On-Lending and Interest Rate Risk in Brazilian Banks

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Abstract

On-lending (OL) operations—a form of government earmarked credit—have been widely debated in the literature, particularly in Brazil, where their quantitative relevance is substantial. This paper examines the effect of OL on a previously unexplored dimension: banks' exposure to interest rate risk (IRR). Using a System-GMM model and a panel of 104 Brazilian bank holding companies (BHCs) from 2012 to 2021, we find that BHCs with greater reliance on OL exhibit significantly lower IRR exposure. Given the systemic nature of IRR, these findings have important implications for its allocation within the Brazilian financial system. We also test whether a higher share of OL affects bank profitability and find no statistically significant relationship. Overall, the evidence suggests that OL reduces banks' IRR exposure without adversely affecting profitability. Results are robust across alternative specifications.

Keywords: Brazilian banking economy, Interest rate risk, On-lending credit.

JEL codes: G21; E43; G32; G28.

1 Introduction

Financial crises, particularly banking crises, have historically led to significant economic downturns (Claessens et al., 2018; Hoffmann et al., 2019). The severity of such crises is evident from past events, including the Savings and Loan Crisis of the 1980s and the Global Financial Crisis (GFC) of 2008. More recently, in early 2023, the collapse of several U.S. financial institutions, such as Silicon Valley Bank, First Republic Bank, and Signature Bank, led to what became known as the U.S. 2023 Regional Banking Crisis. Interest rate risk (IRR) eposure was a determining factor in these events. The mere mention of these crises underscores the importance of research in banks IRR exposure. However, despite the profound effects of banking crises, several aspects remain underexplored in the literature, particularly concerning IRR (Kirti, 2020).

According to Freixas and Rochet (2008), IRR is the risk that fluctuations in interest rates impact the banks' cash flows. Consider a bank with loan operations as assets, pre-fixed at 6% per annum. Suppose this bank funds these assets with post-fixed funding at Secured Overnight Financing Rate (SOFR) + 1%

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per annum. If SOFR is at 3% per annum, the institution earns a 2% per annum spread. Now, consider an increase in SOFR by 100 basis points, from 3% to 4%. In this scenario, the institution's funding cost also rises by 100 basis points, while its asset yield remains unchanged due to its pre-fixed nature. Consequently, the spread decreases to 1% per annum. Conversely, a reduction in SOFR lowers funding costs, increasing the spread. A bank that is immune to IRR is one whose cash flows remain unaffected by fluctuations in interest rates.

This empirical essay aims to investigate the determinants of IRR exposure among Brazilian bank holding companies (BHCs). Specifically, we investigate whether the use of on-lending (a type of earmarked credit), which accounts for a significant share of the total credit stock in Brazil, affects banks' IRR exposure. IRR exposure is typically linked to a fundamental characteristic of the banking sector: maturity mismatch, i.e., the difference between the maturity of assets and liabilities. This concept has shaped the empirical literature on IRR, encapsulated in the phrase "banks borrow short and lend long" (Flannery, 1981; Flannery and James, 1984; Purnanandam, 2007; Esposito et al., 2015).

From a theoretical standpoint, a seminal contribution to this topic was made by Diamond and Dybvig (1983), whose model became known as modern banking theory. By examining bank run equilibria and potential preventive measures, Diamond and Dybvig (1983) established maturity transformation as the core of banking activity. Subsequent contributions by Hellwig (1994), in contrast to Diamond and Dybvig (1983), directly address IRR in banking. The primary implication of Hellwig (1994) is that IRR is a systemic risk and, therefore, cannot be diversified away at the aggregate level. This implies that some economic agents must bear this risk, and their exposure is determined by contractual agreements.

The Brazilian government's earmarked credit is structurally significant, accounting for approximately 42% of total bank credit in 2025 and about 23% of GDP. This credit is implemented through two main channels: (i) direct and (ii) indirect (BNDES, 2023). In the direct channel, government entities, typically publicly controlled banks or the Brazilian National Development Bank (BNDES), lend directly to the real sector. Conversely, the indirect channel employs financial intermediaries (usually other banks) to manage and distribute credit. This approach leverages the extensive banking network, increasing credit access for deficit agents in need of funds. Under this model, state-owned entities (BNDES, for instance) lend to intermediary banks, which then pass the funds on to final borrowers. This category includes the type of credit that is the focus of our research, the so called the on-lending (OL) operations.

A crucial feature of OL operations is that transactions at all stages of the chain are executed under identical conditions[1]. Specifically, the agreement between the resource provider and the intermediary bank mirrors the terms of the transaction between the intermediary and the final borrower, including maturity, amortization schedule, installments, and indexation. Given this structure, these transactions naturally hedge intermediary banks against both interest rate risk and liquidity risk. Their assets (loans to final borrowers) match their liabilities (funding from official institutions) in terms of financial conditions. Our central hy-

[1] https://www.bndes.gov.br/wps/portal/site/home/financiamento/guia/taxa-de-juros

pothesis in this essay is that the presence of this type of credit in a bank's portfolio reduces its exposure to IRR.

To achieve the proposed objectives, we first estimate the exposure of Brazilian banks to IRR through the net interest margin (NIM) beta. At the aggregate level, the Brazilian banking system exhibits limited exposure to IRR. When we relate IRR exposure to the use of OL operations, the results are consistent with our central hypothesis: banks that rely more heavily on these operations display lower exposure to IRR. We also examine whether bank profitability may be associated with the use of such operations. In this regard, our findings indicate no statistically significant relationship between the use of OL operations and bank profitability. Taken together, our results suggest that OL operations may reduce banks' exposure to IRR without generating adverse effects on profitability.

We believe this paper contributes to the existing literature in at least two important respects. First, the determinants of banks' exposure to interest rate risk (IRR) in emerging market economies remain an under-explored area. Most prior studies have focused on advanced economies, particularly the United States and European countries. Second, to the best of our knowledge, no study has directly examined how government interventions in credit markets affect banks' exposure to IRR. The existing literature on such interventions has primarily concentrated on their effects on economic growth, the efficiency of credit allocation, and their indirect implications for monetary policy (Bonomo et al., 2015; Silva et al., 2021). Our analysis advances a distinct perspective by investigating how a type of earmarked credit influences the allocation of IRR within the economy and, consequently, banks' IRR exposure.

The findings may offer relevant insights for policymakers involved in the design and implementation of on-lending operations, as well as for financial regulators assessing the exposure of Brazilian banks to IRR. This paper is structured as follows. Section 2 synthesizes the literature on the topic and presents the key hypothesis. Section 3 presents the method. The Section 4 presents the results, and Section 5 concludes the paper.

2 Related Literature

2.1 Interest rate risk: theoretical foundations

Interest rate risk (IRR) refers to the risk that fluctuations in interest rates affect banks' cash flows (Freixas and Rochet, 2008). Because banks operate by entering into a variety of contracts on both the asset and liability sides of their balance sheets, often with different maturities and pricing dynamics, movements in interest rates may influence the cash flows generated by these institutions and, consequently, their economic valuation.

The theoretical foundations of IRR in banking are embedded in a broader literature that studies financial intermediation, maturity transformation, and bank runs (liquidity risk). A central reference is the seminal model of Diamond and Dybvig (1983), which, together with other influential contributions, forms part of what is commonly referred to as modern banking theory (Drechsler et al., 2021). The Diamond-Dybvig framework focuses on the risk of bank runs and analyzes how banks transform illiquid long-term assets into liquid deposits. In its original formulation, however, interest rates are assumed to be deterministic variables. As a result, banks may exhibit maturity transformation—that is, a difference between the maturity of assets and liabilities—without necessarily being exposed to IRR.

Subsequently, Hellwig (1994) introduced an important theoretical development by incorporating uncertainty about future interest rates into the classical Diamond-Dybvig framework. This extension helped clarify several key aspects of IRR. In this setting, IRR does not arise directly from maturity transformation itself but rather from uncertainty in the intertemporal structure of returns in the real economy. Consequently, IRR can be interpreted as a systemic and non-diversifiable risk at the aggregate level. This implies that some agent in the economy must ultimately bear this risk. Banks, as financial intermediaries, may either absorb or transmit such risk depending on the contractual characteristics of their assets and liabilities, such as whether contracts are indexed to floating or fixed interest rates Hellwig (1994).

Over time, a significant portion of the literature has emphasized maturity mismatch as the main source of banks' exposure to IRR. In this view, banks that "borrow short and lend long" are more vulnerable to fluctuations in interest rates (Flannery, 1981; Flannery and James, 1984). The canonical case of the Savings and Loan (S&L) crisis in the United States during the 1980s reinforced this perspective. During that period, S&L institutions extended long-term fixed-rate loans while funding themselves through short-term liabilities with floating interest rates. When U.S. interest rates increased sharply, these institutions experienced severe disruptions in their cash flows, as interest expenses rose above interest income.

More recent contributions, however, place greater emphasis on the contractual characteristics of bank assets and liabilities rather than solely on their maturities as proxies for measuring IRR. This is the approach adopted by Drechsler et al. (2021). The authors develop a theoretical framework based on the concept of the deposit franchise, whereby banks acquire market power in retail deposit markets. This market power allows banks to pay deposit rates that are persistently below prevailing market rates. As a consequence, deposit funding becomes relatively insensitive to fluctuations in interest rates. In such an environment, a bank seeking to immunize its cash flows against interest rate movements may engage in long-term lending at fixed rates. Under this structure, both assets (fixed-rate loans) and liabilities (deposit funding) become relatively insensitive to interest rate fluctuations, thereby protecting the bank's cash flows. Importantly, such a bank may exhibit a substantial maturity mismatch, yet without significant exposure to IRR. Their empirical findings confirm this hypothesis. Banks exhibit an average maturity of approximately 3.6 years on the asset side and 0.4 years on the liability side of their balance sheets. This implies a maturity mismatch of roughly 3.2 years. Despite this substantial maturity mismatch, however, banks' cash flows appear to be largely invariant to fluctuations in interest rates (Drechsler et al., 2021).

This paper follows a similar line of reasoning to that of Drechsler et al. (2021). Due to the contractual structure of on-lending operations, in which both asset contracts (on-lending credit operations) and liability contracts (obligations with official financial institutions) are established under similar terms—such as indexation, maturity, and amortization structure—banks that engage more intensively in these operations may better protect their cash flows from interest rate fluctuations. A more detailed discussion of the theoretical foundations of bank interest rate risk, including the formal structure based on the models of Diamond and Dybvig (1983) and Hellwig (1994), is presented in Appendix A.

2.2 Empirical evidence on interest rate risk

The empirical literature on IRR in banking institutions, particularly in North America and Europe, is extensive. It can be categorized into four groups: (i) the determinants of interest rate risk exposure; (ii) the effect of interest rate fluctuations on stock prices, margins and profitability; (iii) the relationship between the interest rate environment and banking activity; and (iv) how banking institutions manage their exposure to IRR. The present essay primarily belongs to the first and fourth category, examining the determinantes of IRR exposure, and how institutions manage their exposure.

Regarding topic (i) the determinants of interest rate risk exposure, on the determinants of banks' exposure to interest rate risk (IRR), the empirical literature has advanced by employing both direct and indirect measures of exposure, with growing emphasis on asset-liability mismatch sensitivity and the behavior of net interest margins (NIM). Flannery (1981) provides an early conceptual framework, arguing that IRR arises primarily from mismatches in the maturity and repricing of assets and liabilities. Alessandri and Nelson (2015) demonstrate that capital adequacy and liquidity buffers mitigate the transmission of IRR to bank profitability, supporting the hypothesis that well-capitalized banks actively manage their exposure. English et al. (2018) use panel data on U.S. banks to show that larger institutions and those with more stable core deposits exhibit lower IRR, as proxied by the sensitivity of NIM to interest rate changes.

