Pontifícia Universidade Católica do Rio de Janeiro

Luiz Claudio Ferreira Sacramento Junior

Essays in Banking Seasonality

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Economia of PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Economia.

Advisor: Prof. Juliano Assunção

Rio de Janeiro
April 2024

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Abstract

Sacramento Junior, Luiz Claudio Ferreira; Assunção, Juliano (Advisor). **Essays in Banking Seasonality**. Rio de Janeiro, 2024. 98p. Tese de doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Bank seasonality has been extensively examined in the literature, yet the scarcity of granular data has hindered branch-level analysis. In this study, I investigate branch-level seasonality to identify credit peaks, defined as the month in which a specific branch exhibits its highest average lending volume. Notably, branches within the same bank in a given municipality demonstrate different 'main months', suggesting a form of branch specialization tailored to their clientele. In the first paper, I explore the impact of branch seasonality on the transmission of monetary policy, examining how fluctuations in the reference interest rate affect lending volume differently during branches' main months. The findings suggest that monetary policy is less effective during these periods. There is evidence that relationship lending or similar behaviors preclude branches to pass-through interest rate changes in the months that are most important for them. In the second paper, I examine the role of public banks in electoral periods, showing evidence that politicians exploit branches' seasonality to further increase credit in elections. The use of 'main months' adds a new layer for identification and suggests that credit is reallocated from politically unattractive to politically attractive municipalities. Finally, in the third paper, I use machine learning to predict and describe the main months based on detailed balance-sheet data, for the top five largest banks in Brazil. Results reinforce the idea that branches adapt their lending practices to local markets. Collectively, these findings offer valuable insights for policymakers and practitioners into the dynamics of the banking market.

Keywords

Seasonality Credit Market Monetary Policy Political Lending Bank Branches

Resumo

Sacramento Junior, Luiz Claudio Ferreira; Assunção, Juliano. **Ensaios em Sazonalidade Bancária**. Rio de Janeiro, 2024. 98p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

A sazonalidade bancária tem sido amplamente examinada na literatura, no entanto, a escassez de dados granulares tem dificultado a análise em nível de agência. Neste estudo, investigo a sazonalidade em nível de agência para identificar picos de crédito, definidos como o mês em que uma agência específica apresenta seu maior volume médio de empréstimos. Notavelmente, agências dentro do mesmo banco em um município dado demonstram diferentes 'meses principais', sugerindo uma forma de especialização da agência adaptada à sua clientela. No primeiro artigo, exploro o impacto da sazonalidade da agência na transmissão da política monetária, examinando como as flutuações na taxa de juros de referência afetam o volume de empréstimos de forma diferente durante os 'meses principais' das agências. Os resultados sugerem que a política monetária é menos eficaz durante esses períodos. Há evidências de que o relacionamento com os clientes ou comportamentos semelhantes impedem que as agências transmitam as mudanças na taxa de juros nos meses que são mais importantes para elas. No segundo artigo, examino o papel dos bancos públicos em períodos eleitorais, mostrando evidências de que políticos exploram a sazonalidade das agências para aumentar ainda mais o crédito nas eleições. O uso dos 'meses principais' adiciona uma nova camada de identificação e sugere que o crédito é realocado de municípios politicamente não atrativos para municípios politicamente atrativos. Finalmente, no terceiro artigo, utilizo aprendizado de máquina para prever e descrever os 'meses principais' com base em dados detalhados de balanço, para os cinco maiores bancos do Brasil. Os resultados reforçam a ideia de que as agências adaptam suas práticas de empréstimo aos mercados locais. Coletivamente, esses resultados oferecem insights valiosos para formuladores de políticas e profissionais sobre a dinâmica do mercado bancário.

Palavras-chave

Sazonalidade Mercado de Crédito Política Monetária Political Lending Agências Bancárias

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Ipse se nihil scire id unum sciat.
I only know that I know nothing.

Socrates, *?*.

1
Bank Branches' Seasonality, Relationship Lending, and Monetary Policy Transmission

Abstract: Discretion over the reference interest rates is one of the most used instruments for the conduction of monetary policy. But, bank branches have incentives to not fully transfer this cost to their clients. This study shows that a contractionary policy is responsible for a slight decrease in lending if the branch is in the month of highest historical demand, but in the following periods, the branches start to pass the remaining costs to their clients. This dynamic effect is best explained by relationship lending, in which branches protect their clients to establish new long-term relationships. Consequently, this behavior also imposes burdens on the bank lending channel. I also show which types of branches are more protective of their clients and consequently more detrimental to the clear transmission of monetary policy. Monetary authorities can be more effective if consider the composition and timing when deciding interest rates.
Keywords: seasonality, financial intermediation, monetary policy, relationship lending, credit markets

1.1 Introduction

Banks facing an increase in reference interest rates will have to decide whether they pass the increase in the cost of credit to their clients or not. If they do charge more, credit demand decreases and monetary policy is effective. However, banks have incentives to not pass - at least momentarily - the cost to their clients. Two distinguishing hypotheses are present in the literature that possibly explain this behavior: adverse selection and relationship lending. For the former, banks do not pass this cost because riskier clients will accept borrowing at higher rates leading to a decrease in the quality of banks' portfolios (Stiglitz & Weiss, 1981; Holmstrom & Tirole, 1997). For the latter, banks might partially protect their clients in the present aiming to extract rents in the long run with the relationship formed between the two (Sharpe, 1990). This duality is incipient in the literature and requires a thoughtful investigation. In this study, I explore this phenomenon by addressing the question: Do bank branches protect their clients from rises in interest rates?

The answer is yes. Considering that the entire effect of a change in interest rate affects the current and subsequent periods, the transmission of costs is attenuated in the first months and the remaining cost is passed after some time. It can be observed by the flat line in branches' lending volume after the change in interest rates, followed by a decline after some months. This non-flat curve in the results is consistent with the hypothesis of marketable incentives for relationship lending. Banks form links with their clients and protect them in the short run by smoothing the immediate transfer of a higher cost in credit. However, after some time, the total cost charged is higher, consistent with the hold-up problem described by Sharpe (1990). More recent literature also explore the relationship between borrowers and lenders. Jiménez *et al.* (2014) mentions that the majority of firms apply for loans from multiple borrowers. Jiménez *et al.* (2012) mentions that firms with longer and fewer bank relationships are more likely to be successful in applying for loans. The consequence for the Bank Lending Channel is that it offers a burden to a clear policy transmission to the economy. This behavior disturbs the effect of monetary policy since it acts as a constraint that deviates the optimization from the unconstrained optimal level of credit in the economy. If policymakers do not consider this phenomenon they might be strongly overestimating the effect and timing of monetary policy.

The mechanism that suggests why this effect is observed in the data can be best explained by the literature on relationship lending. Relationship lending is a market practice in which banks repeatedly interact with borrowers, mostly small and opaque, to acquire soft information that helps mitigate the asymmetry of information and potentially be able to offer loans at competitive prices. Thus, to establish a long-term relationship, private branches that are new in the market, and with a small portion of the market share, show a smaller reduction in the volume lent. However, branches from public banks with a high market share and long presence in a given market, despite charging more, help their clients by smoothing the reduction in lending volume. These two findings together are consistent with a large scope of findings in banking literature. For instance, public banks do not appear to compete with private banks in the Brazilian credit market as they often differ from the objective of profit maximization (Beck *et al.*, 2005; Coelho *et al.*, 2013). Branches that are still developing relationships with their clients - proxied by the time in which they are present in the data - charge less than those that already developed a longer relationship (Sharpe, 1990; Beck *et al.*, 2018).

Therefore, my results point out that relationship lending is an important component, but likely not unique, to explain why branches charge more but protect their clientele in the advent of an increase in the cost of capital. As described by Hachem (2011), both relationship lending and competition play an important role in describing the smoothing patterns consistent with my analysis. However, it is a challenge to disentangle the two aspects, because they are usually simultaneously determined. For instance, firms with larger market participation might be those with longer relationships developed. I try to address this problem by relying on the Brazilian dataset to compute branch-level metrics for each dimension separately. Although these two variables are correlated, they still offer valuable conclusions.

