) can indeed be a signal of unobservable quality. We contribute by demonstrating that the role of credit enhancements can vary depending on the type of originator and its reputation, that recurrence may function as a reputation mechanism and that signals about the quality of receivables exhibit a dynamic nature.

Most of the limitations of the study are related to the opacity of information in the Brazilian securitization market: we could not identify information about the cost structure of each fund, which, from the point of view of practitioners, is useful when analyzing such funds because FIDCs are usually more cost effective than banks due to their tax advantages. Second, we could not gather data on originators' cost of capital or on the average rating of their portfolios because most of these companies do not release such information on a structured public basis. Finally, recent studies (Kuncl, 2019) demonstrate that the relationship between enhancements and the performance of securitized assets varies depending on the stage of the business cycle. A possible extension of this study can analyze whether the buffer hypothesis or the signaling hypothesis holds depending on the stage of the business cycle.

References

Acharya, V., Schnabl, P., Suarez, G. (2013). Securitization without risk transfer. *Journal of Financial Economics*, 107, 3, 515-536. https://doi.org/10.1016/j.jfineco.2012.09.004

Adrian, T. (2011). Dodd-Frank One Year On: Implications for Shadow Banking. Federal Reserve Bank of New York Staff Reports, 533, 1-5. https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr533.pdf

Akerlof, G.A. (1970). The Market for Lemons: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, 84(3), 488-500

Anbima (2015). Produtos Especiais de Captação: Fundos de Investimento em Direitos Creditórios. https://www.anbima.com.br/data/files/89/A0/02/F5/EDB675106582A275862C16A8/FIDC_1_.pdf

Arner, D.W., Avgouleas, E., Busch, D., Schwarcz, S.L. (2019). Systemic Risk in the Financial Sector: Ten Years after the Great Crash. Centre for International Governance Innovation (CIGI).

Ashcraft, A. B., Schuermann, T. (2008). "Understanding the Securitization of Subprime Mortgage Credit." Federal Reserve Bank of New York Staff Reports, 318.

Assis, L.R., Peraçoli, F.A., Frascino, I.S., Zabaglia, R., Dias, R., Figueiredo, P.B. (2020). Structured finance and securitisation in Brazil: overview. Levy & Salomão Advogados – Thomson Reuters Practical Law. Available at https://uk.practicallaw.thomsonreuters.com/2-501-1573?transitionType=Default&contextData=(sc.Default)&firstPage=true

Austin Rating (2017). Metodologia de ratings de securitização. https://www.austin.com.br/Documentos/Metodologia-Securitizacao-de-Recebiveis.html

Benea, I.; Duma, F. (2013). Financing with Receivables: Factoring, Securitization and Collateral. Finance – Challenges of the Future, University of Craiova, Faculty of Economics and Business Administration, 1, 15, 79-86.

Berger, A. N., Udell, G.F. (1990). Collateral, Loan Quality, and Bank Risk. *Journal of Monetary Economics*, 25, 1, 21-42.

Besanko, D., Thakor, A. (1987). Collateral and Rationing: Sorting Equilibria in Monopolistic and Competitive Credit Markets. *International Economic Review*, 28, 3, 671-689. https://doi.org/10.2307/2526573

Buchak, G., Matvos, G., Piskorski, T., Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130, 3, 453-483. https://doi.org/10.1016/j.jfineco.2018.03.011

Buchanan, B. G. (2016). Securitization: A financing vehicle for all seasons? 138, 559-577. *Journal of Business Ethics*, 138, 559-577. DOI: 10.1007/s10551-015-2636-y

Budinger, V. (2012) Analyzing Brazilian ABS: FIDCs. *The Journal of Structured Finance*, 18(1), 100-122. https://doi.org/10.3905/jsf.2012.18.1.100

Catão, G.C., Rodrigues, R.N., Libonati, J.J., Lagioia, U.C.T. (2009). Securitization in the Brazilian Banking Industry: An Empirical Study. *Brazilian Review of Finance*, 7, 3, 327-345. http://dx.doi.org/10.12660/rbfin.v7n3.2009.1309

Comissão de Valores Mobiliários (2014). Retenção de Risco na Securitização: um estudo a partir da metodologia de análise de impacto regulatório. Trabalhos para Discussão. http://www.cvm.gov.br/export/sites/cvm/menu/acesso_informacao/serieshistoricas/estudos/anexos/AIR_retencao-de-riscos.pdf

Connely, B.L., Hoskisson, R.E., Tihanyi, L., Certo, S.T. (2010). Ownership as a Form of Corporate Governance. *Journal of Management Studies*, 47(8), 1561-1589. Available at https://onlinelibrary.wiley.com/doi/10.1111/j.1467-6486.2010.00929.x

Daley, B., Green, B., Vanasco, V. (2019). Securitization, Ratings and Credit Supply. *The Journal of Finance*, 75, 2, 1037-1082. https://doi.org/10.1111/jofi.12866