In a more recent contribution, Drechsler et al. (2021) challenge the traditional link between maturity mismatch and IRR by showing that banks engaging in maturity transformation through deposit funding are not necessarily exposed to interest rate risk. In fact, their findings suggest that banks with high maturity mismatch can remain largely immune to IRR if they rely on deposit funding, effectively decoupling maturity transformation from interest rate sensitivity. A recent strand of the literature has operationalized IRR through a two-stage estimation strategy: in the first stage, a net interest margin (NIM, the difference between interest income and interest expenses) beta is constructed by regressing bank-level NIMs on changes in short- and long-term interest rates, while in the second stage, bank characteristics are used to explain cross-sectional variation in this exposure (e.g., English et al., 2018; Drechsler et al., 2021). This empirical design allows researchers to isolate the structural determinants of interest rate sensitivity beyond pure accounting volatility, offering robust insight into how bank size, funding structure, and asset composition shape interest rate risk exposure.

Some studies argue that banks do not experience significant impacts on profitability following interest rate movements, suggesting effective IRR management (Flannery, 1981; English, 2002). However, Alessandri and Nelson (2015); Borio and Gambacorta (2017); Gomez et al. (2021) provide evidence that interest rate hikes tend to increase bank profitability, at least in the short run. Regarding (ii) the effect of interest rate fluctuations on bank stock prices, previous findings suggest that interest rate changes are negatively related to the stock prices of banking institutions (Lynge and Zumwalt, 1980; Booth and Officer, 1985; Aharony et al., 1986; Mitchell, 1989; Bae, 1990; Kwan, 1991; Akella and Greenbaum, 1992). This relationship is associated with banks characterized by greater maturity mismatch (maturity gap), low capital adequacy ratios, higher reliance on core deposits, significant lending to households, and greater use of subordinated debt (Flannery and James, 1984; English et al., 2018; Foos et al., 2022).

In category (iii), investigating the effects of different interest rate environments, the literature has explored how banking activity responds to prolonged periods of extremely low interest rates (the so-called "low for too long" environment). The findings suggest a "quest for yield," where banks, facing increased pressure on spreads due to low interest rates, assume greater risk exposure in search of higher returns (Borio and Gambacorta, 2017; Chaudron, 2018; Claessens et al., 2018; Brei et al., 2020). This behavior, in turn, could make them highly sensitive to subsequent interest rate shocks, such as a rapid interest rate hike (Molyneux et al., 2022).

2.3 Interest rate risk management

Theoretical perspectives on hedging against risk offer insights into how companies should position themselves. Based on non-financial firms, Smith and Stulz (1985) show that hedging activities can enhance shareholder value by reducing bankruptcy costs. Froot et al. (1993), considering bankruptcy costs as endogenous, argue that firms engage in hedging to avoid the costs of external financing in states of the world with low internal funding availability. In a seminal paper, Diamond (1984) argues that banks should fully hedge their risk exposures, as such hedging improves their ability to function as intermediaries and potentially take on more credit risk.

Some early empirical evidence, such as Gorton and Rosen (1995), suggests that banking institutions use derivatives primarily to reduce their IRR exposure. Conversely, studies like Hirtle (1997) argue that banks use these instruments to increase their IRR exposure and, consequently, enhance their profitability. Sinkey and Carter (2000) find evidence that banks utilizing derivatives tend to be larger, have riskier capital structures, lower net interest margins, and greater maturity mismatch between assets and liabilities.

In a seminal work on IRR management, Purnanandam (2007) investigates how U.S. banks manage their exposure to IRR based on their characteristics and macroeconomic shocks. Specifically, the study seeks to answer two questions: (i) what motivates banks to engage in immunization activities?; and (ii) does immunization support banks' intermediation activities? The autor finds that large banks predominantly use derivatives for immunization, whereas smaller banks rely on their asset and liability structures for the same purpose. Banks facing higher distress probabilities engage in greater immunization activity, consistent with the theoretical implications of Diamond (1984) and Smith and Stulz (1985). This behavior is also observed among high-growth banks with lower levels of liquid assets.

Furthermore, regarding the second question — whether immunization affects financial intermediation — Purnanandam (2007) examines immunization in conjunction with monetary policy shocks. The findings suggest that during contractionary monetary policy periods, banks tend to reduce their exposure. In particular, banks using derivatives remain relatively unaffected in terms of credit supply following monetary policy shocks, aligning with Froot et al. (1993).

Au Yong et al. (2009), analyzing a sample of Asia-Pacific banks from 1999-2003, investigate the motivations of interest rate derivative usage. Their results indicate that the use of interest rate derivatives is positively associated with long-term IRR exposure and negatively related to short-term IRR exposure. In other words, derivatives usage appears to aim at reducing short-term exposure at the expense of long-term exposure.

Esposito et al. (2015) analyze how Italian banks managed their IRR exposure during 2008-2012. Their findings indicate that these institutions maintained limited exposure, below regulatory thresholds, and that their immunization strategies—whether through balance sheet techniques or derivatives—were not primarily intended to increase profitability. The authors also suggest that Italian banks were unlikely to face significant difficulties in the event of a rise in monetary policy rates following the period of extremely low interest rates.

Examining the exposure of U.S. listed banks between 1995-2012, Entrop et al. (2017) find that, on average, banks exhibit low exposure to IRR, though the distribution of IRR exposure (IRR beta) is characterized by fat tails. Their findings indicate that leverage and size are positively correlated with IRR exposure. Bazih and Vanwalleghem (2021), analyzing banks from emerging markets, find evidence that derivative usage is primarily motivated by lower net interest margins, lower banking concentration, and higher institutional quality.

2.4 The Brazilian case and hypothesis development

This research focuses on banks operating in the Brazilian economy. The Brazilian case is particularly relevant for several reasons. First, the Brazilian economy is classified as a bank-oriented economy (Silva et al., 2021), where the banking sector is the primary source of financing for firms and households. Figure 1 presents stock market capitalization across various economies. Thus, the main alternative to bank credit, the capital market, remains relatively underdeveloped in Brazil, leading surplus and deficit agents to primarily utilize the credit market. Consequently, understanding how Brazilian banking institutions manage their exposure to interest rate risk, as well as their financial soundness, is particularly important.

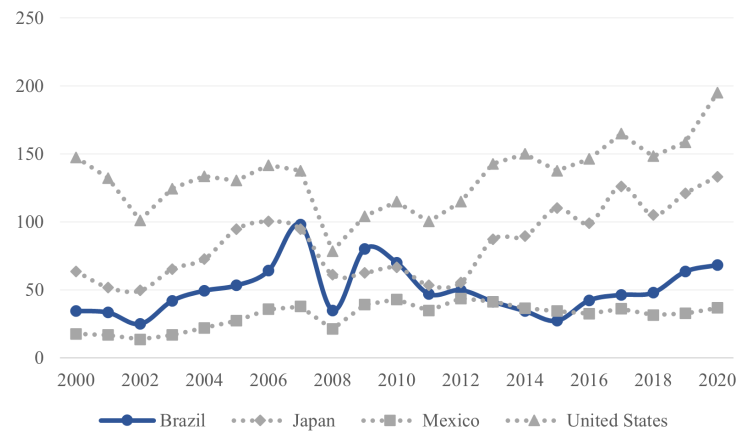

Figure 1: Stock market capitalization (% of GDP). Source: World Bank.

Second, the Brazilian banking sector is highly concentrated. Figure 2 compares the concentration of the Brazilian credit market with other economies. The Brazilian banking market has undergone a series of reforms aimed at increasing competitiveness and reducing historically high banking spreads (Azevedo et al., 2019; Garcia and Meurer, 2022). This increase in competition encourages institutions to manage their resources efficiently and seek alternative ways to enhance profitability (Molyneux et al., 2022). Third, the empirical literature on IRR has focused primarily on developed markets such as the USA and European countries. For emerging economies like Brazil, where banking institutions play a crucial role, empirical evidence remains scarce (Bazih and Vanwalleghem, 2021).

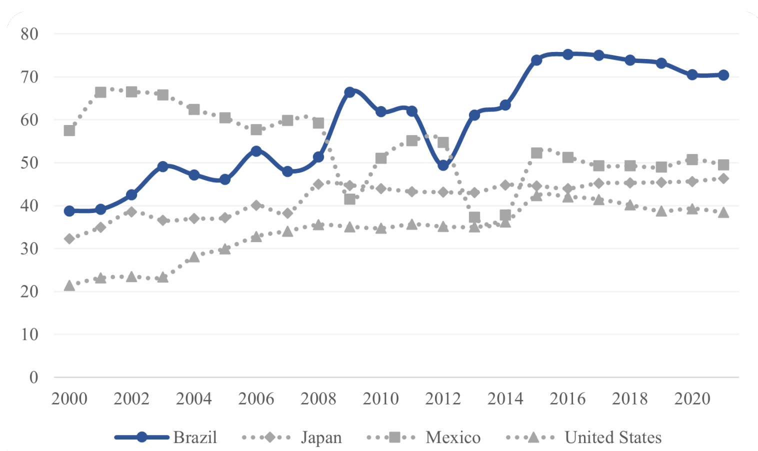

Figure 2: Bank concentration ratio (assets of five largest commercial banks as a share of total commercial banking assets). Source: World Bank.

Fourth, and no less important, the Brazilian credit market has historically been marked by government interventions. Figure 3 illustrates the ratio of credit allocated to government and state-owned enterprises as a percentage of GDP. Brazil stands out as a country with significant state intervention in the credit market. The empirical literature has explored evidence on the potential adverse effects of these interventions, such as reduced access to financing for private firms, lower economic and financial growth, and decreased productivity (La Porta et al., 2002; Becker and Ivashina, 2014).

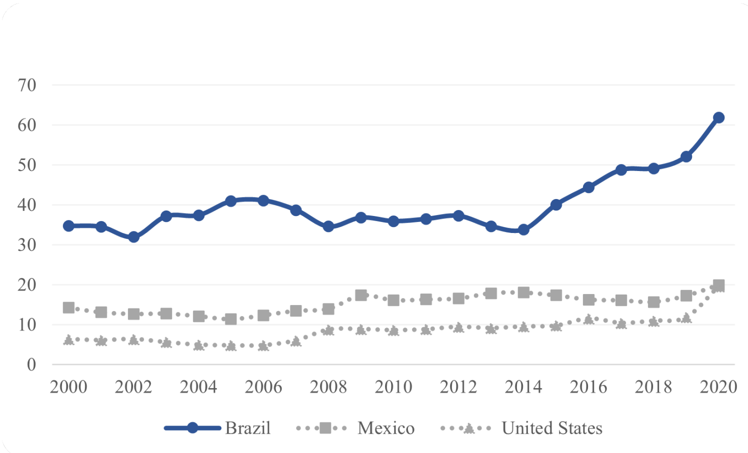

Figure 3: Credit to government and state-owned enterprises (% of GDP).
Source: World Bank.

One of the ways governments intervene in the credit market is through so-called earmarked credit. This is credit provided by the government, usually for a specific purpose and at subsidized rates. This topic has been the focus of various studies in the literature. For example, Guan and Yam (2015), in examining the effect of the Chinese government's earmarked credit policies on firm innovation, found evidence that earmarked credit not only failed to foster innovation but sometimes had negative effects. The authors suggest that the Chinese government should consider market forces in its reforms. Madeira et al. (2018) study the effects of earmarked credit on the Brazilian economy. Their findings indicate that earmarked credit is associated with lower total factor productivity, greater income inequality, reduced demand for bank capital, higher banking spreads, and smaller non-financial companies.

Unlike previous studies that analyzed the effects of earmarked credit on other factors, this research aims to investigate the potential influence of on-lending operations (a type of earmarked credit) on the IRR exposure of Brazilian banking holding companies (BHCs). Figure 4 shows the ratio of earmarked credit to GDP and non-earmarked credit (all other types of credit) to GDP. The literature has documented the significant increase in the share of earmarked credit following the Global Financial Crisis of 2008, which continued until Brazil's deep recession in 2015 and 2016. During this period, the Brazilian Development Bank (BNDES) substantially expanded, funded by the National Treasury, as part of a government credit policy. Even after this period, earmarked credit remains significant, representing approximately 24% of GDP (Renato et al., 2021; Grimaldi et al., 2024).