Brazil constitutes a convenient laboratory for testing this theory for at least five reasons. First, interest rates in Brazil are far from the zero-lower bound. The Brazilian Central Bank (henceforth BCB) has the autonomy to freely move interest rates in open-market transactions as a tool of monetary policy. Second, in intervals of approximately 45 days, a group of monetary authorities decides upon the interest rate that will be in force from then on. Not only these meetings are recurrent, but changes in interest rates as well. Third, the concentration in the Brazilian banking market is one of the highest in the world (Joaquim *et al.*, 2019). As an illustration, 86.13% of branches in my sample are from five banks. Hence, opportunities for branches to pursue new clients and maintain old ones are more stringent. Fourth, the firms in Brazil are typically small and do not have access to credit markets unless they borrow from banks. According to the theory, the bank lending channel should be more prominent in those cases[1.1]. Five, the granularity of publicly available data enables the researcher to address this question at a lower level than usual in the literature. Using each municipality as an individual market, I estimate regressions at the branch level, considering each branch's clientele seasonality and decomposing the aggregate macroeconomic effects into local markets.

This study circumvents important limitations for a clearer identification of monetary policy effects. As Bernanke & Blinder (1992) and Jiménez *et al.* (2012) mention, it is hard to distinguish supply from demand effects in macroeconomics. This occurs because a tighter monetary policy might contract the demand for credit. After all, firms' expectations about future cash flows may be reduced. Simultaneously, banks might reduce the supply of credit due to the increase in agency costs of banks. Therefore, this context likely suffers from omitted variable bias. One contribution of this paper is to provide a way of addressing this issue. I can control for a large portion of branch heterogeneity by using a dummy for each branch-month combination (approximately 270,000 dummies), similarly to Jiménez *et al.* (2012). These dummies are expected to control for numerous unobserved characteristics related to the branches, such as seasonal patterns by its clients. The reference interest rate is the same for the whole economy but each branch reacts differently to the stimuli. Additionally, as will be further explained, my setting guarantees that each branch is its own counterfactual at different moments. Hence, controlling for this large set of demand effects, the results obtained are more likely to be supply-driven.

I link the branch-level panel data to the reference interest rate in Brazil (Selic). To capture this heterogeneity that contributes to identification, I build on the methodology used by Chang *et al.* (2016) and Almeida *et al.* (2018) to characterize seasonal patterns. While the authors apply the method for publicly traded firms on a quarterly basis, I adapt this variable for bank branches on a monthly basis. The variable is intended to capture the month in which the demand for loans is at its peak based on each branch's historical volume of credit in each month. Therefore, I recover each branch's most important month to capture the effect of the interest rate in branches from the same main month. Similarly to the authors, I assume that this variable captures the seasonality of branches. In their paper Chang *et al.* (2016) finds the same evidence when using a continuous version of the measure, attesting the capacity of capturing the concept of seasonality.

The advantage of using this technique is twofold. It incorporates the

[1.1] While several studies find evidence of smaller firms suffering more (e.g. Peek & Rosengren, 1995a,b; Kashyap & Stein, 1995), others challenge this conclusion. For instance, Greenstone *et al.* (2020) find that while loan origination for small firms reduced in the US during the 2008 crisis, there is no economically meaningful real effect on employment.

moment in which the relevance of the relationship is more salient (the month with the highest demand) and also for identification because the same branch is compared with itself in and out of its main month, consisting of a convenient control group. Furthermore, by including branch-month fixed effects, I can remove a substantial set of confounders such as common monthly patterns other than the ones related to credit.

My study contributes both to the literature on relationship lending and to the transmission of monetary policy through the Bank Lending Channel. Banks have incentives to develop relationships and not harm their clients by fully passing the cost of credit, otherwise, other banks might capture their clientele. This imposes a burden on a clear transmission of monetary policy to the real economy. Additionally, this result highlights the consequences of too-big-to-fail banks. Branches with higher local market power are less protective, being the ones that the monetary authority should target for a more effective policy. This suggests that bank concentration might help the transmission of monetary policy. Coelho *et al.* (2010) find, opposing to existing literature, that larger banks are more sensitive to changes in interest rates and a possible explanation is that after privatization (Beck *et al.*, 2005; Mariani, 2020) and mergers (Joaquim *et al.*, 2019), banks became larger and developed more market power in Brazil.

1.2 Literature Review

In the nineties, a large body of researchers investigated the role of relationships in bank lending with a particular focus on small firms. In the absence of informational frictions, all NPV-positive projects should be funded (Stiglitz & Weiss, 1981; Holmstrom & Tirole, 1997), but smaller firms are usually more opaque and more likely to bypass valuable projects due to a lack of finance. This is the case for most firms in developing countries (98.5% are formally registered as micro or small enterprises in Brazil) whose firms hugely depend on banks for funding their projects. As Bethune *et al.* (2022) describes firms in lending relationships hold fewer liquid assets than unbanked firms. Since these small firms rarely have other sources of financing and do not rely on formal ways of demonstrating their repayable capacity, banks offer special conditions to them. In this setting, banks mostly rely on soft information to learn through interactions about the quality of a borrower.

For a country with continental dimensions such as Brazil, distance is an important driver of the volume of soft information available. Degryse & Ongena (2005) and Nguyen (2019) document that distance is a relevant aspect of the strength of a relationship, even with the advancements in technology. Closer borrowers develop stronger ties with their banks, an effect that can be explained by transportation costs in the acquisition of soft information. Degryse & Ongena (2005) also underscores the importance of balancing competition in the banking sector while maintaining the incentives for banks to build and develop lending relationships. Therefore, developing a relationship can be considered a competitive advantage that seems particularly important for small municipalities, where the distances are smaller. In a theoretical model, Boot & Thakor (2000) describes that in a sufficiently competitive market, relationship lending becomes the dominant strategy, and suggests that its predictions should be empirically tested in an adequate setting. The Brazilian context together with the novel identification strategy used in this paper has the goal to offer such testing.

Despite a lot of research on relationship lending, the empirical literature has been divided between the benefits and harms of the practice. On one hand Berger & Udell (1995) identifies that borrowers with longer relationships pay lower interest rates and obtain better loan conditions. Petersen & Rajan (1994) finds that relationships are important, but mostly for non-price loan terms such as lending volume or collateral requirements. The authors also describe that borrowers with multiple lenders are charged more for their loans because they are treated as risky clients, otherwise, they would have gotten credit with the bank they already have a relationship with. This is the so-called hold-up problem, in which borrowers face barriers to obtaining loans with other banks. As the name suggests, the borrowers are incapable of obtaining loans from other banks and end up paying higher interest on their loans. Sharpe (1990) designs a stylized model and explains how banks can offer loans with losses to capture new clients to extract future rents. A cross-country meta-analysis conducted by Kysucky & Norden (2016) find evidence of smaller interests charged and larger volume contracted for firms with relationships that are long-lasting, exclusive, and in use of multiple products offered by the banks (e.g. credit cards, short-term loans, etc). My study contributes to this literature by taking advantage of a novel methodology to identify how branches protect their clients in the advent of an increase in interest rates.

This study also contributes to the literature on monetary policy and its transmission channels to the economy. The bank lending channel is a broad theory that delineates the mechanisms of how monetary policy might affect the real economy through bank assets (loans) and liabilities (deposits). Firstly described by Bernanke & Blinder (1988), as long as loans and bonds are treated as different instruments (with different costs), there is a particular role for banks and a direct relation between credit and GNP. A contractionary monetary policy (increase in interest rates) is expected to reduce loan volumes, due to an increase in the cost of capital, leading clients to borrow less and reduce aggregate output. Consistent with this rationale, Jiménez *et al.* (2012) and Greenstone *et al.* (2020) show that firms are unable to turn to other banks to undo a rejection that is due to tightening monetary or economic conditions.