De Mendonça, H.F., Barcelos, V.I. (2015). Securitization and credit risk: Empirical evidence from an emerging economy. *The North American Journal of Economics and Finance*, 32, C, 12-28. http://doi.org/10.1016/j.najef.2015.01.002

Deku, S.Y., Kara, A., Marques-Ibanez, D. (2021). Bank reputation and securitization quality: European evidence. Finance Research Letters, 1-7. https://doi.org/10.1016/j.frl.2021.102427

Di Maggio, M., Yao, V. (2021). Fintech borrowers: lax-screening or cream-skimming? *The Review of Financial Studies*, 34, 10, 4565-4618. https://doi.org/10.1093/rfs/hhaa142

Gorton, G., Pennacchi, G. (1995). Banks and loan sales: Marketing nonmarketable assets. *Journal of Monetary Economics*, 35, 3, 389–411. https://doi.org/10.1016/0304-3932(95)01199-X

Gorton, G., Souleles, N. (2006). Special purpose vehicles and securitization. In: Carey, M. and Stulz, R. (Eds.), The risks of financial institutions. University of Chicago Press, Chicago, 549–602. https://doi.org/10.3386/w11190

Iacobucci, E.M., Winter, R.A. (2005). Asset Securitization and Asymmetric Information. *The Journal of Legal Studies*, 34, 1, 161-206.

Jobst, A., (2006). Asset securitization as a risk management and funding tool, Emerald, Managerial Finance, Emerald Publishing, 32, 9.

Katz, A., Blatt, J. (2008). Funding through the use of trade receivables securitization. *The Handbook of finance*, ch. 76, 780-788. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.554.7597&rep=rep1&type=pdf

Korgaonkar, S. (2009). Receivables Securitization and the Non-Financial Firm. Wharton Research Scholars Journal. University of Pennsylvania. Available at http://repository.upenn.edu/wharton_research_scholars/65

Krznar, I., Matheson, T. (2017). Financial and Business Cycles in Brazil. IMF Working Paper 17/12. Available at https://www.imf.org/en/Publications/WP/Issues/2017/01/24/Financial-and-Business-Cycles-in-Brazil-44577

Kuncl, M. (2019). Securitization under asymmetric information over the business cycle. European Economic Review, 111, 237-256. https://doi.org/10.1016/j.euroecorev.2018.09.001

Mandel, B.H., Morgan, D., Wei, C. (2012). The Role of Bank Credit Enhancements in Securitization. *Federal Reserve Bank of New York Economic Policy Review*, 35-46. Available at https://www.newyorkfed.org/medialibrary/media/research/epr/12v18n2/1207mand.pdf

Myers, S.C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5, 147-175. https://www2.bc.edu/thomas-chemmanur/phdfincorp/MF891%20papers/Myers%201977.pdf

Odinet, C.K. (2018). Consumer bitcredit and fintech lending. *Alabama Law Review*, 69, 4, 781-858.

Odinet, C. K. (2020). Securitizing Digital Debts. University of Iowa Legal Studies Research Paper. Available at http://ssrn.com/abstract=3583688

Ozerturk, S. (2017). Moral hazard, skin in the game regulation and CRA performance. *International Review of Economics and Finance*, 52, 147-164. https://doi.org/10.1016/j.iref.2017.10.006

Palia, D., Sopranzetti, B.J. (2004). Securitizing Accounts Receivable. *Review of Quantitative Financing and Accounting*, 22, 29-38. DOI: 10.1023/B:REQU.0000006185.39802.83

Peppe, F., Wellichen, E. (2013). Brazilian receivables funds: an evolving investment opportunity. Ernst & Young – Viewpoint. https://www.ey.com/Publication/vwLUAssets/Brazilian_receivables_funds:_an_evolving_inv

estment_opportunity/$File/EY-Brazilian-receivables-funds-an-evolving-investment-opportunity.pdf

Pinheiro, F.A.P., Savoia, J.R.F. (2009) Securitization of Receivables – An Analysis of the Inherent Risks. *Brazilian Review of Finance*. 7, 3, 306-326. http://dx.doi.org/10.12660/rbfin.v7n3.2009.1353

R7. "Cias driblam buscam na securitização opção para financiamento". https://noticias.r7.com/economia/cias-driblam-buscam-na-securitizacao-opcao-para-financiamento-06092015

Roever, W.A., Fabozzi, F.J. (2003). A primer on securitization. *The Journal of Structured Finance*, 9(2), 5-19. https://doi.org/10.3905/jsf.2003.320307

Ross, S. (1973). The Economic Theory of Agency: The Principal's Problem. *The American Economic Review*, 63, 2, 134-139. Available at https://www.jstor.org/stable/1817064

Sarkisyan, A., Casu, B. (2013). Retained Interests in Securitisations and Implications for Bank Solvency. European Central Bank Working Paper Series, no. 1538.