The earmarked credit is distributed by official institutions in two ways: (i) directly or (ii) indirectly. In the direct channel, official institutions offer credit directly to the borrower. In the indirect channel, official institutions use intermediary banks to distribute credit. In this form, official institutions provide a special

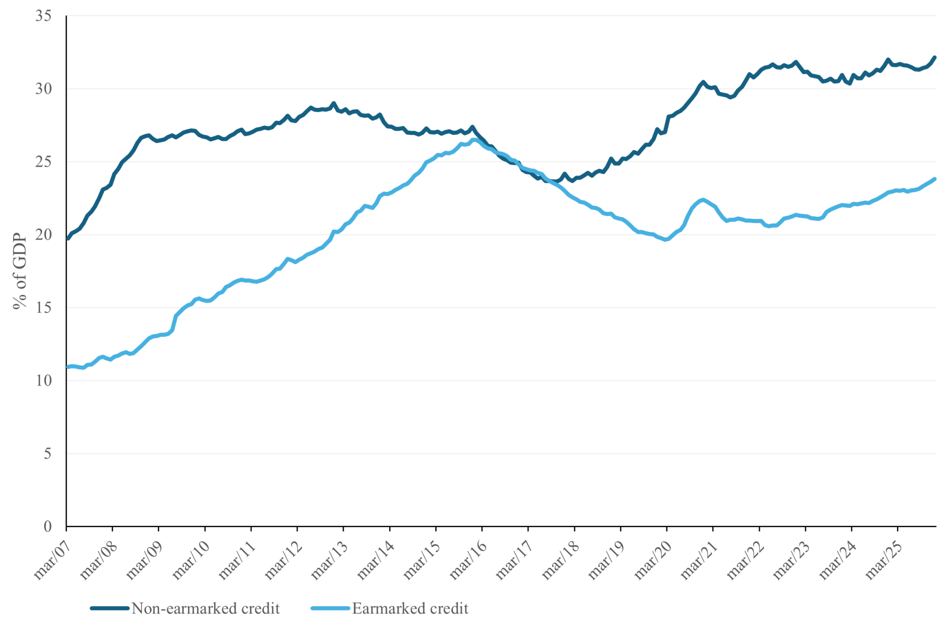

Figure 4: **Credit stock breakdown.** The figure presents the time series of the composition of the Brazilian credit stock, decomposed into non-earmarked credit, which is offered freely by financial institutions, and earmarked credit, which is subject to government interventions, as a percentage of GDP. The data were obtained from the Central Bank of Brazil.

credit operation, known as on-lending, to the intermediary bank, which in turn grants the credit to the final borrower under the same terms. For example, if the final borrower takes a BRL 50 million loan from the intermediary bank, indexed to the Selic rate (Brazil's monetary policy rate), with a 5-year maturity and monthly installments, the official institution will fund the intermediary bank under the same conditions. The intermediary bank charges the final borrower a default spread to compensate for credit risk.

Now, consider a scenario in which the Selic interest rate fluctuates. The intermediary bank would not be affected by these fluctuations because both its assets (loans to final borrowers) and liabilities (obligations to the official institution) are matched under the same terms. Imagine an institution that exclusively operates with this type of credit. All else being equal, this institution would be entirely immune to IRR. Therefore, our main hypothesis is that banking institutions with greater use of on-lending operations exhibit lower exposure to interest rate risk (IRR).

3 Method

Our hypothesis relates to the allocation of interest rate risk (IRR). In particular, if on-lending operations has immunizing properties for financial intermediaries, we expect a negative relationship between the use of this type of credit and the absolute exposure of banks to IRR. To test this hypothesis, we first require a measure of banks' exposure to IRR. A widely used proxy in the literature is the 12-month maturity gap (Flannery, 1981; Flannery and James, 1984; Esposito et al., 2015), which serves as a proxy for the aggregate level of maturity mismatch in banks' balance sheets. However, in the Brazilian case, there are no publicly available data that would allow us to accurately calculate the 12-month maturity gap. Furthermore, Drechsler et al. (2021) argue that banks may exhibit significant maturity mismatches without necessarily being exposed to IRR, consistent with the theoretical implications of Hellwig (1994).

Therefore, we follow an approach similar to that employed by English et al. (2018) and Drechsler et al. (2021) to measure banks' exposure to IRR: interest rate betas. Specifically, Drechsler et al. (2021) estimate the sensitivity of banks' Interest Income Ratio (the ratio of interest revenues to average total assets) and Interest Expense Ratio (the ratio of interest expenses to average total assets) to changes in monetary policy rates (for their case, the Federal Funds Rate). This procedure yields the Interest Income Ratio (IIR) beta and the Interest Expense Ratio (IER) beta. By definition, the difference between these two betas can be interpreted as the net interest margin (NIM) beta, given that NIM = IIR − IER. To measure the sensitivity of interest income and expenses to interest rate shocks, we follow Drechsler et al. (2021) and estimate regressions in first differences. This approach isolates the marginal response of bank cash flows to changes in interest rates and avoids spurious correlations driven by common trends in interest rates and bank income variables. Thus, we estimate the Interest Income Ratio (IIR) beta as follows:

$$\Delta IIR_{i,t} = \alpha_i + \gamma_t + \sum_{\tau=0}^{2} \beta_{i,\tau} \Delta MP_{t-\tau} + \epsilon_{i,t} \tag{1}$$

where $\Delta IIR_{i,t}$ denotes the change in bank i's interest income ratio from t to $t+1$; ΔMP_t is the change in Brazil's monetary policy rate (the Selic rate) over the same period; α_i represents bank fixed effects; and γ_t captures time fixed effects. The IIR is calculated as the total interest income of banks divided by the average of their total assets over the previous two semesters. The change in the monetary policy rate in Equation (1) covers a one-year horizon, capturing both the contemporaneous change and a two-period lag (we use semiannual data for Brazilian banks, as detailed in Section 4.1). Following the Drechsler et al. (2021) framework, we estimate Equation (1) using rolling time windows. This procedure generates bank-specific time-varying interest rate sensitivities, denoted by $\beta_{i,t}^{IIR} = \sum_{\tau=0}^{2} \beta_{i,\tau,t}^{IIR}$, which capture the response of banks' interest income ratios to interest rate shocks over time.

We calculate the beta of the IER analogously. By definition, the NIM beta is obtained as the difference between the IIR beta and the IER beta. This constitutes the first stage. To investigate the determinants of banks' exposure to IRR, we specify a panel data model in which the dependent variable is the NIM beta ($\beta_{i,t}^{NIM}$). We employ the absolute value of $\beta_{i,t}^{NIM}$, as IRR is associated with both negative and positive fluctuations in banks' NIM (Freixas and Rochet, 2008). The main explanatory variable of interest is the usage of on-lending operations:

$$\mathrm{Abs}\beta_{it}^{NIM} = \alpha + \beta_1 \text{On-Lending}_{i,t} + \mathbf{X}_{i,t}'\gamma + \mu_i + \varepsilon_{i,t} \tag{2}$$

where $\mathbf{X}_{i,t}$ denotes a vector of bank-specific and macroeconomic control variables, μ_i represents unobserved bank-specific effects, and $\varepsilon_{i,t}$ is the idiosyncratic error term.

The coefficient of interest is β_1, which measures the association between on-lending usage and IRR exposure. A negative and statistically significant β_1 would provide evidence that the use of on-lending is associated with a lower volatility of banks' net interest margins following monetary policy shocks, consistent with our hypothesis. Conversely, a positive and statistically significant β_1 would suggest that on-lending usage is positively associated with IRR exposure, contrary to our hypothesis.

Table 1 presents the set of control variables used in the model, their definitions, and their expected signs. In addition to on-lending usage, we control for other bank-specific characteristics and macroeconomic variables. The first control variable is bank size. The empirical literature suggests that larger banks tend to exhibit greater exposure to IRR (Entrop et al., 2017). The equity-to-assets ratio may be associated with IRR exposure because equity is a non-interest-bearing liability (Fraser et al., 2002; Entrop et al., 2017; Vuillemey, 2019) and is therefore more stable with respect to interest rate fluctuations. The demand deposits ratio captures the proportion of deposits that, while theoretically responsive to interest rate changes, tend to display relatively low short-run interest rate elasticity compared to other deposit categories. Consequently, we expect banks with a higher share of this type of deposit to exhibit lower sensitivity to interest rate fluctuations (Fraser et al., 2002; Drechsler et al., 2021). Banks with a higher proportion of fixed-rate loans in their credit portfolios, all else equal, could be more exposed to IRR due to fluctuations in interest expenses (Fraser et al., 2002; Gomez et al., 2021). For this reason, we control for the proportion of fixed-rate loans in the total loan portfolio (FR).

Table 1: Variables and expected signs

Variable	**Classification**	**Code**	**Definition**	**Source**	**Expected Sign**
On-lending operations	Bank variables	OL	On-lending / Total Assets	BCB	−
Size	Bank variables	Size	ln(Total Assets)	BCB	+
Equity-to-assets	Bank variables	EQ	Shareholders' Equity / Total Assets	BCB	−
Demand deposits ratio	Bank variables	DDR	Demand deposits / Total Deposits	BCB	±
Fixed-rate loans	Bank variables	FR	Fixed-rate loans / Total Loans	BCB	+
Non-performing loans	Bank variables	NPL	Loan losses / Total Loans	BCB	+
Liquidity	Bank variables	LIQ	Cash and equivalents / Total Assets	BCB	−
Derivatives usage	Bank variables	DER	Derivatives / Total Assets	BCB	−
Brazilian Crisis	Macro variables	BC	2015-16 year fixed effects (binary)	–	+
Covid-19 Crisis	Macro variables	C19	2020 year fixed effects (binary)	–	+
Interest rate volatility	Macro variables	IR Vol	SD of MP rate	BCB	+
Interest rate level	Macro variables	IR Level	MP rate level	BCB	+

Regarding credit risk exposure (measured by the non-performing loans ratio, NPL), we consider two possibilities. The first is a negative relationship, as credit risk may incentivize banks to better manage their IRR exposure: following defaults in their loan portfolios, banks might actively reduce exposure to other sources of risk (such as IRR) to avoid further declines in profitability. Alternatively, there could be a positive relationship if banks with higher credit risk exposure also exhibit higher IRR exposure. This could result from a "quest for yield": faced with loan defaults, banks may seek additional yield by taking on greater IRR. We also control for derivative usage. Given the literature's suggestion that derivatives are primarily used for hedging purposes (Bartram, 2019; Drechsler et al., 2021), we expect banks that make greater use of derivatives to exhibit lower exposure to IRR. We include indicator variables to control for significant periods of economic instability, which may have a notable impact on banks' IRR exposure. Specifically, we control for the period of the Brazilian crisis of 2015-16 (BC) and for the period of the Covid-19 crisis (C19), 2020. We present the accounting accounts used to calculate all the variables used in Table 8.

We estimate Equation (2) using different econometric specifications. First, we apply the classical static panel approaches: fixed effects (FE) and random effects (RE). Additionally, we employ a more sophisticated method, the System-GMM. One of the key econometric challenges in empirical banking research lies in addressing three interrelated problems: (i) endogeneity, (ii) unobserved heterogeneity, and (iii) persistence in the dependent variable. First, endogeneity arises when explanatory variables are correlated with the error term, either due to reverse causality or omitted variables. In the context of this paper, the share of on-lending in a bank's portfolio may be endogenous to its IRR exposure, as banks might adjust their funding structure in response to anticipated changes in monetary policy. Second, unobserved heterogeneity refers to time-invariant bank-specific characteristics—such as risk management sophistication, managerial ability, or business model orientation—that are not observable but may influence both the use of on-lending and the sensitivity to interest rate movements. Failing to control for this heterogeneity could bias the estimated impact of on-lending. Third, persistence is a common feature in bank-level performance metrics, including the interest income ratio and interest expense ratio, due to regulatory frictions, sticky balance sheet structures, or institutional inertia. Given these challenges, we adopt the System-GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), which simultaneously controls for endogeneity through internal instrumentation, accounts for unobserved fixed effects via first-differencing, and accommodates persistence in the dependent variable. Potentially endogenous variables were instrumented in our model. This method is widely used in the banking literature (e.g., Altavilla et al. (2018); Jha (2019); Garcia and Meurer (2022); Berrospide and Edge (2024)). We present the accounting accounts used to calculate all the variables used in the Appendix.