The recent economics literature has been showing alternative channels for monetary policy transmission (e.g Drechsler *et al.*, 2017; Ippolito *et al.*, 2018; Sterk & Tenreyro, 2018) and revisiting more standard channels with better data and identification methods (e.g Coelho *et al.*, 2010; Jiménez *et al.*, 2012, 2014; Daniel *et al.*, 2021; Alfaro *et al.*, 2021; Gomez *et al.*, 2021; Duquerroy *et al.*, 2022; Ivashina *et al.*, 2022). Increases in interest rates have been shown to strongly reduce lending for smaller (Kashyap & Stein, 1995; Black & Rosen, 2007), less liquid (Kashyap & Stein, 2000), less risky banks (Acharya *et al.*, 2020), and in more concentrated deposits markets (Drechsler *et al.*, 2017). This paper integrates this sizable strand in the literature focused on identifying barriers to the transmission of monetary policy[1.2]. More recently, Ippolito *et al.* (2018) find that monetary policy can be harmed if the bank has fewer loans floating with the interest rates, and Gomez *et al.* (2021) find that banks with larger income gap (the difference in the proportion of accounts maturing between the asset and liability side) are more affected by changes in interest rate. Also, public banks in Brazil have more earmarked loans, varying more with market indicators as described by Coelho *et al.* (2010). My paper adds to this literature by showing that more primary and local characteristics of banks play an important role in explaining the transmission of monetary policy.

Finally, the link between monetary policy and relationship lending has been called to researchers' attention in more recent years. Evidence has shown that increases in interest rates affect more clients with short or no relations with their banks (Gambacorta & Mistrulli, 2014; Amiti & Weinstein, 2018). My results converge with the models presented by Hachem (2011), in which banks smooth the transmission of a higher cost to the clients they develop relationships with. In the author's study, competition also plays an important role in describing this behavior by decreasing the cost of credit in a more competitive setting. Together, competition and relationship help to explain the smooth steady state and less volatile response to monetary shocks. For Brazil, Joaquim *et al.* (2019) has shown that after several mergers in Brazil, interpreted as a reduction of competition, the loan interest rates rose and volume decreased. Also, the bargaining power of banks allows them to extract

[1.2] See Boivin *et al.* (2010) for an extensive review on the scientific evolution of this topic.

rents from their clients through relationships previously established and to create incentives to develop new ones. In their study, Bethune *et al.* (2022) calibrated a model and used the global economic crisis of 2008 as a shock that terminated a large number of relationships in the banking sector. The authors find that in the optimal monetary policy that makes the supply of liquid assets constant, the spreads initially rise creating incentives for the development of new relationships. However, the reduction in the level of investment is stronger, because relationships are yet required to mature. This paper adds to this literature by empirically showing how relationships matter for the transmission of monetary policy, as theoretical papers have suggested.

1.3 Contextual Framework

In this section, I present how monetary policy is conducted and what are the idiosyncrasies regarding the credit market in Brazil. The contextual framework is quite similar to other countries with a Central Bank that is sovereign about the interest rates. Also, similarly to other developing countries, the Brazilian credit market is one of the most concentrated credit markets in the globe, with a huge informality and reliance on soft information.

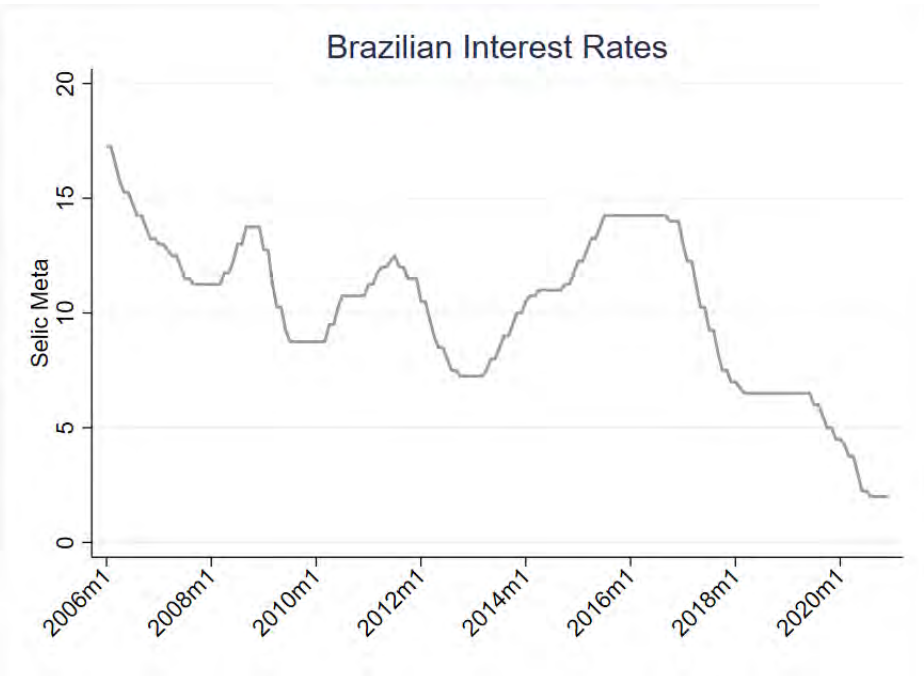
To illustrate the degree of maturity observed in the Brazilian credit market a formal credit score, namely the Serasa Credit Score, was introduced in Brazil only in 2017 and still faces problems with data availability. In 2021 there was a substantial change in its computation that put a stronger weighting in Cadastro Positivo. This change in methodology reduced the score of several people, as few people (8.3%) were registered on the platform at the time. The Cadastro Positivo consists of a register that the borrower has to allow financial institutions to consult about individuals' private credit history and repayment behavior. Despite large efforts for formalization and support of hard information, the current market remains informal for a large set of the population. According to a 2014 survey promoted by (Demirgüç-Kunt *et al.*, 2015), only 42% of interviewed adults reported having a bank account to make or receive payments in Brazil.

1.3.1 Monetary Policy in Brazil

The Committee of Monetary Policy (henceforth COPOM) meets at intervals of approximately 45 days. In these meetings, directors of the Brazilian Central Bank decide upon several aspects of monetary policy, and more importantly for my study, the reference interest rate Selic. The team reunites in a room for usually two days to deliberate about the next prevailing interest rate. Initially, the board defines an interest rate target (Selic Meta), and the Brazilian Central Bank (BCB) trades securities in the open market to guarantee an operational rate close to the target.

The convergence between the target and the practiced interest rate is achieved customarily. Thus, I decided to use the target interest rate since it is less noisy. Since open-market transactions are flexible, adjusting interest rates constitutes the most common way monetary policy is conducted in Brazil and worldwide. The annual reference interest rate time series can be observed in Figure 1.1

Figure 1.1: Selic Meta over Time



Historically, Brazil is among the countries with the highest real interest rates. The series used in this study is composed of small jumps that occur in the months when the COPOM meetings take place. Despite the downward trend, the graph comprises the period right before the Covid-19 crisis, concomitantly before the interest rates were raised again to help the treasury support the expenditures during the crisis.

1.3.2 Brazilian Bank Sector

After several problems due to the bad management of public banks, in addition to the hyperinflation in the eighties, the Brazilian bank market faced a myriad of changes. Even after a large reform in the banking sector to reduce federal and state participation in the Brazilian banking sector (Assunção, 2013a; Mariani, 2020), the public banks are still relevant. For my sample, the total lending amount of public branches corresponds to 46.19 % of the total lending volume. Additionally, Public banks play an important role in other areas. For instance, in Brazilian elections, as described by Carvalho (2014). The author finds that politicians use loans from the Brazilian Development Bank to attract employment for firms in politically attractive regions when there is a close election.

More generally, the Brazilian credit market is marked by a huge concentration of credit in the top five banks. For the top 5 banks with the most branches in the Brazilian territory (Banco do Brasil, Bradesco, Itaú-Unibanco, Caixa Econômica, and Santander, respectively), I observe a concentration of 74.64% of total credit. After the privatization at the end of the last century, there were some important merging episodes involving private banks. The largest is the merger involving Itaú and Unibanco, which occurred in October 2008. At the time, the two banks corresponded to the third and sixth largest banks acting in Brazil, managing over 100 billion dollars in assets (Joaquim *et al.*, 2019). After the approval by the responsible entity, the two banks increased their market power while expanding their presence over the Brazilian municipalities.