Scholz, M. (2013). Securitization and Credit Risk: Evidence from Retained Interest in Securitized Mortgages. Available at SSRN. http://dx.doi.org/10.2139/ssrn.2294553

Smith, J., Schnuker, C. (1994). An empirical examination of organizational structure: the economics of the factoring decision. *Journal of Corporate Finance*, 1(1), 119-138. https://doi.org/10.1016/0929-1199(94)90012-4

Sopranzetti, B.J. (1998). The Economics of Factoring Accounts Receivable. *Journal of Economics and Business*, 50, 339-359. DOI:10.1016/S0148-6195(98)00008-3

Sopranzetti, B.J. (1999). Selling accounts receivable and the underinvestment problem. *The Quarterly Review of Economics and Finance*, 39, 291-301. https://doi.org/10.1016/S1062-9769(99)00016-2

Spence, A. (1974) Competitive and optimal responses to signals: An analysis of efficiency and distribution. *Journal of Economic Theory*, 7, 3, 296-332.

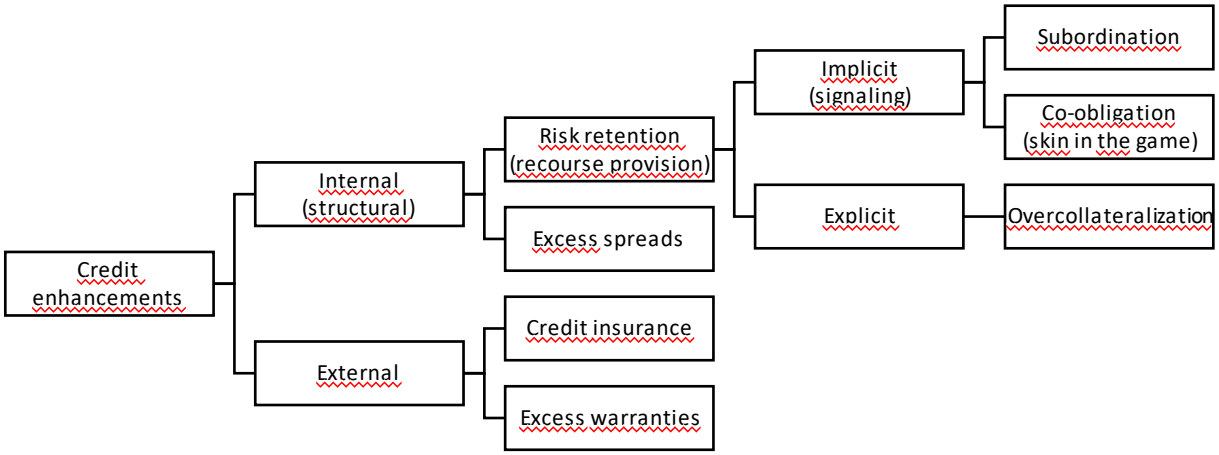
Tsang, J. (2019). The Risk Retention Rule as a Framework for Marketplace Lending Funding Arrangements. *Business & Financial Law Review*, 2, 2, 256-285.

Wang, Y. (2020). FinTech Mortgage Lenders Solving or Exploiting a Friction? Evidence on Risk Layering and Prepayment Risk of Conforming Loans. Master of Science in Management Research Dissertation, Massachusetts Institute of Technology. Available at https://dspace.mit.edu/bitstream/handle/1721.1/126966/1191221609-MIT.pdf?sequence=1&isAllowed=y

Winton, A., Yerramilli, V. (2021). Monitoring in Originate-to-Distribute Lending: Reputation versus Skin in the Game. *The Review of Financial Studies*, 34, 12, 5886-5932. https://doi.org/10.1093/rfs/hhab012