4 Results

4.1 Data and descriptive statistics

The primary dataset used in this research comprises semiannual financial information from Brazilian banking institutions, obtained from the Central Bank of Brazil, the regulatory authority for the Brazilian banking sector. The data spans from the first half of 2012 to the second half of 2021, totaling $t = 20$ time observations. Our sample period extends through 2021 due to data availability constraints for the balance sheet statements of bank holding companies (BHCs), at the level of detail required to measure the share of on-lending operations. All variables were adjusted to the price level of the second half of 2021 using the IPCA index. The sample includes 104 banking holding companies (BHC). However, we allow for entries and exits of banks in our sample, maintaining an unbalanced panel to avoid losing degrees of freedom in the econometric tests.

The key variable of interest is the ratio of on-lending to total assets (OL). The numerator of this variable includes a balance sheet account that records the amount owed by banks to official financial institutions, which channel earmarked credit policies (see Table 8, in the Appendix, for more details on financial statements accounts). Specifically, this account records obligations to the Banco do Brasil, the Brazilian Development Bank (BNDES), a subsidiary agency of BNDES responsible for administering the program which provides Financing for Machinery and Equipment (FINAME), Funding Authority for Studies and Projects (FINEP), a public agency that supports science, technology, and innovation in Brazil, and other official institutions. These institutions are the primary vehicles for implementing government credit policies.

We processed the data as follows: (i) all observations of banks with missing data for a given period were removed; (ii) observations of banks with negative equity were excluded; (iii) we selected only banks with the minimum number of observations required for calculating interest rate betas via a rolling window approach, initially set at 10 semesters (5 years) immediately prior; and (iv) we winsorized the data at the 1% level to mitigate the influence of outliers, in line with what is used in the related literature on IRR (English et al., 2018; Drechsler et al., 2021). We conducted robustness checks for different data treatment approaches, as discussed in section 4.3. Table 2 presents the descriptive statistics for the main variables, for the sample of BHCs used in the analysis, segmented between all institutions and the top 5 largest institutions.

In Table 2, we can identify some important patterns. Starting with the interest rate betas, we find that, on average, Brazilian BHCs exhibited a higher sensitivity of interest income (IIR beta) than of interest expense (IER beta). Economically, this means that institutions with these characteristics tend to temporarily benefit from a positive interest rate shock in terms of net interest margin (NIM). Specifically, a 100 basis point increase in interest rates is associated with an increase of 44 basis points in interest income and 30 basis points in interest expenses, respectively. In terms of the net interest margin (NIM), this same interest rate hike would result in an increase of 14 basis points in the NIM. Institutions with a NIM beta below the median display, on average, a controlled exposure to interest rate risk (IRR), with an average NIM beta of -0.04. Institutions with a NIM beta above the median present a higher, yet economically small, exposure (0.33% average NIM beta). These results are economically important, showing that Brazilian BHCs had limited IRR exposure during the period under analysis (2012-21).

Figure 5 illustrates the trajectory of the aggregate NIM of Brazilian institutions, as well as the monetary policy rate (Selic rate). It is clear that, in the aggregate, Brazilian banking institutions maintained a stable and protected NIM despite large interest rate swings, as observed in the Brazilian economy's historical record. Regarding the characteristics of institutions, those with lower IRR exposure have twice the use of directed credit (EC) compared to institutions with higher IRR exposure. As for the institutions in the top 5 in terms of size, we observe a more controlled exposure to IRR compared to the aggregate average. This is evidenced by an average NIM beta of -0.07%, compared to the aggregate average of 0.14%. From an

Table 2. Descriptive Statistics

Panel A: All Banks

	All		Low Beta / High Beta	
	Mean	SD	Mean	Median
Interest Rate Sensitivity				
IIR beta (%)	0.44	1.68	0.14	0.75
IER beta (%)	0.30	0.66	0.18	0.42
NIM beta (%)	0.14	1.84	-0.04	0.33
Abs(NIM beta) (%)	0.67	1.27	0.10	1.24
Bank Characteristics				
OL (%)	4.36	10.90	5.93	2.79
TA ($'000)	86,800	276,000	123,000	50,700
Size	22.50	2.42	22.40	22.60
EQ (%)	17.50	16.20	18.90	16.10
DDR (%)	24.30	30.10	25.80	22.70
FR (%)	46.10	28.30	50.10	41.50
LIQ (%)	2.56	6.91	3.10	2.02
NPL (%)	2.40	3.89	1.82	2.97
DER (%)	5.44	11.60	5.58	5.29

Panel B: Top 5% Banks

	All		Low Beta / High Beta	
	Mean	SD	Mean	Median
Interest Rate Sensitivity				
IIR beta (%)	0.19	0.26	0.13	0.25
IER beta (%)	0.26	0.22	0.18	0.34
NIM beta (%)	-0.07	0.24	-0.05	-0.09
Abs(NIM beta) (%)	0.20	0.14	0.09	0.31
Bank Characteristics				
OL (%)	7.89	3.90	8.90	6.86
TA ($'000)	949,000	465,000	974,000	923,000
Size	27.40	0.82	27.40	27.40
EQ (%)	7.90	1.72	7.59	8.21
DDR (%)	42.80	16.90	45.60	40.00
FR (%)	46.00	16.20	39.10	51.40
LIQ (%)	1.61	1.00	1.73	1.49
NPL (%)	3.04	1.09	2.74	3.35
DER (%)	5.99	8.86	7.54	4.40

Notes: This table reports the mean and standard deviation (SD) of interest rate sensitivity measures and bank characteristics for the full sample of banks (Panel A) and the top 5% of banks (Panel B), classified based on asset size. For each group, descriptive statistics are reported for the full sample as well as for banks with low and high interest rate betas, classified according to the median of interest rate beta. Interest Income Ratio (IIR) beta represents the sensitivity of interest income to monetary policy changes. The same logic applies to Interest Expense Ratio (IER) and Net Interest Margin (NIM). The bank-specific characteristics examined include on-lending operations (OL), total assets (TA), size (the natural logarithm of total assets), the equity-to-assets ratio (EQ), the demand deposits ratio (DDR), fixed-rate loans to total loans (FR), the ratio of cash and equivalents to total assets (LIQ), the non-performing loans ratio (NPL), and derivative positions scaled by total assets (DER).

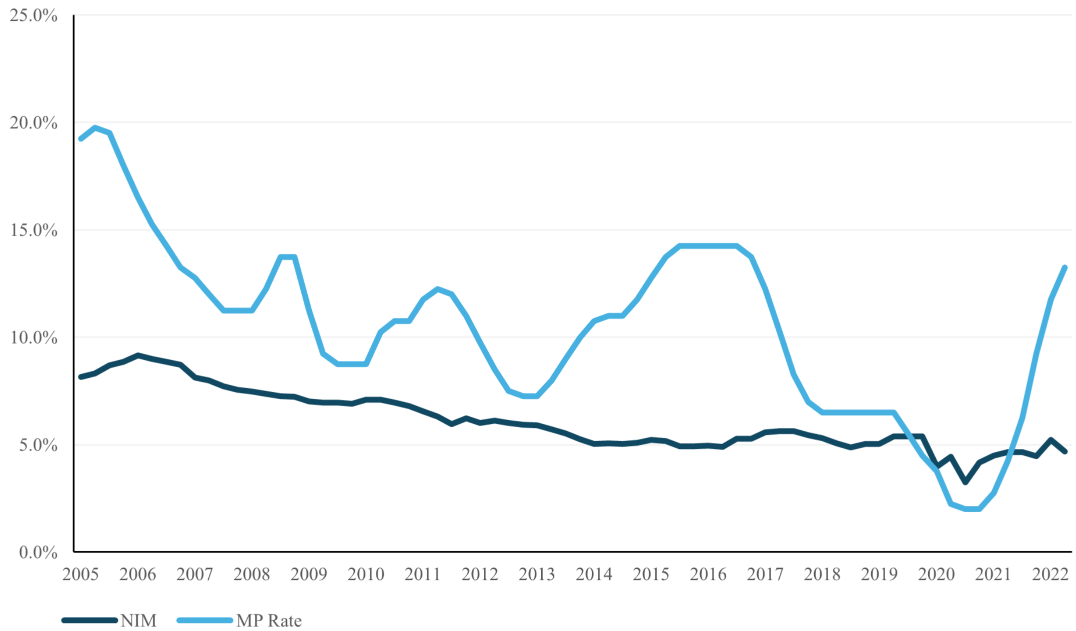

Figure 5: **Aggregate time series**. The figure presents the aggregate time series of the net interest margin (NIM) of Brazilian financial institutions, as well as the Brazilian monetary policy rate (Selic rate). The net interest margin (NIM) is defined as the difference between interest revenue and interest expenses, divided by the average total assets of the banking system. The data were obtained from the Central Bank of Brazil.

economic perspective, this suggests that for large bank holding companies (BHCs), a 100 basis point increase in interest rates is associated with a 7 basis point reduction in the NIM. This modest decline occurs because interest expenses are more sensitive to fluctuations in interest rates than interest income.

4.2 Main results

This section presents the econometric results and discusses their implications. Table 3 reports the main regression results, structured to compare estimations without the inclusion of the on-lending variable (OL) in columns (1) to (3) and with its inclusion in columns (4) to (6). Three alternative econometric specifications were employed: the Fixed Effects (FE) estimator, the Random Effects (RE) estimator, and the dynamic panel System-GMM estimator. The Hausman test rejects de null hypothesis, indicating that the RE model is inconsistent. Additionally, given the theoretical framework of this study—which posits that unobserved heterogeneity (such as managerial skill, bank risk culture, or access to earmarked credit) is likely correlated with the included covariates—the FE and dynamic System-GMM estimators remain the most appropriate for inference. The narrative that follows therefore emphasizes the economic interpretations derived from these models. However, we also present the results of the RE model for reference.

Baseline results (without OL). The first set of estimations (columns 1–3) investigates the determinants of banks' exposure to interest rate risk (IRR), proxied by the absolute value of the NIM beta, without

Table 3. Main Regression Results

Dependent variable: Abs(NIM beta)						
	Without OL			**With OL**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Abs(NIM beta)$_{t-1}$	–	–	0.6431***	–	–	0.6873***
			(0.1531)			(0.1580)
Intercept	–	-0.0468*	–	–	-0.0457***	–
		(0.0246)			(0.0240)	
OL	–	–	–	-0.017**	-0.0191*	-0.0139***
				(0.0074)	(0.0069)	(0.0046)
Size	0.0065**	0.0015*	-0.0004*	0.0064**	0.0014**	-0.0002**
	(0.0027)	(0.0008)	(0.0001)	(0.0027)	(0.0008)	(0.0001)
FR	0.0020	0.0007	0.0087	0.0017	0.0012	0.0013
	(0.0040)	(0.0032)	(0.0025)	(0.0040)	(0.0033)	(0.0027)
EQ	0.1575***	0.1207***	0.0453**	0.1576***	0.1209***	0.036*
	(0.0449)	(0.0458)	(0.0187)	(0.0447)	(0.0454)	(0.0197)
DDR	0.0057	0.0008	0.0018	0.0068*	0.0019	0.0040
	(0.0036)	(0.0039)	(0.0036)	(0.0038)	(0.0041)	(0.0037)
DER	0.0064	0.0065	0.0139	0.0052	0.0069	0.0077
	(0.0068)	(0.0062)	(0.0064)	(0.0068)	(0.0060)	(0.0069)
LIQ	-0.0354*	-0.0084	-0.0174	-0.0379**	-0.0107	-0.0176
	(0.0189)	(0.0126)	(0.0193)	(0.0190)	(0.0130)	(0.0113)
NPL	0.0320	0.0248	-0.0117	0.0324	0.0304	0.0133
	(0.0244)	(0.0230)	(0.0225)	(0.0244)	(0.0229)	(0.0221)
BC	-0.0048***	-0.0043***	-0.0008	-0.0050***	-0.0050***	-0.0009
	(0.0008)	(0.0009)	(0.0011)	(0.0008)	(0.0009)	(0.0011)
C19	0.0013	0.0018**	0.0007	0.0014	0.0022**	0.0007
	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0010)
IR Volatility	-0.0021	-0.0019	-0.0035*	-0.0021	-0.0026	-0.0031
	(0.0022)	(0.0021)	(0.0019)	(0.0022)	(0.0021)	(0.0019)
IR Level	0.0004***	0.0003**	0.0001	0.0005***	0.0004**	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Estimator	Fixed Effects	Random Effects	System-GMM	Fixed Effects	Random Effects	System-GMM
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,529	1,529	1,529	1,529	1,529	1,529
Bank Holding Companies (BHCs)	104	104	104	104	104	104
Instruments	–	–		–	–	
Sargan test (p-value)	–	–	0.150	–	–	0.180
AR(1) (p-value)	–	–	0.0186	–	–	0.0060
AR(2) (p-value)	–	–	0.4694	–	–	0.4890
Wald test	–	–	0.0000	–	–	0.0000

Notes: This table presents the estimation coefficient results for the dependent variable Abs(NIM beta). Columns (1) and (4) report the fixed-effects estimators, and Columns (2) and (5) report the random-effects estimators. Columns (3) and (6) report the two-step System-GMM estimates. Standard errors are reported in parentheses below each coefficient. For the fixed-effects and random-effects specifications, standard errors are Arellano-type HC1 and clustered at the bank level. For the System-GMM specifications, robust standard errors are reported. Statistical significance levels are denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. The System-GMM columns include the p-values of the Sargan test for overidentifying restrictions, the Arellano–Bond test for first-order autocorrelation (AR(1)), and second-order autocorrelation (AR(2)). All models include time and bank fixed effects (not reported for brevity). The bank-level variables Abs(NIM beta), *OL*, *FR*, *EQ*, *Size*, *DDR*, *DER*, *LIQ*, and *NPL* are treated as endogenous and are therefore instrumented.

accounting for OL. Across the FE and RE models, bank size (*Size*) consistently shows a positive and significant association with IRR exposure, suggesting that larger banks—due to their scale and balance sheet complexity—are more exposed to interest rate fluctuations. For instance, the FE coefficient of *Size* is positive and statistically significant at the 5% level (0.0065), echoing findings in Entrop et al. (2017); Foos et al. (2022) that larger banks engage more intensively in interest-sensitive activities.