It is widely known that commercial banks are specialized in certain types of clients. For instance, Banco do Brasil, is a public bank responsible for the logistics of several governmental actions towards rural credit. Another public bank, Caixa Econômica Federal, is responsible for the transmission of real estate subsidized credit in a similar fashion. The Itaú-Unibanco Bank usually focuses on a high-income clientele. However, this specialization might not be true if one takes a deeper look at the municipality level. As we will see in the next section, two branches from the same bank in the same municipality, present different seasonal patterns suggesting that their borrowers' demands vary considerably.

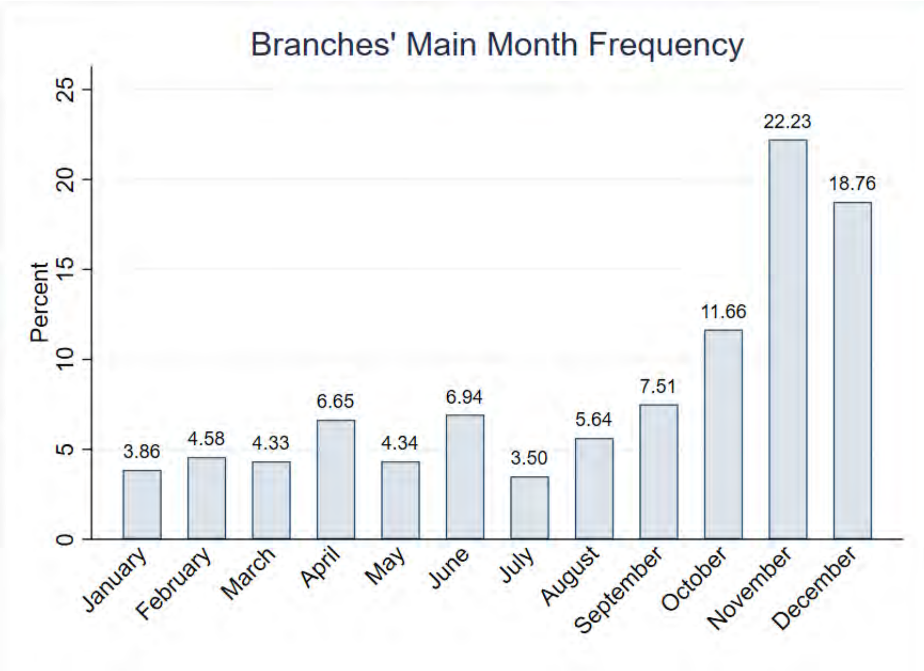
1.4 Data

Due to Brazilian regulatory requirements, bank branches must provide recurrent reports to the Brazilian Central Bank (BCB). The Banking Statistics System (Estban) groups and organizes this data to make it publicly available. The data comprises balance sheets of each branch reported on a monthly frequency. Thus, credit volume can be tracked in a small time interval for all commercial bank branches in Brazil. This rich dataset is used to construct most variables in this study.

The type of ownership for each bank is required for some analyses. Thus, I merged Estban with the IF Data using the bank's CNPJ, a unique identification number for Brazilian companies. IF Data contains information about the ownership of banks operating in Brazil. I use the referencing in IF Data for the last period of my data: December 2020. Thus, I observe only the current ownership status of banks[1.3].

To capture the branch's unique borrowers' behavior, I compute the variable *Main Month* by using the monthly patterns in Loan Volume for each branch's historical data. First, I require branches to have at least 60 months of sequential data available to compute average rank. This requirement guarantees that each month is observed at least 5 times. Second, I sort the branch's observations by loan volume and generate a rank of these observations. Finally, I calculate the average rank per month for each branch[1.4]. Hence, the *Main Month* variable indicates when the branch is in its month with the highest average ranking. In other words, this dummy variable takes the value of one if the branch is in its month with higher historical demand and zero in the remaining months.

Figure 1.2: Frequency of Branch's Main Month



[1.3] The banks' ownership status is available every quarter. However, I do not use it for two main reasons: the mismatch of bank balance sheets and current status of ownership, and because no episodes of privatization happened during my time spam (see Mariani, 2020 for a complete list).

[1.4] Using average loan volume may be problematic due to outliers. Using the average rank produces more consistent patterns in seasonality (Almeida *et al.*, 2018).

In Figure 1.2 we observe the distribution of the Main Month for the 23,051 branches in the data. The frequency of observations for the main month is larger in November and December, corresponding to 41% of branches. This agrees with anecdotal evidence that consumers spend more during festive dates such as Christmas and New Year. Yet, important taxes are paid with a discount in this period (e.g. automobile taxes - IPVA, and property taxes - IPTU). Conversations with loan officers indicate that borrowers might anticipate these tax advantages and borrow at the end of the year taking into consideration that the evaluation of credit can take some time.

The seasonality that each branch faces varies according to its clientele. An illustrative example is the municipality of Valença in Rio de Janeiro state. The small town has 6 branches from 5 different banks. There are four distinct main months for those branches and even those from the same bank present dissimilar main months. This interpretation agrees with Duquerroy *et al.* (2022) evidence for branch specialization. The authors use bank branches' portfolio data to identify disproportionate lending volume for one sector. They show that banks do specialize, and branches from the same bank have borrowers from distinct industries at the local level. While Duquerroy *et al.* (2022) uses the cross-sectional heterogeneity of the branches' portfolio, I delve into the *timing* of each branch's clients.

Despite its advantages, the data has some limitations. For instance, we can only observe the total stock of loans being offered by each branch at a given month. Also, the dataset not distinguish between loans offered to individuals or firms. The same limitations are present in studies such as Joaquim *et al.* (2019) and Ponticelli & Alencar (2016) that relies on the same dataset. The authors circumvent some of the problems by relying on a confidential loan-level dataset.

Data about the COPOM meetings, its decisions, and the current interest rate are available on the Brazilian Central Bank website. I manually assign each meeting to a given month since it occurs in intervals of 45 days and lasts for usually two days. If the meeting occurs in two subsequent months, I use the second day's month due to the interest rate being valid from that moment onwards. Then, I merge the interest rate time series with the panel of bank branches by month-year observation. I use the interest rates in level for my specifications and the use of an unexpected interest rate (predicted minus realized) is unfeasible because the market analysts predict correctly more than 80% of the cases even one day previous to the COPOM meetings.

Table 1.1 reports how the reference interest rate is distributed over the year. The average monetary shock is reasonably uniformly distributed, which avoids concerns that monetary policy shocks are seasonal. One can also observe that all months have COPOM meetings occurring, with October as the month with the highest frequency. More importantly, there is enough heterogeneity for the Main Month variable while having randomness in the Selic values, which translates into a substantial variation at the branch level. The joint distribution of the two variables is of prior importance for my identification strategy, which will be discussed in the next section.

Table 1.1: Distribution of the Reference Interest Rate

	Selic on Main Month		Selic on Month		Copom
	Mean	Obs.	Mean	Obs.	# Meetings
January	10.037	109,951	10.500	286,165	10
February	10.095	145,457	10.430	286,043	5
March	10.062	138,559	10.267	286,037	13
April	9.997	199,729	10.213	287,224	12
May	10.006	140,591	10.074	287,586	8
June	10.091	225,884	10.083	287,238	10
July	10.087	121,874	10.030	287,607	13
August	10.065	167,625	9.975	288,363	7
September	10.048	225,225	9.907	288,799	10
October	10.058	342,786	9.776	288,493	15
November	10.082	777,105	9.795	289,705	4
December	10.081	858,832	9.771	290,358	9
Total	10.067	3,454,000	10.067	3,454,000	116

Further, I made few adjustments to exclude abnormal cases in the data. First, using the National Wide Consumer Price Index (IPCA), I correct the monetary variables for inflation and report them as December 2020 values. In addition, I exclude branches that have reported zero lending volume since these branch's main businesses are not related to the credit market. In Table B1, I present the computations for all variables.