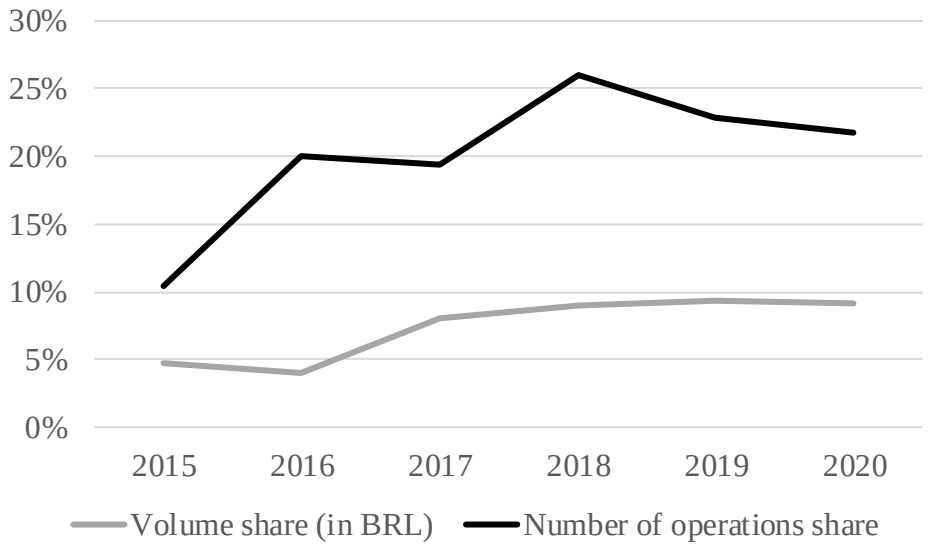
Figures and tables

Figure 24: Credit enhancements in securitization structures



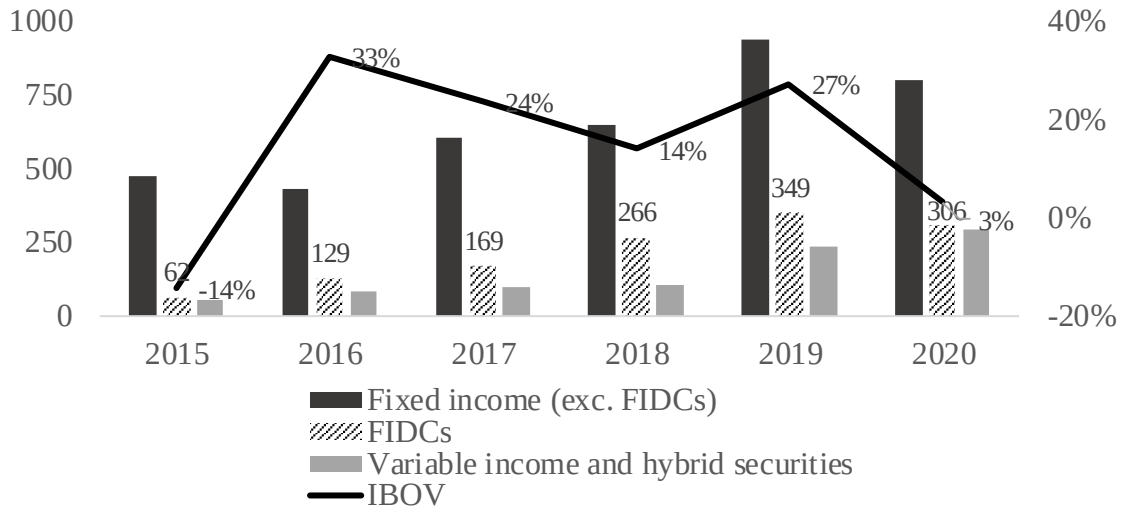
Source: Elaborated by the authors.

Figure 25: The share of FIDCs in Brazilian capital markets



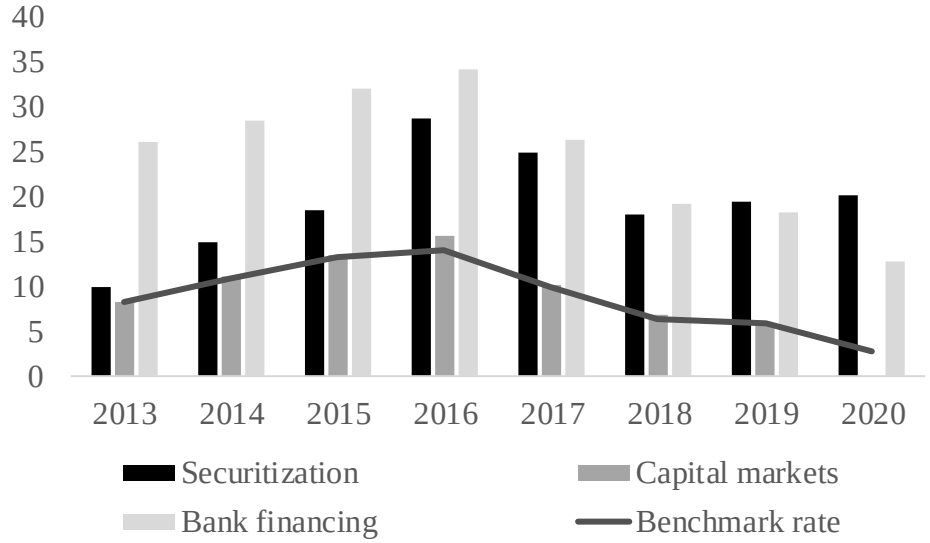
Source: Anbima. Elaborated by authors

Figure 26: Ciclicality in Brazilian Capital Markets: Number of offerings vs. Ibovespa performance*