Equity-to-assets ratio (*EQ*) also emerges as a strong predictor of IRR exposure in these baseline models. The FE estimate of EQ (0.1575, $p < 0.01$) suggests that better-capitalized banks may adopt more aggressive strategies, thereby amplifying their exposure to interest rate changes (Bikker and Vervliet, 2018; Gomez et al., 2021). Conversely, the liquidity ratio (*LIQ*) has a negative and significant effect (0.0354, $p < 0.1$) in the FE specification. This aligns with the liquidity risk mitigation hypothesis (Diamond and Rajan, 2001), indicating that banks with more liquid assets presents lower IRR exposure.

The dynamic System-GMM estimation (column 3) introduces the lagged dependent variable to account for persistence in IRR exposure. The coefficient of the lagged dependent variable is positive and highly significant (0.6431, $p < 0.01$), underscoring the path-dependent nature of IRR in banks' balance sheets (Delis and Kouretas, 2011). Notably, the coefficient on *Size* reverses sign and becomes marginally negative and significant (0.0004, $p < 0.1$). This suggests that, once dynamic effects and endogeneity are accounted for, larger banks may in fact exhibit slightly lower IRR exposure. This reversal highlights the importance of using dynamic specifications to reveal deeper insights into banks' risk management practices. *EQ* remains positive and significant (0.069, $p < 0.05$), though at a lower magnitude compared to the FE model, indicating that better-capitalized banks remain more exposed to IRR even when controlling for dynamics.

Including on-lending (Columns 4–6). Introducing the on-lending variable (OL) in columns (4–6) yields important new insights. In the FE model, OL exhibits a negative and significant coefficient (0.017, $p < 0.05$), indicating that a one percentage point increase in the share of on-lending is associated with a reduction of 0.017 in the absolute value of NIM beta. Economically, this supports our main hypothesis of *the allocation effect*, whereby the stabilizing nature of on-lending dampens banks' sensitivity to IRR.

This result also resonates with the theoretical perspective of Hellwig (1994), which posits that IRR is a systemic, non-diversifiable risk. On-lending, by partially immunizing banks from interest rate fluctuations, reshapes the allocation of IRR across the economy: banks become insulated, while borrowers (households and firms) or official providers ultimately bear the residual risk. This interference in the direction of IRR exposure has meaningful economic implications in a bank-centered financial system like Brazil's, where credit is a primary channel for monetary policy transmission and external financing is costly.

In the FE specification with *OL*, *Size* remains positive and significant ($0.0063, p < 0.05$), consistent with the notion that larger banks engage more actively in interest-sensitive intermediation. *EQ* retains a positive and significant coefficient ($0.158, p < 0.01$), reinforcing the idea that higher capitalization enables greater IRR. The liquidity ratio (LIQ) continues to present a negative and significant coefficient ($0.037, p < 0.05$).

Turning to the dynamic System-GMM model (column 6), the key result that *OL* is related to a lower IRR exposure persists and becomes even more robust $(0.014, p < 0.01)$. This suggests that the dampening effect of *OL* is resilient to concerns about endogeneity and dynamic panel bias (Arellano and Bover, 1995; Blundell and Bond, 1998). The lagged dependent variable remains strongly significant $(0.687, p < 0.01)$, reinforcing the presence of path dependence in IRR exposure.

Importantly, *Size* again shows a sign reversal in the dynamic specification, turning negative and significant. While static models (FE and RE) indicate that larger banks are more exposed to IRR, the dynamic specification suggests that, once controlling for unobserved heterogeneity and dynamic bias, larger banks might deploy superior risk management strategies that reduce their exposure to interest rate shocks (Chaudron, 2018; Kirti, 2020). *EQ* remains significant at the 10% level. These patterns highlight the nuanced economic roles of these covariates in shaping IRR exposure once dynamics are accounted for.

The convergence of FE and System-GMM results strengthens the confidence in the validity of these findings. From an economic perspective, the consistently negative and significant impact of *OL* across models underscores the immunizing role of on-lending in the Brazilian banking sector. Moreover, the dynamic sign reversal for *Size* underscores how apparent static vulnerabilities (larger banks appearing riskier) may be reconciled by dynamic adjustments and superior risk management.

The diagnostic tests support the validity of the System-GMM specification. The Arellano–Bond test indicates the presence of first-order serial correlation in the differenced residuals, as expected, while the null hypothesis of no second-order serial correlation cannot be rejected (AR(2) p-values of 0.469 and 0.489). This result suggests that the moment conditions based on lagged instruments are valid. In addition, the Sargan test of overidentifying restrictions does not reject the null hypothesis of instrument validity (p-values of 0.15 and 0.18), providing further support for the overall validity of the instrument set.

Taken together, these results provide compelling evidence that on-lending operations (OL) are associated with lower exposure to IRR for Brazilian banks, as proxied by the absolute value of NIM beta. This effect is robust across multiple model specifications, including static (FE) and dynamic (System-GMM) frameworks. Notably, the stability of the negative and significant *OL* coefficient across models reinforces the economic narrative of earmarked credit acting as a buffer for banks in an environment of substantial interest rate volatility.

The inclusion of *OL* also clarifies the roles of other significant variables: while bank size (*Size*) appears to heighten IRR exposure in static models, it reverses sign in the dynamic framework, suggesting that larger banks may deploy more sophisticated interest rate risk management practices. The equity-to-assets ratio (*EQ*) consistently emerges as a positive driver of IRR exposure, in line with a risk-taking hypothesis, where well capitalized banks are able to engage in more riskier activities (Bikker and Vervliet, 2018; Gomez et al., 2021).

These findings carry substantial economic implications. In the Brazilian context—characterized by high credit costs and a bank-dominated financial system—on-lending serves as a immunization tool, potentially reshaping the allocation of systemic interest rate risk. However, this insulation of banks comes at the cost of transferring IRR to other economic agents, such as households and firms, who may be less capable of managing it. Overall, by using both static and dynamic panel data approaches, this analysis offers a nuanced understanding of how on-lending interacts with bank-level characteristics to shape exposure to interest rate risk, highlighting the importance of these channels in the Brazilian financial system.

4.3 Robustness tests

To ensure the robustness of the previously reported results, we re-estimate the baseline model using an alternative specification of the key variable of interest, on-lending (OL). In the main estimations, OL was defined as the ratio of on-lending to total assets of bank holding companies (BHCs). Table 4 presents the results of the econometric estimations when OL is alternatively defined as the ratio of on-lending to total loans.

Overall, our main results remain qualitatively unchanged under this alternative specification of OL. Focusing on columns (4)–(6), which are directly affected by the redefinition, we observe that OL remains negative and statistically significant across all model specifications. When dynamic effects are included (column 6), the results are consistent with those of the baseline estimations: (i) OL maintains a negative and significant relationship with interest rate risk exposure, indicating that BHCs with a higher share of on-lending tend to exhibit lower IRR exposure; (ii) larger banks are less exposed to IRR; and (iii) more capitalized banks tend to display greater exposure to IRR.

The diagnostic tests support the validity of the System-GMM specification in the robustness analysis. The Arellano–Bond test detects first-order serial correlation in the differenced residuals, as expected in dynamic panel models, while the null hypothesis of no second-order serial correlation cannot be rejected (AR(2) p-values of 0.469 and 0.476). This result suggests that the lagged variables used as instruments are not correlated with the error term. Moreover, the Sargan test of overidentifying restrictions does not reject the null hypothesis of instrument validity (p-values of 0.148 and 0.167), providing additional support for the appropriateness of the instrument set.

We also conducted a series of additional robustness checks to validate these findings. Specifically, we tested (i) alternative levels of winsorization, including models without winsorization and with stronger winsorization at the 5% level. The core results remained unchanged, indicating that outlier treatment is not driving the main conclusions. Further, we estimated (ii) alternative model specifications by removing potentially redundant explanatory variables, and again the main results held. Finally, we (iii) included time fixed effects alongside individual fixed effects in the FE and RE models, and the principal findings remained robust. These robustness tests provide additional assurance of the reliability of our inferences. The results of these tests are available upon request.

Regarding our dependent variable (net interest margin beta – NIM beta), which serves as a proxy to measure exposure to interest rate risk (IRR), we also perform robustness tests to assess the consistency of

Table 4. Robustness Results

Dependent variable: Abs(NIM beta)						
	Without OL			**With OL**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Abs(NIM beta)$_{t-1}$	–	–	0.6431***	–	–	0.6956***
			(0.1531)			(0.1560)
Intercept	–	-0.0468*	–	–	-0.0450*	–
		(0.0246)			(0.0242)	
OL	–	–	–	-0.0177**	-0.0196***	-0.0154**
				(0.0077)	(0.0054)	(0.0061)
Size	0.0065**	0.0015*	-0.0004*	0.0063**	0.0014*	-0.0002**
	(0.0027)	(0.0008)	(0.0001)	(0.0028)	(0.0008)	(0.0001)
FR	0.0020	0.0007	0.0087	0.0011	0.0003	0.0004
	(0.0040)	(0.0032)	(0.0025)	(0.0039)	(0.0032)	(0.0027)
EQ	0.1575***	0.1207***	0.0453**	0.1578***	0.1218***	0.0347*
	(0.0449)	(0.0458)	(0.0187)	(0.0444)	(0.0453)	(0.0188)
DDR	0.0057	0.0008	0.0018	0.0073*	0.0036	0.0057
	(0.0036)	(0.0039)	(0.0036)	(0.0038)	(0.0038)	(0.0041)
DER	0.0064	0.0065	0.0139	0.0052	0.0050	0.0084
	(0.0068)	(0.0062)	(0.0064)	(0.0060)	(0.0056)	(0.0073)
LIQ	-0.0354*	-0.0084	-0.0174	-0.0427**	-0.0125	-0.0185
	(0.0189)	(0.0126)	(0.0193)	(0.0196)	(0.0137)	(0.0117)
NPL	0.0320	0.0248	-0.0117	0.0334	0.0237	0.0143
	(0.0244)	(0.0230)	(0.0225)	(0.0244)	(0.0232)	(0.0195)
BC	-0.0048***	-0.0043***	-0.0008	-0.0051***	-0.0046***	-0.0010
	(0.0008)	(0.0009)	(0.0011)	(0.0008)	(0.0009)	(0.0010)
C19	0.0013	0.0018**	0.0007	0.0015	0.0020**	0.0008
	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0011)
IR Volatility	-0.0021	-0.0019	-0.0035*	-0.0021	-0.0020	-0.0032*
	(0.0022)	(0.0021)	(0.0019)	(0.0022)	(0.0021)	(0.0018)
IR Level	0.0004***	0.0003**	0.0001	0.0005***	0.0004***	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Estimator	Fixed Effects	Random Effects	System-GMM	Fixed Effects	Random Effects	System-GMM
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,529	1,529	1,529	1,529	1,529	1,529
Bank Holding Companies (BHCs)	104	104	104	104	104	104
Instruments	–	–		–	–	
Sargan (p-value)	–	–	0.148	–	–	0.167
AR(1) (p-value)	–	–	0.0186	–	–	0.0082
AR(2) (p-value)	–	–	0.4694	–	–	0.4765
Wald test	–	–	0.0000	–	–	0.0000