In Table 1.2, I present the descriptive statistics. After adjustments, I obtained a comprehensive dataset with almost 3.5 million observations. It covers 23,051 branches from 134 financial institutions in 3,613 out of 5,570 Brazilian municipalities (64.86%). Also, the data spam from January 2006 to December 2020, covers a total of 180 months, 116 COPOM meetings, and 73 changes in the interest rate. The average (median) branch has a lending volume of R$ 22,297,831 (R$24,940,411) for their clients, whereas the branch size is R$ 110,000,998 (R$ 110,221,220) in total assets. Moreover, the number of branches and banks per municipality is skewed towards large markets. There are 419 (22) branches per municipality and 22 (7) banks per municipality in my sample.

Table 1.2: Descriptive Statistics

Variable	Mean	S.D.	Min	Median	Max
Main Month	0.108	0.310	0	0	1
Selic Meta (%)	10.067	3.309	2	10.750	17.250
Ln(Loan Volume)	16.920	1.807	0.039	17.032	26.779
Size	18.516	1.573	0.039	18.518	31.860
Share	17.868	30.584	0	1.974	100
Private	0.549	0.498	0	1	1
Public	0.449	0.497	0	0	1
MS $\geq$ 95%	0.579	0.494	0	1	1
20% < MS < 95%	0.157	0.364	0	0	1
MS $\leq$ 20%	0.264	0.441	0	0	1
n = 180	0.547	0.498	0	1	1
150 < n < 180	0.140	0.347	0	0	1
n $\leq$ 150	0.313	0.464	0	0	1
Presence (months)	159.524	30.637	60	180	180
Branches per Muni.	419.004	832.188	1	22	2612
Banks per Muni.	22.304	32.144	1	7	105

The data comprises 23,051 branches from 134 financial institutions in 3,613 municipalities over the period of January 2006 to December 2020, covering 180 months, 116 Copom Meetings, and 73 changes in the reference interest rate. In total, all variables have 3,453,618 observations. For a more complete description of variables check Appendix B1.

Some statistics call attention at first sight. The average reference interest rate for the sample is 10.67% per year. The high market concentration in the Brazilian banking sector can be seen in the raw data. Roughly 58% of observations are from branche*itive market, where its market share is below 20%. The average branch in the data, conditional on the requirement of at least 60 months of data, is observed for approximately 160 months[1.5].

1.5 Empirical Strategy

The main goal of this study is to take advantage of the idiosyncrasy of each bank branch's clientele to observe how branches react to a change in the reference interest rates. More importantly, I aim to obtain an estimate of how this increase in cost is transmitted to the clients. Ideally, we would have an exogenous source of variation impacting bank branches' cost of capital. A simple interest rate is likely correlated to the banking sector, macroeconomic factors making identification hard. However, if interest rates were exogenous

[1.5] A related issue is the inclusion of lags of the dependent variable, that might lead to biased estimates in short panels. As described by Nickell (1981), the degree of bias decreases at rate $1/T$ where T is the number of observations within a group. Since the average branch is observed for roughly 160 months, this bias is likely to be considered second-order.

we would have no reason to use open market operations, that define the interest rate, as a tool for monetary policy. For instance, suppose agents face good opportunities for investment and demand more loans. These loans being provided would increase money in circulation leading to inflation and forcing Central Banks to increase interest rates to curb inflation.

To overcome this limitation, I interact the reference interest rate with the main month from each branch. Hence, each branch will be affected according to its clientele seasonality pattern. This variable takes the value of one if the branch is at the month with the highest historical lending volume. I assume that during its main month, it will be more problematic for the branch to cut credit because it is exactly when it has its highest demand. Statistically speaking, one may interpret *Main Month* as a treatment variable that identifies a branch as treated in its main month and control otherwise. Both groups are composed of the same unit of analysis, but not for all periods. This property makes treated vs. control groups largely comparable. Also, the main months are based on a historical measure, which helps mitigate concerns about contemporaneous relations with other variables.

For testing the effect of a more contractionary policy on lending volume, I use this interaction term to capture a plausibly exogenous variation from the temporal and cross-sectional dimensions in the transmission of monetary policy. The interaction of these variables results in a different effect for each month. The identification assumption is questioned if any other event occurs simultaneously with the change in the Selic Meta rate for the treatment group (inside the main month) but not for the control group (outside the main month). These assumptions are enough to establish a causal link to a government policy through the average effect (Kahn & Whited, 2018). Thus, I use the following specification to estimate the response in lending from changes in monetary policy during the branches' costlier months:

$$\begin{aligned} Y_{imt} = \alpha Selic\ Meta_t + \sum_{\tau=1}^{11} \beta_\tau Main\ Month_{imt+\tau} \times Selic\ Meta_t \\ + \theta_{i(t)} + \varepsilon_{imt} \end{aligned} \tag{1.1}$$

where the dependent variable Y_{imt} is the $Log(Loan\ Volume)_{imt}$ measured for branch i, located at municipality m, during month-year t; α captures the effect of monetary shocks in the main month due changes in $Selic\ Meta_t$; the $Main\ Month_{imt}$ variable is an indicator that assumes value one if the branch is in its month with the highest value in its loan volume, being $\tau = 0$ the omitted category. Therefore, when $\tau = 1$, it refers to one month after the main month of that branch. Finally, $\theta_{i(t)}$ is a branch-month fixed-effect[1.6], which is used to take into account possible seasonal patterns that each branch might face across months. With this specification, if an event occurs affecting the treated group, and it is not related to month or branch specificities – which are already controlled by fixed effects – then the interpretation is impaired. Because such an event is unlikely to occur, my identification strategy presumably allows β_τ to capture the desired effect. To show the effect on $Log(Loan\ Volume)_{imt}$ I use the conditional expectation operator in the above equation to obtain:

$$\mathbf{E}[Y_{imt}|\cdot] = \alpha Selic\ Meta_t + \sum_{\tau=1}^{11} \beta_\tau Main\ Month_{imt+\tau} \times Selic\ Meta_t + \theta_{i(t)} \tag{1.2}$$

To easily see how the coefficients β_τ can capture the marginal effect of a change in interest rates during the dates after the main month, I derive with respect to the reference interest rate. Thus, we end up with the following expression that accounts for the total effect of a change in interest rates:

$$\frac{\partial \mathbf{E}[Y_{imt}|\cdot]}{\partial Selic\ Meta_t} = \alpha + \sum_{\tau=1}^{11} \beta_\tau Main\ Month_{imt+\tau} \tag{1.3}$$

As can be seen from the previous Equation the total effect of a change in $Selic\ Meta$ has to take into account the month in which the change is being made. Therefore, to see the total effect of a change in interest rate one month later, one should sum the current period effect α and the subsequent period effect captured by β_1. All regression tables have a term called $\sum_{\tau=1}^{11} \beta_\tau$ and $\alpha + \sum_{\tau=1}^{11} \beta_\tau$ to separate the dynamic effect of interest rates from the total effect, respectively. These coefficients are tested to indicate if, taking into account the whole dynamic of the shock, it is more or less pronounced during subsequent months. Thus, when the test rejects the null hypothesis, we have evidence that - in at least one month after the main month - there is a significant increment or reduction in the effect α for the $Selic\ Meta$.

1.6 Results

In this section, I provide the estimated regressions using Equation 1.1 and depict a visual representation of the effects for a clearer understanding of the transmission path of a change in interest rates. All graphs in this paper have the same y-axis range so that results can be easily comparable. I focus on exposing the results in three dimensions. First, about the initial reduction

[1.6] The (t) subscript is used to remind the reader that it is not a time (i.e. month-year) fixed effect. Rather, I used a dummy for each month, consisting of a total of twelve for each branch.

in credit volume at date t. It shows how branches transfer the cost in credit *immediately* to clients, observing a reduction in volume. Second, the dynamic effect is captured by the path in the loan volume. The presence of a non-horizontal line is indicative that relationship lending is playing a role in the transmission of monetary policy, as will be further explained. Finally, the total elasticity of credit is obtained to compute the dimension of the effect for the whole period.