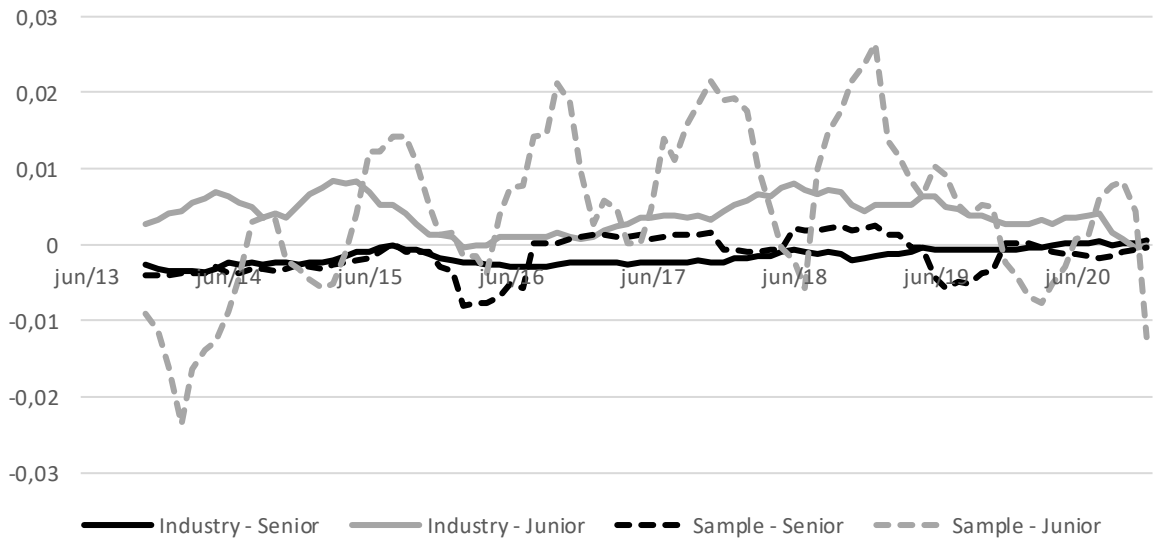
Sources: Anbima and Bloomberg
*End-of-year vs. last twelve months

Figure 27: Sources of external funding for Brazilian firms (nominal rates – % per annum)



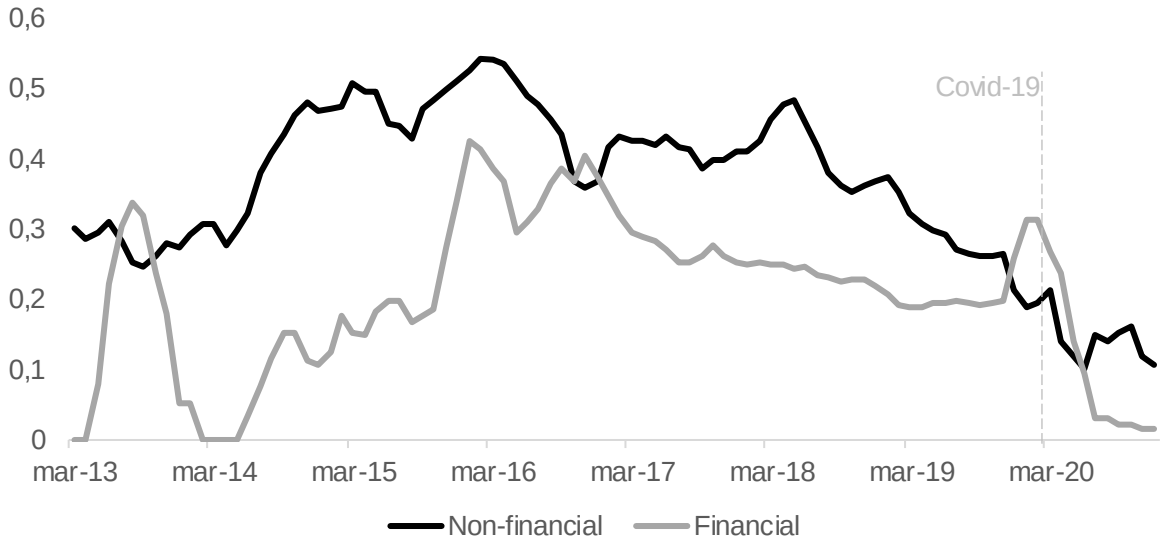
Sources: Central Bank of Brazil, Ipeadata, CVM, B3 and Anbima.