Notes: This table reports robustness results for the dependent variable Abs(NIM beta). Columns (1) and (4) report fixed-effects estimates, Columns (2) and (5) report random-effects estimates, and Columns (3) and (6) report two-step System-GMM estimates with robust standard errors. Standard errors are reported in parentheses below each coefficient. For the fixed-effects and random-effects specifications, standard errors are cluster-robust at the bank level (Arellano-type, HC1 correction). The System-GMM specifications report robust standard errors. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The System-GMM specifications report the p-values of the Sargan test for overidentifying restrictions and the Arellano–Bond tests for first- and second-order serial correlation, AR(1) and AR(2). All models include time and bank fixed effects. The bank-level variables *Abs(NIM beta)*, *OL*, *FR*, *EQ*, *DDR*, *Size*, *DER*, *LIQ*, and *NPL* are treated as endogenous and instrumented accordingly.

our results. As previously discussed, one common approach in the literature to measure IRR is the 12-month maturity gap, defined as the difference between assets and liabilities with maturities up to 12 months, divided by total assets (Flannery, 1981; Flannery and James, 1984). This metric captures the maturity mismatch of banks' balance sheets over a one-year horizon. However, in our case, such information is not publicly available, preventing us from computing this measure.

Therefore, to conduct robustness tests specifically focused on modifying the dependent variable, we adjust the temporal window used for its computation. In particular, our baseline specification measures the NIM beta using one-year lags for each bank, requiring at least five years of historical data. As robustness checks, we recompute the NIM beta using longer lags—two-year and three-year intervals. Even with these extended in-sample estimation windows, our main results remain qualitatively unchanged.

We argue that the NIM beta represents a reasonable measure of banks' exposure to interest rate risk. Since the maturity gap is not necessarily associated with actual exposure to IRR—that is, a bank may present a maturity mismatch without necessarily experiencing shocks to its NIM—we contend that the NIM beta provides a more direct measure of IRR exposure, as it captures the sensitivity of a bank's profitability to fluctuations in interest rates (English et al., 2018; Drechsler et al., 2021).

The institutional environment of on-lending operations in Brazil underwent important changes during our sample period. Until 2017, a large share of BNDES credit was indexed to the TJLP (Taxa de Juros de Longo Prazo), an administratively determined rate set quarterly by the National Monetary Council. The TJLP was typically below market-based long-term rates and implied a significant subsidy embedded in development bank lending (Bonomo et al., 2015). However, this structure also generated concerns about allocative distortions, financial repression, and the potential crowding-out of private capital markets (Bonomo et al., 2015; De Bolle, 2015)

In 2017, Law No. 13,483 replaced the TJLP with the TLP (Taxa de Longo Prazo), which is linked to the yield on five-year inflation-indexed government bonds (NTN-B). This reform substantially reduced the degree of implicit subsidization and aligned BNDES funding costs more closely with market conditions (De Bolle, 2015). As a consequence, on-lending operations became less financially attractive relative to alternative market-based financing sources, and the competitive landscape between public development credit and capital market instruments changed. The reform marked a structural shift in the pricing and risk characteristics of development bank credit, consistent with the broader literature on development banks and state intervention in credit markets (La Porta et al., 2002; Cull et al., 2013).

These institutional changes must be analyzed in light of the theory of interest rate risk (IRR). Following the well-established definition in Freixas and Rochet (2008), IRR refers to the risk that fluctuations in interest rates affect banks' cash flows, either positively or negatively. Regarding its determinants, theory predicts that IRR is shaped by the contractual structure of banks' assets and liabilities (Hellwig, 1994). In other words, exposure to IRR depends fundamentally on how asset and liability contracts are specified, including maturity, repricing frequency, and indexation clauses. In the case of on-lending operations, one of their defining features is that contracts are typically structured with matched terms across stages of the intermediation chain (maturity, indexation, and pricing formula). As a result, intermediary banks earn a fixed spread to compensate primarily for credit risk, rather than bearing repricing risk.

In light of this framework, we do not expect the institutional transition from TJLP to TLP to alter the core immunization mechanism emphasized in this paper. That is, regardless of the specific benchmark index used in on-lending operations, intermediary banks that pass through these funds should remain largely insulated from IRR in these transactions, as long as contracts continue to be structured symmetrically across funding and lending stages.

To examine whether the 2017 reform in the indexation of development bank funding altered the relationship between on-lending operations and interest rate risk exposure, we estimate a dynamic fixed-effects specification interacting the share of on-lending (OL) with regime indicators. While our baseline results rely on System-GMM to address potential endogeneity and dynamic persistence, the inclusion of interaction terms in the GMM framework leads to numerical instability and weak identification due to the limited time-series variation and the proliferation of instruments. In this context, the dynamic fixed-effects estimator provides a more stable and transparent framework for comparing coefficients across institutional regimes. Given that our panel spans up to 20 semiannual observations per bank, the Nickell (1981) bias associated with the inclusion of a lagged dependent variable is expected to be small. Therefore, for the purpose of testing for structural differences across regimes—rather than for structural parameter identification—the dynamic fixed-effects approach constitutes an appropriate and econometrically sound complement to the baseline System-GMM estimates.

The results are presented in Table 9, in the appendix. The interaction terms between OL and the period dummies are statistically insignificant. These findings suggest that the results documented in the main specification are not driven by a particular subperiod. In other words, the estimated relationship does not change as a consequence of the reform in the benchmark rates applied to on-lending operations.

These findings are consistent with the institutional interpretation developed earlier. Even after the transition toward a more market-based benchmark rate, on-lending operations continued to be structured with matched contractual terms along the intermediation chain, preserving the fixed spread earned by intermediary banks. Therefore, the "immunization" mechanism highlighted in the main specifications—whereby on-lending reduces sensitivity to interest rate fluctuations without necessarily altering risk pricing—does not seem to depend on the specific indexation regime in place. Importantly, these results should be interpreted as robustness checks rather than primary identification exercises, as the System-GMM framework remains the baseline estimator given the dynamic nature of the model and the potential endogeneity of on-lending exposure.

4.4 Profitability

A natural question arises when analyzing the results presented for the relationship between interest rate risk (IRR) and the use of on-lending: what is the effect on profitability? Do banks that rely more heavily on on-lending exhibit lower levels of profitability? To address these questions, we rely on the standard framework in the literature on the determinants of bank profitability. More specifically, we estimate the following equation:

$$y_{i,t} = \alpha + y_{i,t-1} + \beta_1 \text{On-lending}_{i,t} + \mathbf{X}'_{,it}\gamma + \mu_i + \varepsilon_{i,t} \quad (3)$$

where $y_{i,t}$ comprises the bank profitability metric (return on assets or return on equity), $\mathbf{X}_{i,t}$ denotes a vector of bank-specific and macroeconomic control variables, μ_i represents unobserved bank-specific effects, and $\varepsilon_{i,t}$ is the idiosyncratic error term. The set of variables used in the estimation of Equation (3) is presented in Table (5) below.

Table 5. Variables and expected signs: determinants of banks profitability.

Variable	Classification	Type	Code	Definition	Source	Expected Sign
Return on assets	Bank variables	Dependent	ROA	Net Income / Total Assets	BCB	
Return on Equity	Bank variables	Dependent	ROE	Net Income / Book Equity	BCB	
Lagged Dependent Variable	Bank variables	Independent	ROA (or ROE)	ROA_{t-1}	BCB	+
On-lending	Bank variables	Independent	OL	On-lending / Total Assets	BCB	−
Size	Bank variables	Independent	Size	ln(Total Assets)	BCB	±
Equity-to-assets	Bank variables	Independent	EQ	Book Equity / Total Assets	BCB	±
Demand deposits ratio	Bank variables	Independent	DDR	Demand deposits / Total Deposits	BCB	+
Non-performing loans	Bank variables	Independent	NPL	Loan losses / Total Loans	BCB	−
Liquidity	Bank variables	Independent	LIQ	Cash and equivalents / Total Assets	BCB	−
Non interest income ratio	Bank variables	Independent	NIR	Fee and service revenue / Total Assets	BCB	+
GDP	Macro variables	Independent	GDP	Real GDP growth rate	BCB	+
Inflation	Macro variables	Independent	INFL	IPCA index (change)	BCB	+
Concentration	Macro variables	Independent	CONC	Top 5 Banks Assets / Total Assets	BCB	+
Interest rate level	Macro variables	Independent	IR Level	MP rate level	BCB	±

The determinants of bank profitability, as documented in the literature, can be grouped into three categories: bank characteristics, market structure, and macroeconomic conditions. Within the group of bank characteristics, the persistence of profitability stands out as a well-documented stylized fact (Berger, 1995; Demirgüç-Kunt and Huizinga, 1999; Athanasoglou et al., 2008). This is one of the reasons why dynamic models are more appropriate for the analysis of bank profitability, since ignoring dynamics may generate omitted variable bias and overestimate the impact of structural determinants (Athanasoglou et al., 2008; Flannery and Rangan, 2008; García-Herrero et al., 2009). Therefore, the lagged profitability variable constitutes one of the central determinants in the model. Therefore, we applied the System-GMM to estimate equation (3) (Garcia and Meurer, 2022).

Another relevant determinant is bank size. For this variable, the evidence points in both directions. Part of the literature finds a positive association between size and profitability, typically attributed to economies of scale and scope (Demirgüç-Kunt and Huizinga, 1999; Athanasoglou et al., 2008). On the other hand, there is also evidence of negative effects, associated with greater organizational complexity, agency costs, and possible diseconomies of scale (Berger and Mester, 1997; Stiroh, 2004).

Capitalization is another fundamental determinant, presenting an ambiguous sign in both theory and empirical evidence. More highly capitalized banks may face lower funding costs and lower perceived risk, which may translate into higher profitability (Berger, 1995; Demirgüç-Kunt and Huizinga, 1999). Conversely, higher capitalization implies lower leverage, which tends to reduce return on equity and potentially return on assets, reflecting a risk–return trade-off (Berger, 1995; Gropp and Heider, 2010).

Another important determinant is asset quality, usually measured by the non-performing loans ratio (NPL). It is a stylized fact that banks with higher levels of non-performing loans exhibit lower profitability, reflecting higher provisions and deterioration in the loan portfolio (Athanasoglou et al., 2008; Demirgüç-Kunt and Huizinga, 1999). Similarly, higher levels of liquidity may reduce profitability due to the opportunity cost associated with holding low-yield assets (Bordeleau and Graham, 2010).

In addition to the bank characteristics discussed above, we include other determinants in line with the main findings of the literature, as shown in Table 5. Regarding market structure, we include bank concentration, whose relationship with profitability is discussed under both the structure–conduct–performance hypothesis and the efficiency hypothesis (Demirgüç-Kunt and Huizinga, 1999). For macroeconomic conditions, we use inflation, GDP growth, and the level of the interest rate, variables widely associated with the business cycle and bank net interest margins (Demirgüç-Kunt and Huizinga, 1999).

We estimate Equation 3 using return on assets (ROA) and return on equity (ROE) as dependent variables, employing the System-GMM approach. The results for both variables are presented in Tables 6 and 7, respectively. The AR(2) tests fail to reject the null hypothesis of no second-order serial correlation, and the Sargan tests do not reject the validity of the overidentifying restrictions, suggesting that the instrument set is appropriate.