Further, I investigate relevant heterogeneous effects commonly present in the literature, but not yet explored using the identification strategy in this study. I test if effects vary for market concentration, and for how long a branch is present in a municipality (proxying for relationship lending). These two characteristics are hard to disentangle in empirical research, but I try to circumvent the problem using two distinct metrics. Additionally, I verify if the type of ownership is relevant to explain the results. Finally, a set of robustness tests is performed to ascertain the external validity of the presented evidence.

1.6.1 Main Effects

In the first column of Table 1.3, the coefficient α for *Selic Meta* is as expected. An increase of 1% in interest rates is associated with a contemporaneous decrease of 2.8% in loan volume. The dynamic effect composing the next months is in the order of 4%. To observe the full effect of a change in interest rates, we should add these two terms and test for significance. The coefficient for $\alpha + \sum_{\tau=1}^{11} \beta_\tau$ is statistically and economically significant. The total effect of a change of 1% in the interest rates is a decrease of 6.7% in Loan Volume for the current and subsequent months of a change in interest rates during the main month. Typically, the changes in interest rates in Brazil are in the order of 25 basis points, thus the usual change in loan volume is one-fourth of the estimated coefficients. Consequently, a usual change of 0.25% in Selic by the Central Bank is associated with a total decrease of 1.7% in loan volume.

A visual inspection of this effect can be seen in Panel a) of Figure 1.3. The volume of loans starts to reduce more prominently after six months, consistent with the idea that branches protect their clients from shocks in months with higher demand for credit and start to charge the remaining costs after a couple of months. Branches smoothing to pass the cost generate consequences for the transmission of monetary policy, being the timing and the amount of costs deviating from the planner's target.

Taken together, the results point to the relevance of the bank lending channel, in which changes in interest rates are transmitted to the economy via

Table 1.3: Regression Table

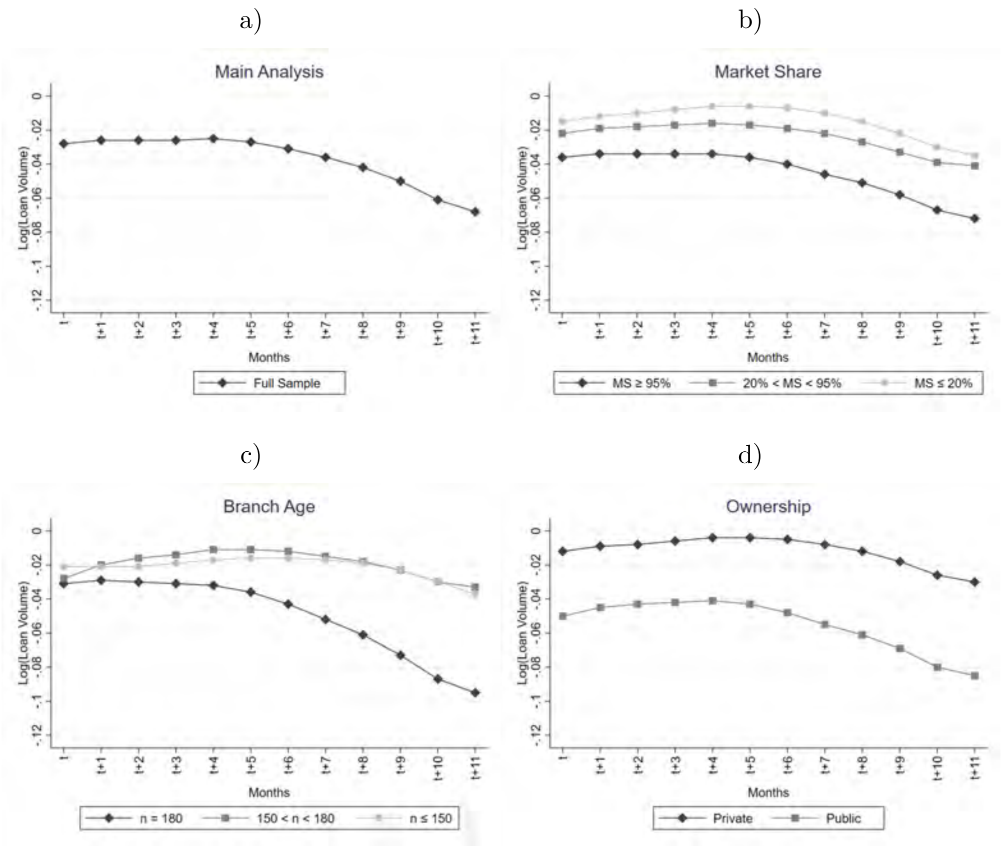
		Market Share			Branch Presence			Ownership	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full	MS $\geq$ 95%	20% < MS < 95%	MS $\leq$ 20%	n = 180	150 < n < 180	n 150	Private	Public
α	-0.028	-0.036	-0.022	-0.015	-0.031	-0.028	-0.021	-0.012	-0.050
	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
β_1	0.002	0.002	0.003	0.003	0.002	0.008	-0.000	0.003	0.005
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
β_2	0.000	0.000	0.001	0.002	-0.001	0.004	0.000	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
β_3	0.000	-0.000	0.001	0.002	-0.001	0.002	0.002	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
β_4	0.001	-0.000	0.001	0.002	-0.001	0.003	0.002	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
β_5	-0.002	-0.002	-0.001	0.000	-0.004	0.000	0.001	0.000	-0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
β_6	-0.004	-0.004	-0.002	-0.001	-0.007	-0.001	0.000	-0.001	-0.005
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
β_7	-0.005	-0.006	-0.003	-0.003	-0.009	-0.003	-0.001	-0.003	-0.007
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
β_8	-0.006	-0.005	-0.005	-0.005	-0.009	-0.003	-0.002	-0.004	-0.006
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
β_9	-0.008	-0.007	-0.006	-0.007	-0.012	-0.005	-0.004	-0.006	-0.008
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
β_{10}	-0.011	-0.009	-0.006	-0.008	-0.014	-0.007	-0.007	-0.008	-0.011
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
β_{11}	-0.007	-0.005	-0.002	-0.005	-0.008	-0.003	-0.007	-0.004	-0.005
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
$\sum_{\tau=1}^{11} \beta_\tau$	-0.040	-0.036	-0.020	-0.020	-0.064	-0.004	-0.017	-0.017	-0.035
	(0.009)	(0.007)	(0.020)	(0.030)	(0.013)	(0.032)	(0.016)	(0.013)	(0.011)
$\alpha + \sum_{\tau=1}^{11} \beta_\tau$	-0.067	-0.071	-0.043	-0.035	-0.095	-0.032	-0.037	-0.028	-0.085
	(0.008)	(0.007)	(0.018)	(0.029)	(0.011)	(0.029)	(0.014)	(0.012)	(0.009)
Observations	3,192,116	1,855,613	484,079	823,889	1,773,317	449,698	969,101	1,749,907	1,436,902
Adj. R-squared	0.843	0.902	0.932	0.824	0.873	0.764	0.799	0.843	0.724
Branch x Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The statistics above indicate the dimension of the dynamic effect and the total effect of a change in interest rates, respectively. Standard errors are clustered at the municipality level. Singletons are dropped to avoid underestimation of standard errors. Standard errors are reported in parenthesis.

bank loans. However, I find evidence that there is not a clear channel from which interest rates can be transmitted to the economy, as is often assumed in many theoretical studies (e.g. Stiglitz & Weiss 1981; Bernanke & Gertler 1995). As described on the Central Bank of Brazil's website, the models used by the Central Bank for estimation are built expecting a full transmission of credit cost by the nineth and twelveth month after a monetary shock. Therefore, my results empirically demonstrate this path and agree with previous evidence by Coelho *et al.* (2010) and Berger & Udell (1992) of price stickiness of credit rates. In sum, the non-horizontal path of credit volume over time suggests that branches do not fully transmit the total cost of credit in the first period, leaving them to fully charge later. This non-linear pattern in lending volume calls for further investigation.