Figure 28: Average monthly spread by tranches (6MMA): industry vs. sample



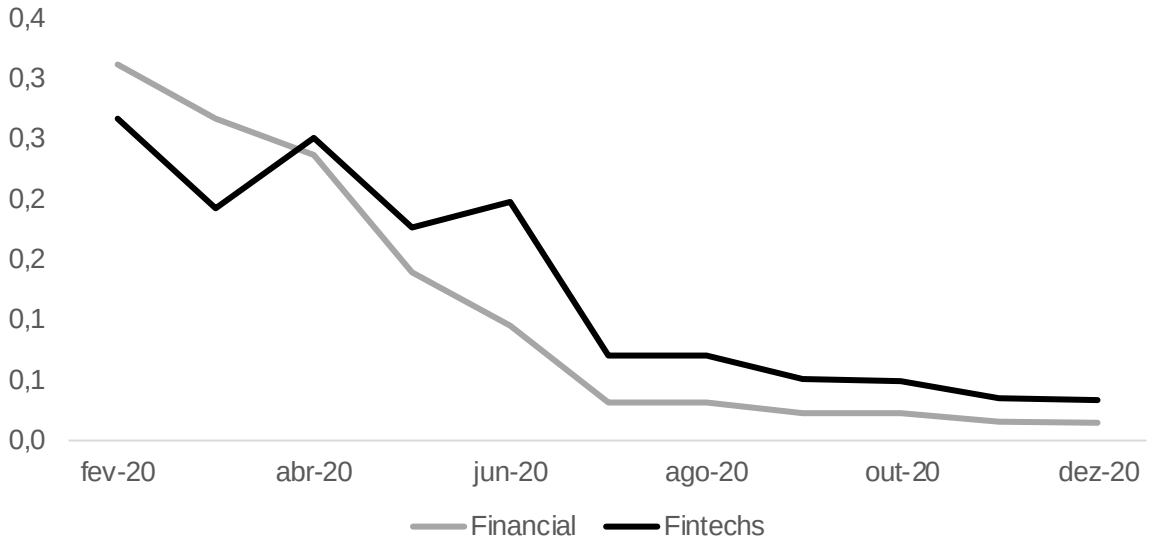
Source: CVM

Figure 29: Enhancements (%) by type of originator (3MMA)



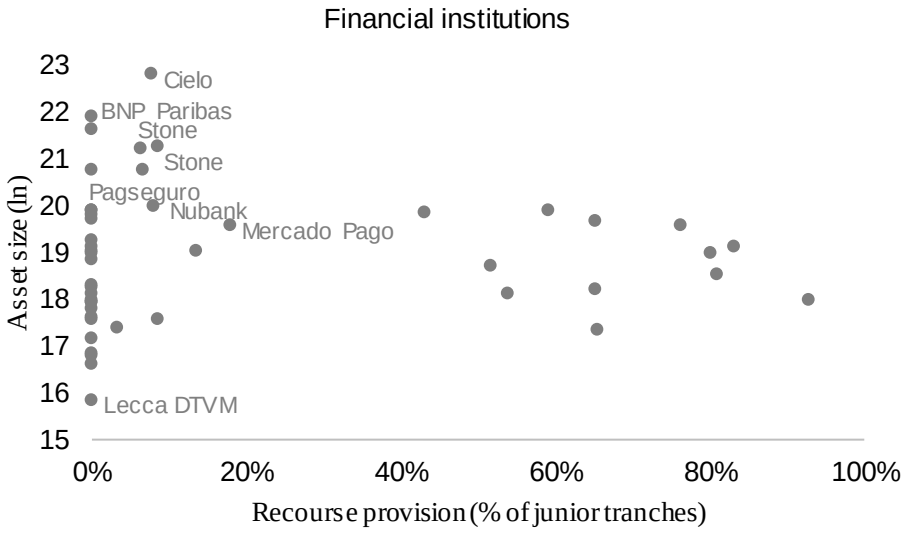
Source: Elaborated by the authors

Figure 30: Enhancements (%) by type of originator: financial institutions vs. fintechs (3MMA)



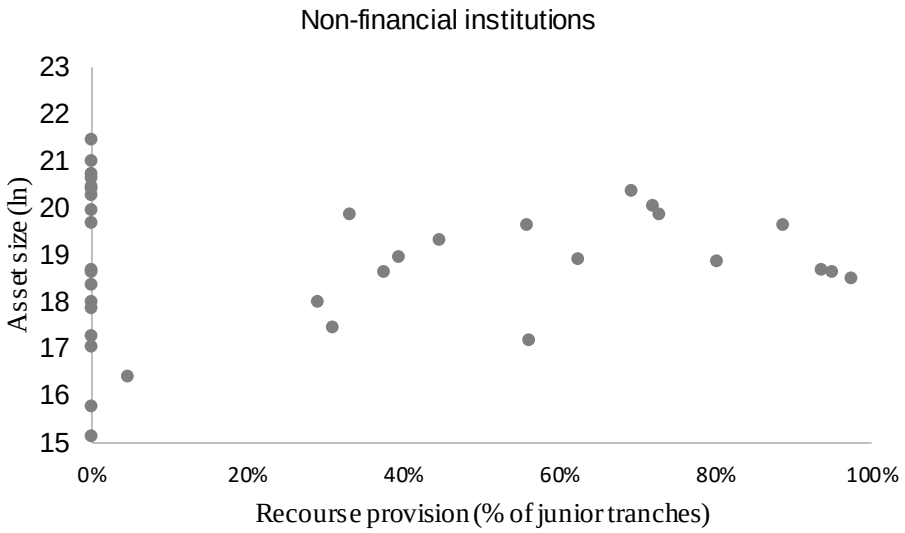
Source: Elaborated by the authors

Figure 31: Skin in the game and asset size by type of originator (financial institutions)