In all specifications, the lagged profitability variable is positive and statistically significant, indicating persistence in bank profitability, consistent with the aforementioned literature. With respect to bank characteristics, the results are consistent with the existing empirical evidence. Capitalization (EQ) exhibits a negative relationship with profitability, in line with the findings of Berger (1995) and Gropp and Heider (2010), suggesting the presence of a risk–return trade-off through leverage.

NPLs are negatively associated with profitability, as is liquidity, results that are widely documented in the banking performance literature (Athanasoglou et al., 2008; Bordeleau and Graham, 2010). Bank size exhibits a non-linear relationship with profitability, evidenced by the inclusion of the quadratic term. The negative effect of the linear term combined with the positive effect of the quadratic term suggests that scale effects are not monotonic, consistent with the evidence reported by Demirgüç-Kunt and Huizinga (1999) and Athanasoglou et al. (2008).

Table 6. Determinants of Bank Profitability (ROA)

Dependent variable: ROA	**(1)**	**(2)**	**(3)**	**(4)**
ROA($t-1$)	0.149**	0.149**	0.139*	0.141*
	(0.073)	(0.073)	(0.073)	(0.074)
OL		-0.0149		-0.0009
		(0.0282)		(0.0266)
Size	-0.0069***	-0.0066***	-0.062***	-0.059***
	(0.0025)	(0.0025)	(0.0200)	(0.0191)
Size^2			0.0012***	0.0011***
			(0.0004)	(0.0004)
EQ	-0.150***	-0.146***	-0.159***	-0.156***
	(0.030)	(0.030)	(0.041)	(0.041)
DDR	-0.0005	-0.0005	0.0044	0.0051
	(0.011)	(0.0112)	(0.0107)	(0.0104)
LIQ	-0.144**	-0.142**	-0.164***	-0.167***
	(0.058)	(0.0578)	(0.0483)	(0.0480)
NPL	-0.068**	-0.070***	-0.059	-0.064**
	(0.027)	(0.0228)	(0.0368)	(0.0301)
NIR	-0.0016	-0.0019	-0.0138	-0.0134
	(0.011)	(0.0111)	(0.0150)	(0.0148)
GDP	0.0003	0.0004	0.0004	0.0005
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
IPCA	0.0010	0.0008	0.0008	0.0006
	(0.0007)	(0.0007)	(0.0009)	(0.0008)
RC5	0.633	0.709	0.520	0.573
	(0.713)	(0.695)	(0.742)	(0.732)
IR level	-0.0014**	-0.0013*	-0.0013	-0.0012
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Observations	1,529	1,529	1,529	1,529
Banks	104	104	104	104
Sargan (p-value)	0.503	0.599	0.097	0.144
AR(1) (p-value)	0.001	0.001	0.002	0.001
AR(2) (p-value)	0.999	0.981	0.913	0.907
Time dummies	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes

Notes: This table reports two-step System GMM estimates of the determinants of bank profitability measured by return on assets (ROA). The panel comprises 104 Brazilian banks observed semiannually, totaling 1,529 bank-semester observations. All specifications include bank and time fixed effects. The dynamic specification incorporates the lagged dependent variable to account for persistence in profitability. Columns (1)–(2) report baseline specifications, while Columns (3)–(4) additionally include a quadratic term in bank size to allow for potential non-linear scale effects. Standard errors (in parentheses) are robust to heteroskedasticity and serial correlation. The Sargan test reports the p-value for overidentifying restrictions. AR(1) and AR(2) correspond to the Arellano–Bond tests for first- and second-order serial correlation in first differences. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The bank-level variables *ROA*, *OL*, *FR*, *EQ*, *DDR*, *Size*, *NIR*, *LIQ*, and *NPL* are treated as endogenous and instrumented accordingly.

Table 7. Determinants of Bank Profitability (ROE)

Dependent variable: ROE	**(1)**	**(2)**	**(3)**	**(4)**
ROE($t-1$)	0.112**	0.110**	0.100*	0.097*
	(0.052)	(0.050)	(0.052)	(0.050)
OL		-0.0446		-0.038
		(0.153)		(0.150)
Size	-0.0129**	-0.0125**	-0.171***	-0.167***
	(0.0063)	(0.0061)	(0.0576)	(0.0555)
Size^2			0.0034***	0.0033***
			(0.0011)	(0.0011)
EQ	-0.322***	-0.315***	-0.397***	-0.389***
	(0.071)	(0.068)	(0.0833)	(0.0804)
DDR	0.0182	0.0172	0.0153	0.0128
	(0.0400)	(0.0391)	(0.0389)	(0.0370)
LIQ	-0.206	-0.212	-0.296	-0.299
	(0.190)	(0.190)	(0.193)	(0.1916)
NPL	-0.216**	-0.221**	-0.248**	-0.250***
	(0.0966)	(0.0929)	(0.1002)	(0.0947)
NIR	-0.0299	-0.0332	-0.0807	-0.0813
	(0.0424)	(0.0447)	(0.0550)	(0.0553)
GDP	0.0035**	0.0036**	0.0037**	0.0037**
	(0.0016)	(0.0016)	(0.0017)	(0.0017)
IPCA	-0.0023	-0.0024	-0.0021	-0.0022
	(0.0034)	(0.0034)	(0.0035)	(0.0036)
RC5	0.338	0.351	1.167	1.026
	(2.637)	(2.590)	(2.716)	(2.681)
IR level	-0.0003	-0.0002	-0.0012	-0.0011
	(0.0020)	(0.0019)	(0.0022)	(0.0022)
Observations	1,529	1,529	1,529	1,529
Banks	104	104	104	104
Sargan (p-value)	0.850	0.902	0.773	0.834
AR(1) (p-value)	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.520	0.544	0.552	0.581
Time dummies	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes

Notes: This table reports two-step System GMM estimates of the determinants of bank profitability measured by return on equity (ROE). The panel comprises 104 Brazilian banks observed semiannually, totaling 1,529 bank-semester observations. All specifications include bank and time fixed effects. Columns (1)–(2) present baseline specifications, while Columns (3)–(4) additionally include a quadratic term in bank size. Standard errors (in parentheses) are robust to heteroskedasticity and serial correlation. The Sargan test reports the p-value for overidentifying restrictions. AR(1) and AR(2) correspond to the Arellano–Bond tests for first- and second-order serial correlation in first differences. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

With respect to our variable of interest, on-lending (OL) is not statistically significant in any specification. Combined with the main results of this paper, the potential reduction in interest rate risk documented earlier does not appear to be associated with lower profitability. Therefore, a higher share of OL may be associated with a more stable portfolio and balance sheet structure, without generating economically significant effects on banks' average profitability.

5 Final remarks

A substantial body of research has examined the effects of earmarked credit on the Brazilian economy. However, most of the attention has been devoted to the direct effects of the two dimensions through which the state intervenes in the credit market via these credit lines: (i) below-market interest rates and (ii) the directed allocation of funds toward specific sectors or purposes. We argue that, by implementing on-lending policies (a type of earmarked credit), the state also interferes with another dimension of the credit market: the allocation of interest rate risk (IRR) across the economy. This represents a third dimension of state intervention.

Since IRR constitutes a systemic risk, it cannot be diversified away at the aggregate level, implying that some economic agent must ultimately bear it. The institutional design of on-lending in Brazil is such that intermediary banks, which act as distribution channels for these credit lines, face fixed returns due to a matching of the characteristics between their assets and liabilities within these operations.

We therefore test the hypothesis that banks with higher reliance on on-lending exhibit lower exposure to IRR. The empirical results support our hypothesis. From an economic perspective, this implies that earmarked credit policies have the potential to affect not only the allocation of credit but also the allocation of IRR in the Brazilian economy, due to the structural features of these contracts. In other words, on-lending operations tend to reduce intermediary banks' exposure to IRR, effectively transferring this risk either to the borrower or, ultimately, to the national treasury. Additionally, our results confirm some findings from the existing IRR literature — larger banks tend to be less exposed to IRR, while more capitalized banks tend to be more exposed. Also, our results are not influenced by the structural change in targeted credit that occurred during 2017, which brought many operations closer to market parameters.

Additionally, we examine whether the use of this type of credit is associated with bank profitability. The variable capturing the share of on-lending in banks' total assets is not statistically significant in any specification, indicating that this type of operation did not affect banks' average profitability over the sample period. Therefore, although this type of credit is associated with lower exposure to IRR, it is not significantly associated with bank profitability. Taken together, the evidence suggests that this type of credit may be linked to the maintenance of a more stable portfolio and balance sheet structure.

We believe this paper contributes to the banking literature in several ways. First, most studies on the determinants of banks' exposure to IRR focus on developed economies, such as the United States and European countries. We contribute by providing evidence for an important emerging Latin American economy — Brazil — which is a bank-oriented financial system. Second, we contribute to the literature on state intervention in the Brazilian credit market from a novel perspective, by investigating how such interventions may affect banks' exposure to risk. To the best of our knowledge, no previous study has examined the effects of earmarked credit policies on the IRR exposure of the banking sector. Future research may further shed light on how such interventions influence banks' behavior and their corresponding effects on credit recipients in the real economy.

A Appendix - Banks interest rate risk theory

In this Appendix, we will discuss the theory underlying interest rate risk (IRR) in banking activity. Before start the main theoretical studies, we will briefly address the overall landscape of this existing literature. Some studies in the literature comment on the lack of a considerable number of empirical papers addressing IRR in banking activity, despite the relevance of the topic, which is already well-known (Kirti, 2020). In addition to the absence of empirical mass, there is an even greater absence of theoretical mass (Drechsler et al., 2021). We will begin this section by addressing the beginning of the study of IRR (Section A.1). Afterwards, we will go through some subtle but extremely important developments in early theoretical models (Section A.2). We will close the section with the main implications that the underlying theory elucidates.

A.1 The beginning

Research on banks interest rate risk in the banking system dates back to the work done by Samuelson (1945). In his work, he argues in favor of two results: (i) an increase in the basic interest rate negatively affects the banking sector if the average maturity of assets is longer than the average maturity of liabilities; and (ii) the banking system benefits after an interest rate hike.

These two statements may seem contradictory at first. In fact, Samuelson (1945), in statement (i), refers to the effect now known as the valuation effect, where the market value of banks' equity is negatively affected by an increase in interest rates. The second argument, on the other hand, deals with the net interest margin (NIM) of the banking system. Due to the rigidity of bank deposits, after an interest rate hike, banks can benefit from higher NIMs. This latter effect is called the cash flow effect or income effect.

We will introduce a preamble about banking activity that guides the structure of the models, as well as some notations and basic assumptions. Classic banking activity, as it is known, consists, in a simple way, of issuing deposits (its liabilities) and lending these funds, often in the form of credit operations (its assets). Modern banking theory starts from this simple structure of banking activity, a current reality for many commercial banks around the world. In particular, we will start with the classic model of Diamond and Dybvig (1983), which was designed to investigate the phenomenon of bank runs and the vulnerabilities of these institutions in terms of liquidity. The model focuses on one of the fundamental characteristics of banking institutions as intermediaries: the creation of liquidity, i.e., transforming illiquid assets into liquid liabilities.

The Diamond and Dybvig (1983) model assume a simple three-period economy, $t = \{0, 1, 2\}$, with a continuous number of consumers and a single homogeneous good. We assume that for each investment made at $t = 0$, the economy's technology can generate a return $R > 1$ at $t = 2$. If the investment is interrupted earlier, for example, at $t = 1$, the return is given by $\gamma < R$. This assumption aims to capture the irreversibility characteristics of long-term investments. Bringing this to the banking reality, $(R - \gamma)$ is the cost, in terms of return, of liquidating an asset before its maturity (in the model, liquidating this long-term asset at $t = 1$).

The model assumes that all consumers are identical at $t = 0$. These consumers can be of type 1, the impatient ones (those who only care about their consumption at $t = 1$), or type 2, the patient ones (those who only care about their consumption at $t = 2$). This reflects differences in preferences regarding intertemporal consumption. Formally, the consumption preference, c_t, for a consumer is given by a utility function $u(c_t)$, which is increasing and strictly concave, and where $u'(0) = \infty$.