It is worth noting that this effect comprises an overall effect on the economy, grouping all types of branches and market characteristics. In the next steps, I will show in which types of branches this behavior is observed. I provide evidence that this result is more than a mere common practice by branches and occurs mostly in contexts of branches competing for clients in their local market. Subsequently, I will show which type of branches are more protective of

Figure 1.3: Dynamic effects of Interest Rates



These graphs depict the sum of coefficients in the expression $\alpha + \sum_{\tau=1}^{11} \beta_\tau$.

their clients and the consequences of such behavior for the monetary authority, as it highlights the mechanism behind this effect.

1.6.2 Competition and Relationship Lending

To investigate what are the possible mechanisms that can explain the dynamic effect shown by the non-flat curve in Panel a) of 1.3, I proceed with the analysis based on branches' characteristics. The hypothesis is that, according to branch characteristics, some might offer more or less protection to their clients. Here, I interpret protection as the smoothing in the reduction of loan volume to the branches' clients. Starting with the market share that each branch possesses at a given time. I divided the sample according to the market power that a branch might exert in its municipality. I arbitrarily defined three intervals based on the branches' market shares' overall distribution. I allow branches to freely move from one group to the other over time which makes it unlikely that the observed effect comes from another branch characteristic that is not related to competition. It is expected that branches with larger market share can extract more rent from their clients, transferring more the increase in credit, but helping in smoothing the reduction in lending volume by having a non-linear reduction in lending.

In columns 2 to 4 of Table 1.3 all estimates for α are negative and significant but with a clear decreasing pattern. Branches with high market shares - measured by the share of loan volume in each municipality -reduce more of the loan volume in the current month (3.6%) than branches with medium (2.2%) and low (1.5%) market shares. Branches with more market power are those with less incentive to compete because they are closer to having monopolistic benefits. Also, those branches already have relationships with a large portion of their clients. Consistent with this rationale, my results point out that branches with higher market share are charging more to their clients.

Further exploring the results, one can see that branches in the group with a high market share transmit more in the next periods than the in other two groups. The dynamic effect of the reduction in the credit is 3.6%, followed by a non-statistically distinguishable change in the other two groups. Thus, the dynamics of lending in markets closer to monopolistic branches are substantially different from those with less concentration in a few branches. The total elasticity is 7.1%, 4.3%, and 3.5% for the three groups respectively, suggesting that branches with more market share have a more inclined path, indicating that they better smooth the transmission of monetary shocks to their clients. In other words, they do charge more, but not entirely in the first month. Panel b) of Figure 1.3 shows visually how the behavior of credit volume strongly differs across market shares. Only the group with more than 90% of the market share seems to hold to charge substantially more in the subsequent months.

Naturally, competition might motivate branches to adopt new practices. Especially for branches with small market share, or operating in markets with competitors already owning a large portion of the credit market. In a textbook example of a Cournot oligopoly with identical goods, it is expected that the same marginal increase in costs (i.e. increase in prices) will affect less the monopolist than the others. The equilibrium quantity of loans will decrease less for the monopolist, which is the opposite that we find in this study[1.7]. Thus, another dimension seems to be important to explain this behavior. I argue that the relationship developed by banks with their clients is at the core of these results. Boot & Thakor (2000) and Degryse & Ongena (2005) mention that relationship lending becomes more relevant when competition

[1.7] Hannan & Berger (1997) find evidence that increases in interest rates is less transmitted to the deposits rates if a bank has more market power. However, the authors have not explored if the same is observed in credit rates is fiercer, being hard to disentangle one from the other. Relationship lending can be interpreted as a competitive advantage that banks adopt to acquire a larger market share. Thus, those branches that already have market power, are more inclined to engage in relationship lending, being more protective with their clients, but charging more for it. My results translate this rationale into showing that the more inclined curve in loan volume is observed in branches with larger potions of market share (closer to monopolists).

To further investigate if relationship lending is a plausible mechanism to explain my results, I observe the role of relationships in branch lending behavior. Unfortunately, in my context, I cannot observe each client's relationship with each branch[1.8]. Therefore, I have to rely on a widely used proxy in the literature. I compute for how many periods each branch is present in the data as a proxy for the relationship developed over time. Branches with a long presence in the market are mainly composed of branches appearing in all periods of analysis.

Consequently, these branches likely have more than 180 months of activity in the Brazilian credit market, but this does not impose an issue on my analysis since I want to observe the relative difference. Additionally, the correlation of 0.78 between the branch presence in months and average market share suggests that branches observed for a long time in the banking market are also owners of a larger market share. According to the literature, it is hard to completely disentangle these two effects, but my analysis appears to partially overcome this limitation.

Columns 5 to 7 of Table 1.3 show that the current shock of interest rates are in similar magnitude, roughly between 2.1 and 3.1%. Despite the three groups starting from a very similar interest rate in date t, their paths change substantially over time. The coefficient $\sum_{\tau=1}^{11} \beta_\tau$ is distinguishable from zero only in the group present for the 180 periods. This group represents the branches that already acquired relationships for a longer time, whereas the other two groups are composed of branches that are still developing their relationships. The branches initially charge the same, but the ones present for a longer time start to extract rents after some time. They do protect their clients in the beginning, but later charge more than the other two groups. The groups of branches with fewer relationships show no significance for the dynamic effect, indicating that they transmit the whole increase in credit cost right in the first period.

To better illustrate this effect, in Panel c) of Figure 1.3 one can see an

[1.8]Several studies rely on credit registry data for Brazil, but the data lacks an identifier that permits the researcher to link a loan to a specific branch.

almost horizontal line for branches with a short presence in data. The total effect is an elasticity of 9.5%, 3.2%, and 3.7% respectively for each band of time. My argument about the competition incentive of branches dialogue with the literature on relationship lending. For instance, Beck *et al.* (2018) argue that banks characterized as "relationship banks" help firms during economic downturns after acquiring enough information about them during good times. This effect is in line with the argument that branches develop relationships using soft information about local borrowers to later extract rents (i.e. the holdup problem presented by Sharpe 1990). Therefore, relationship lending seems to be a relevant dimension, in addition to competition, that can explain the results obtained in my analysis.

1.6.3 Branch Ownership

In this section, I explore whether results differ according to the branch ownership. Whereas both types of branches can engage in relationship lending in the most diverse competitive settings, it is interesting to investigate how an increase in credit cost is transmitted to the economy. One possible explanation consists of the exposition of certain banks to instruments linked to reference interest rates. Ippolito *et al.* (2018) and Gomez *et al.* (2021) find that banks are more exposed to fluctuation due to some of their characteristics, such as the income gap and the proportion of contracts with variable interest rates. In the Brazilian context, exposition has an important role because public banks in Brazil are responsible for two public mandates: the transmission of subsidized loans for firms and governmental programs to promote housing credit.

Another possible explanation is that Public banks have incentives that might differ from profit maximization. For instance, Public banks can be used by politicians to supply credit for supporters or prioritized sectors near elections (Sapienza, 2004; Coelho *et al.*, 2013; Carvalho, 2014). In particular for Brazil, Coelho *et al.* (2013) find that public banks exert little competition compared to private banks even when considering public mandates as a control variable. Moreover, if public banks serve a different clientele, they can be responsible for supplying credit to borrowers that private banks are not intended to supply. For instance, public branches might focus on more opaque firms and borrowers, that require special attention to be included in the banking sector. This predicts that public banks will charge more to these clients but also present a more inclined path because they are smoothing reduction in lending.

In columns (8) and (9) of Table 1.3 we observe a negative effect of

Selic Meta for private and public branches. Notice that the contemporaneous reduction in loan volume in private branches is substantially smaller than for public branches. For private branches, there is a reduction of 1.2% in the loan volume while for public branches this reduction reaches 5%. Also, the dynamic effect is present only for public banks, indicating a dynamic effect of 3.5%. The total effect estimated is a reduction of 8.5% in loan volume for the main month and the next eleven months. The graph in panel d) of Figure 1.3 shows the striking difference between loan volume reduction in public and private branches. The public branches' line has always been below the private line since the first period and also displays a more steep curvature.