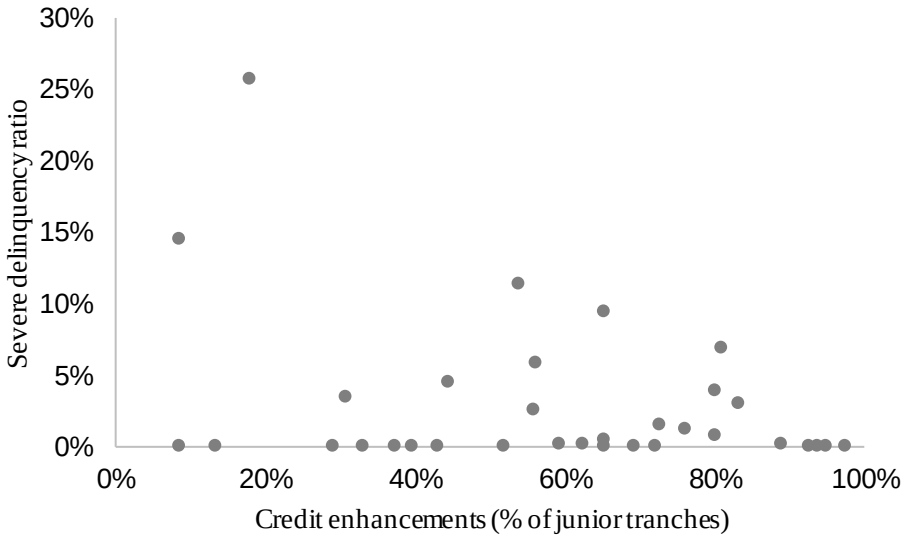
Source: Elaborated by the authors

Figure 32: Skin in the game and asset size by type of originator (non-financial institutions)



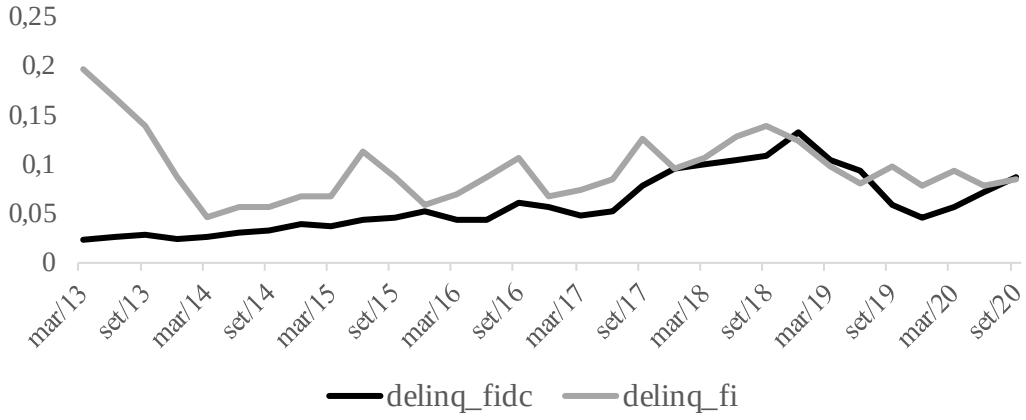
Source: Elaborated by authors

Figure 33: Credit enhancements and severe delinquency ratios



Source: Elaborated by authors

Figure 34: Delinquency rate: Securitized assets vs. financial institutions



Source: Elaborated by authors

Table 10: Internal credit enhancements: variables and references

Credit enhancements	Mechanisms	Forms of guarantees	Measure	Variable	Type	References
Internal	Risk retention	Implicit	Subordination	*Subord_nw*	% (value)	Anbima (2015), Ashcraft, Vickery, and Goldsmith-Pinkham (2010)
			Co-obligation	*Risk_ret_nw*	% (value)	Gorton and Pennachi (1995), Gorton and Souleles (2006), Mandel, Morgan and Wei (2012), CVM (2014), Anbima (2015)
				Skin	Categorical	
				Enhance	% (value)	
		Explicit	Overcollateralization	*Overcoll*	Categorical	Anbima (2015), Austin Rating (2017), Kuncl (2019)
				Overcoll_ratio	% (value)	
	Excess spreads		Cessation rates	*Cess_rate*	% (value)	Anbima (2015)