Agents can invest existing resources at $t = 0$ in projects of different maturities: short-term and long-term. Short-term projects generate a return $r_1 = 1$ at $t = 1$ (for simplicity, we normalize the returns of short-term investment as $r_1 = 1$). This return can be reinvested at $t = 1$ in another short-term project, which returns r_2 at $t = 2$. As mentioned above, investments in long-term projects, made at $t = 0$, yield R at $t = 2$, where $(1 + R) > (1 + r_1)(1 + r_2)$. The long-term investment only yields a payoff at $t = 1$ if liquidated, and this payoff, γ, is such that $\gamma < r_1$. Note, there is an extremely important implication here. The long-term investment, made at $t = 0$, presents a liquidity premium, i.e., it is more profitable than making two short-term investments. Also, liquidating the long-term investment before its maturity is costly, as revealed by the payoff γ.

Let $1 - \theta$ be the probability of being a type 1 consumer (impatient), and let θ be the probability of being a type 2 consumer (patient). Let Γ be the amount of long-term investments liquidated at $t = 1$. Considering a continuum of consumers, and by the law of large numbers, we have that the probability of investing in the long-term asset is exactly given by θ.

Now, let's briefly discuss the sources of uncertainty and their effects. Whether there is uncertainty about consumption preferences in the temporal structure is an extremely important factor for formulating the optimal decision. Let k_1 be the amount of wealth allocated to short-term investment, and let k_2 be the amount of wealth allocated to long-term investment. Assuming certainty about the need for consumption at $t = 1$, the agent's optimal choice will necessarily involve $k_1 > 0$, i.e., the individual will allocate wealth to short-term investment. Another possible source of uncertainty, besides consumption preferences, is about r_2. In the model of Diamond and Dybvig (1983), r_2 is known at $t = 0$, so in aggregate terms, there is no uncertainty in the model, and consequently, we know exactly the aggregate consumption level over the periods at $t = 0$. For this reason, liquidating the long-term investment at $t = 1$ is an inefficient way to provide consumption in this period. As we will see next, Hellwig (1994) obtains important results by assuming uncertainty about r_2. In the model without uncertainty about r_2, i.e., the model of Diamond and Dybvig (1983), the representative consumer solves:

$$\max_{c_1,c_2,k_1,k_2} U = (1-\theta)u(c_1) + \theta u(c_2) \tag{4}$$

s.t.

$$(1-\theta)c_1 = k_1 r_1 \tag{5}$$

$$\theta c_2 = R k_2 \tag{6}$$

$$k_0 = k_1 + k_2 \tag{7}$$

We note that, given that the technologies of the economy are known at $t = 0$, the optimal consumption levels, c_1^* and c_2^*, depend solely on the agents' preferences regarding the timing of their consumption, i.e., on their preferences (whether they are impatient or not). The consumption levels do not depend on aggregate variables (R, r_1, and r_2). In banking terminology, Diamond and Dybvig (1983) argue that there is an optimal allocation using redeemable deposits, i.e., those with liquidity. Thus, with $\theta > 0$, we have long-term investment. Since r_2 is known at $t = 0$, there is no reason to liquidate the long-term investment before its maturity. Therefore, a financial intermediary that invests in a long-term asset, financed by withdrawable deposits, engages in maturity mismatch, even without interest rate risk, since r_2 is known ex-ante.

A.2 Development

Now, we will focus on the insights brought by Hellwig (1994). By incorporating uncertainty regarding future returns, the work of Hellwig (1994) establishes a clear starting point for the theory of interest rate risk in the banking sector. Contrary to common intuition, the author argues that interest rate risk does not stem from the maturity transformation carried out by banks but rather from the real sector of the economy. In a general equilibrium setting, interest rate risk arises from potentially time-inconsistent consumption and production decisions made by households and firms. This implies that interest rate risk is systemic, i.e., it is a non-diversifiable risk. Therefore, some agent must bear this risk.

Hellwig (1994) contends that interest rate risk is transmitted among agents in the economy through financial intermediation contracts. By extending credit with floating interest rates, banks transfer the risk of interest rate fluctuations to the credit recipient (potentially non-financial companies or households). Conversely, by extending credit with fixed rates, banks may assume the risk of interest rate fluctuations. It is important to note this in conjunction with the financing of these operations, i.e., the liabilities of the banking sector, which can be tied to floating or fixed rates. Interest rate risk can be transferred not only to the real sector of the economy but also shared among banking sector agents, and this transfer occurs through derivative instruments, most commonly through interest rate swaps.

We will now analyze the practical implications of this contribution on the foundational model of Diamond and Dybvig (1983). In particular, we now consider uncertainty regarding r_2, where this becomes unknown at $t = 0$. With uncertainty introduced, the representative consumer faces the following problem:

$$\max_{c_1,c_2,k_1,k_2,\Gamma} \mathbb{E}[U] = \mathbb{E}[(1-\theta)u(c_1) + \theta u(c_2)] \tag{8}$$

s.t.

$$\underbrace{(1-\theta)c_1}_{\text{Consumption at } t=1} \leq \underbrace{k_1 + \gamma\Gamma}_{\text{Resources available for } c_1} \tag{9}$$

$$\theta c_2 \leq R \underbrace{(k_2 - \Gamma)}_{\text{Long term investment}} + r_2 \underbrace{[\gamma\Gamma + k_1 - (1-\theta)c_1]}_{\text{Short term investment}} \tag{10}$$

$$0 \leq \Gamma \leq k_2 \tag{11}$$

$$k_1 + k_2 = 1 \tag{12}$$

$$\tag{13}$$

The inclusion of uncertainty about r_2 significantly alters the consumer's problem. Thus, this formulation by Hellwig (1994) elucidates an aggregate trade-off between long-term investment (k_2) and short-term consumption needs (k_1). Long-term investment, whose return R exceeds the sum of short-term returns, has the potential to generate more future consumption. On the other hand, the need for short-term liquidity for consumption presents the counterbalance to this trade-off. In this trade-off, the production risk of the economy plays a fundamental role. Patient consumers (θ) bear the valuation risk of long-term investment, whereas impatient investors ($1-\theta$) bear the reinvestment risk.

The important contribution brought by Hellwig (1994) is that the risk is not originated by financial intermediaries. It is not the maturity mismatch that creates interest rate risk, but rather the temporal inconsistency between consumption and production preferences. That is, it arises from changes in consumption preferences, productivity of the economy, or a combination of both (Hellwig (1994) specifically addresses uncertainty about the productivity of the economy). This is generated in the non-financial sector and is a systemic risk, and therefore, non-diversifiable.

In the banking sector, what guides its exposure to risk is the format of its operations. In particular, banking institutions that link their deposit contracts to r_2 are transferring possible shocks to the non-financial sector. Similarly, banking institutions that do not link their deposit contracts to r_2 are assuming possible shocks in this variable. These types of contracts are called floating and fixed-rate, respectively. Thus, idiosyncratic consumption can be immunized, but there is a risk on aggregate consumption that cannot be diversified.

A.3 Theory at a glance

The model by Diamond and Dybvig (1983), known as one of the models that, together, form modern banking theory, brought contributions regarding banking activity and its intrinsic liquidity problem. It is also the starting point for analyzing interest rate risk in the banking sector. The aforementioned model presents a maturity mismatch without interest rate risk: agents finance their consumption with investments of different maturities from their consumption expenditure (maturity mismatch), but in the model, the term structure of interest rates consists of constants (there is no aggregate uncertainty). Hellwig (1994) builds on the classic model by (Diamond and Dybvig, 1983) to investigate the allocation of interest rate risk among agents in an economy. His contribution is the inclusion of uncertainty about future interest rates (aggregate uncertainty), thus generating a model with maturity mismatch and interest rate risk. Summarizing this underlying theory on IRR in 4 bullets, we would list:

i Maturity mismatch per se does not create interest rate risk;

ii Interest rate risk is a systemic risk (non-diversifiable);

iii Banks' exposure to IRR is defined by the type of contract in which their operations are conducted;

iv Banking institutions may not be the most prepared to bear IRR.

A Appendix - Additional tables

Table 8. Construction of Variables from COSIF Regulatory Accounts

Variable	**Code**	**Source**	**COSIF Accounts/Definition**
On-lending	OL	Central financial statements of the national financial system	46400004 / (10000007 + 20000004)
Size	Size	Central financial statements of the national financial system	ln(10000007 + 20000004)
Equity-to-assets	EQ	Central financial statements of the national financial system	60000002 / (10000007 + 20000004)
Demand-deposits ratio	DDR	Central financial statements of the national financial system	(41000007 - 41500002) / 41000007
Non-performing loans	NPL	Central financial statements of the national financial system	31900007 / 31000000
Liquidity	LIQ	Central financial statements of the national financial system	11000006 / (10000007 + 20000004)
Non-interest income	NIR	Central financial statements of the national financial system	71700009 / 70000009
Derivatives	DER	Central financial statements of the national financial system	(13300003 + 47000001) / (10000007 + 20000004)
Return on assets	ROA	Central financial statements of the national financial system	(70000009 + 80000006) / (10000007 + 20000004)
Return on equity	ROE	Central financial statements of the national financial system	(70000009 + 80000006) / 60000002
Interest income ratio	IIR	Central financial statements of the national financial system	(71100001 + 71400000) / (10000007 + 20000004)
Interest expense ratio	IER	Central financial statements of the national financial system	(81100008 + 81200001) / (10000007 + 20000004)
Fixed-rate loans	FR	IF Data	Fixed-rate banking book / Total banking book

Notes: This table details the construction of the main variables used in the empirical analysis based on regulatory accounting data from the Central Bank of Brazil. All accounting items are obtained from the Central Financial Statements of the National Financial System and follow COSIF (*Plano Contábil das Instituições do Sistema Financeiro Nacional*), the official chart of accounts governing financial institutions in Brazil. The numerical codes reported in the last column correspond to specific COSIF balance-sheet and income-statement accounts used to compute each variable. Total assets are defined as the sum of COSIF accounts 10000007 and 20000004, while book equity corresponds to account 60000002. Income-statement items are derived from COSIF revenue and expense accounts in groups 7 (revenues) and 8 (expenses). Ratios are constructed by scaling the relevant account balances by total assets, total loans, total deposits, or book equity, as indicated in the table. The variable Fixed-rate loans (FR) is obtained from supervisory IF Data and corresponds to the share of fixed-rate exposures in the banking book. All variables are constructed at the bank-semester level, ensuring consistency with supervisory definitions and replicability of the empirical analysis.

Table 9. Regime Test: On-Lending (OL) and Interest Rate Risk Exposure

Dependent variable: Abs(NIM beta)	**(1) OL × Pre-2017**	**(2) OL × Post-2017**
Abs(NIM beta)$_{t-1}$	0.416***	0.416***
	(0.154)	(0.154)
OL	-0.017*	-0.016***
	(0.010)	(0.005)
Pre-2017 dummy	0.004**	
	(0.002)	
Post-2017 dummy		-0.004**
		(0.002)
OL × Pre-2017	0.001	
	(0.008)	
OL × Post-2017		-0.001
		(0.008)
FR	0.006	0.006
	(0.004)	(0.004)
Size	0.005**	0.005**
	(0.002)	(0.002)
EQ	0.097**	0.097**
	(0.045)	(0.045)
DDR	0.005**	0.005**
	(0.002)	(0.002)
DER	0.002	0.002
	(0.002)	(0.002)
LIQ	-0.028*	-0.028*
	(0.017)	(0.017)
NPL	0.013	0.013
	(0.017)	(0.017)
BC	-0.002*	-0.002*
	(0.001)	(0.001)
C19	-0.001	-0.001
	(0.001)	(0.001)
IR_vol	-0.005***	-0.005***
	(0.002)	(0.002)
IR_level	-0.000	-0.000
	(0.000)	(0.000)
Bank fixed effects	Yes	Yes
SE (Arellano HC1), clustered by bank	Yes	Yes

Notes: This table reports dynamic bank fixed-effects estimates for the relationship between on-lending exposure (OL), measured as the share of on-lending in total assets, and banks' interest rate risk exposure, proxied by the absolute NIM beta, Abs(NIM beta). Column (1) interacts OL with a pre-2017 indicator, while Column (2) interacts OL with a post-2017 indicator to assess whether the relationship differs across the institutional regimes surrounding the TJLP–TLP reform. All specifications include bank fixed effects and the lagged dependent variable to capture persistence. Standard errors, reported in parentheses, are heteroskedasticity-robust (Arellano HC1) and clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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