Source: Elaborated by authors

Table 11: Controls

Control	Definition	Variable	References
Asset size	Total asset size of FIDCs in natural logarithm	*Tot_asset_ln*	Sopranzetti (1998), Palia and Sopranzetti (2004), Mandel, Morgan and Wei (2012), Sarkisyan and Casu (2013)
Leverage	Common equity/total assets	*Leverage*	Mandel, Morgan and Wei (2012)
Recurrence	Number of months the fund is active	*Recurr*	Sarkisyan and Casu (2013)
Subordination level	The sum of the total value of first-loss tranches as a proportion of net worth.	*Subord_nw*	Ashcraft, Vickery, and Goldsmith-Pinkham (2010)
Rating	Prime funds are rated AAA, AA+ or AA- and subprime funds are the ones with a rating equal or less to A+ (standards converted using Fitch ratings local scale).	*Prime*	Ashcraft, Vickery, and Goldsmith-Pinkham (2010), Ozerturk (2017), Daley, Green and Vanasco (2019),

Source: Elaborated by authors

Table 12: Summary statistics

Receivables funds by sector of originator	# FIDCs	Severe delinquency ratio			Credit enhancements (ratio)		
		Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Paper, pulp and printing	1	32	5.898%	8.038%	32	56.075%	19.147%
Consumer credit, credit cards, financial assets and payroll loans	38	1439	5.929%	9.844%	1439	24.126%	41.335%
Energy	5	174	0.625%	9.301%	174	32.440%	44.434%
Entertainment	1	23	0.000%	0.000%	23	4.515%	21.177%
Food and agriculture	10	369	0.333%	8.621%	369	38.962%	38.686%
Infrastructure and sanitation	8	399	0.372%	8.302%	399	53.491%	39.167%
Petrochemical, chemicals and pharmaceuticals	6	295	1.129%	9.545%	295	29.301%	41.533%
Real estate	2	155	0.000%	8.416%	155	0.000%	43.522%
Retail	6	194	4.560%	9.781%	194	5.346%	41.942%
Vehicle financing	7	366	5.707%	9.571%	366	19.167%	42.206%

Source: Elaborated by authors.

*The sample also includes a fund with an originator from the mobile services sector. Due to the lack of data on enhancements and delinquency ratios, its statistics are not reported in this table.

Table 13: Correlation matrix: Internal credit enhancements

	Enhance	Subord_nw	Overcoll_ratio	Cess_rate
Enhance	1			
Subord_nw	-0.0451	1		
Overcoll_ratio	-0.0047	-0.1589	1	
Cess_rate	-0.0764	0.4363	0.0055	1

Source: Elaborated by authors

Table 14: Regression results

Dependent variable: *Severe_delinq*	(1) Whole sample	(2) Financial institutions	(3) Fintechs	(4) Bull Markets	(5) Existence of Risk retention
Enhance	0.0482***	0.0288	-0.0892*	0.0498***	
	(0.0154)	(0.0281)	(0.0466)	(0.0144)	
*Enhance*Prime*	-0.00479	-0.00612		-0.00731	
	(0.0126)	(0.0315)		(0.0141)	
Tot_asset_ln	-0.0285	-0.0389*	-0.0527*	-0.0343	-0.0128
	(0.0216)	(0.0211)	(0.0274)	(0.0254)	(0.0187)
Leverage	-0.00814	-0.0230***	0.0574	-0.0199**	-0.00155
	(0.00775)	(0.00348)	(0.0800)	(0.00804)	(0.00491)
Subord_nw	-2.13e-08	1.18e-09	3.57e-06***	-3.01e-08	-2.75e-08
	(1.73e-08)	(1.24e-08)	(8.30e-07)	(2.06e-08)	(2.94e-08)
Recurr	0.00176***	0.00310***	0.00713***	0.00176***	0.00202***
	(0.000478)	(0.000602)	(0.00208)	(0.000508)	(0.000525)
Skin					0.0194
					(0.0155)
Constant	0.516	0.706*	0.855*	0.634	0.211
	(0.407)	(0.387)	(0.447)	(0.477)	(0.354)
Observations	2,079	1,171	469	1,216	2,754
R-squared	0.220	0.403	0.471	0.239	0.188
Number of fund	68	39	18	66	82

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Robustness checks

Dependent variable: *Delinq_fidc*	(1) General	(2) General_2
Enhance_lag	0.00575	0.00837
	(0.0197)	(0.0200)
Reputation	0.0134***	
	(0.00450)	
Reputation2		0.00842*
		(0.00477)
Response	0.00601	0.00721
	(0.00622)	(0.00504)
Ln_assets	0.0773**	0.0779**
	(0.0296)	(0.0298)
Constant	-1.447**	-1.466**
	(0.579)	(0.586)
Observations	155	152
R-squared	0.367	0.372
Number of financial institutions	16	16

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.