This large effect on public banks is expected according to the literature as previously explained: in which public banks might be less profit-oriented and more exposed to the reference interest rates. Public branches have more earmarked loans that are usually linked to the national interest rate. Coelho *et al.* (2010) mentions that for 2006, the first year of my data, earmarked loans accounted for 15.1% of total lending, and for 2017 this rate reached 48.7% (Castro, 2019). Given such a large portion of credit in earmarked loans, changes in interest rates are automatically transferred to borrowers, leaving little room for public banks to protect their clients, which explains the difference in levels. To explain the different shapes in the curves - as captured by the dynamic effect - the rationale behind relationship lending seems to be a good candidate. Public banks smooth the transmission to their clients, offering protection to the larger decrease in credit volume compared to private branches.

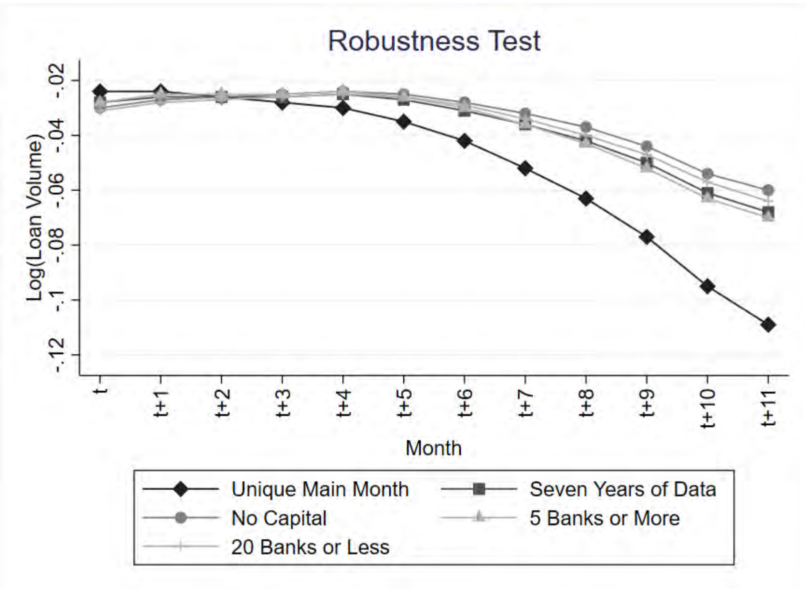
1.6.4 Robustness Tests

To ascertain whether the estimates are robust to different requirements in data and markets' characteristics, I re-estimate the main analysis in five different subsets. In Table 1.4 I show the estimates and in Figure 1.4, I plot the estimates in a graph to better observation of the dynamic effect. The lines drawn are almost overlapping but for the Unique Main Month subset. In the first column, I dropped branches with more than one main month identified. The reason for exclusion is that some branches might be counted more than once in the analysis. However, other relevant aspects of the local clientele might be unconsidered in this setting. Regardless of the pros and cons, the total effect is slightly larger at the farther months but the dynamics remain similar over time. This can be explained because the remaining branches have one main month to act, thus having only one time window to pass the cost to their clients.

Another data dimension is taken into consideration in column two. I changed the requirement of at least 5 years of data for computing the main month. This requirement guarantees that each month is observed at least 7 times and the main month is better computed. When I consider 7 years of data the number of observations falls slightly, but the results also do not change. The total effect is 6.6% which is similar to the total effect 6.7% in reduction of loan volume for the full sample.

The subsequent analysis considers market characteristics that might drive the results. In the third column, I removed the 26 municipalities that are capitals of their states plus the federal district. Because one might expect that the effect is present only in places with more dynamic economies, I removed these observations. The analysis suggests this is not the case as the estimates remain similar. Further, I exclude too-small and too-large banking markets. In other words, I check if it is possible to identify the dynamic effect in credit markets that are more usual for the general Brazilian context. Column 4 reports coefficients for markets with 5 banks or more and column 5 for 20 banks or less. Once again, the coefficients are roughly the same, suggesting that the effect is robust across several subsamples.

Figure 1.4: Robustness Tests



1.7 Conclusion

The mechanism through which banks transmit monetary shocks to the real economy is a frequently studied topic in economics. In this paper, I explore the fact that bank branches specialize in different types of clients

Table 1.4: Robustness Tests

	(1) Unique Main Month	(2) Seven Years of Data	(3) No Capitals	(4) 5 Banks or More	(5) 20 Banks or Less
α	-0.024	-0.028	-0.030	-0.028	-0.031
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
β_1	-0.000	0.002	0.003	0.003	0.003
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_2	-0.002	0.000	0.001	0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_3	-0.002	0.000	0.001	0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_4	-0.002	0.001	0.001	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_5	-0.005	-0.002	-0.001	-0.002	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_6	-0.007	-0.004	-0.003	-0.004	-0.003
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_7	-0.010	-0.005	-0.004	-0.006	-0.005
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_8	-0.011	-0.006	-0.005	-0.007	-0.006
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_9	-0.014	-0.008	-0.007	-0.009	-0.007
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
β_{10}	-0.018	-0.011	-0.010	-0.011	-0.010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β_{11}	-0.014	-0.007	-0.006	-0.007	-0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sum_{\tau=1}^{11} \beta_\tau$	-0.086	-0.039	-0.029	-0.041	-0.034
	(0.004)	(0.010)	(0.011)	(0.012)	(0.010)
$\alpha + \sum_{\tau=1}^{11} \beta_\tau$	-0.110	-0.066	-0.059	-0.065	-0.065
	(0.004)	(0.008)	(0.010)	(0.010)	(0.009)
Observations	2,461,087	3,160,862	2,150,410	2,314,381	2,345,237
Adj, R-squared	0.851	0.843	0.852	0.829	0.850
Branch x Month	Yes	Yes	Yes	Yes	Yes

The statistics above indicate the dimension of the dynamic effect and the total effect of a change in interest rates, respectively. Standard errors are clustered at the municipality level. Singletons are dropped to avoid underestimation of standard errors. Standard errors are reported in parenthesis.

within local credit markets. More specifically, I use for identification purposes the month of the year in which each branch's clientele borrows more. Using this heterogeneity at the branch level, I highlight the protective behavior of some branches in favor of their clients. This mechanism is mostly explained by relationships that branches develop with their clients and has unintended consequences of imposing a burden on the clear transmission of monetary policy. Since this effect consequently disturbs the transmission of monetary policy, it must be taken into consideration by the monetary entity.

I provide evidence of a barrier in the bank lending channel by showing that the expected contraction in credit supply due to a change in the cost of capital (increase in the reference interest rates) is smoothed in periods after high demand. After a couple of months, according to the visual inspection provided, branches differ in the way their increase in the cost of capital is transmitted to their clients. Hence, branches are reluctant to immediately pass the total increase in credit cost to their clients allowing for the interpretation of sticky prices that are reflected in the loan volume.

Further, this study explores which types of branches present a more inclined decline in lending volume due to the increase in interest rates. This non-horizontal pattern is interpreted as the protection that branches offer to their clients due to the relationships developed. Branches with larger market shares, despite charging more, do it smoothly. Comparably, branches with market shares lower than 90% do not present this pattern. Regarding the time in which the branch is present (usually a proxy for relationships developed over time), only branches with longer presence offer such protection, albeit charging more than branches present for less time. Private banks seem to not show such protective behavior, in addition to charging less comparable to public branches. However, public branches do show a non-horizontal pattern in their lending volume suggesting that they serve a different clientele.

The main takeaway of this study is that policymakers should consider local market practices to be more effective when designing monetary policy. Policies can be improved by considering an optimal composition and timing when adjusting reference interest rates. Some branches are more eager to protect their clients by avoiding the complete transmission intended by the monetary authority at a given time. Branches from public banks, with larger market participation, and a longer presence in the local market, are more eager to smooth the cut in lending to their clientele but also cut more lending when there is a change in *Selic*.

On the other hand, this evidence is important for borrowers because branches try to match the seasonal demand by keeping credit volume. Even when the cost of credit increases due to a change in Selic, some branches smooth this transmission to their borrowers. Thus, ceteris paribus, clients are more likely to obtain credit at smaller cost from branches of private banks, that are new in their markets, and that have lower market share. However, they might suffer more from monetary shocks since these branches do not offer a smoothing mechanism as their counterparts.

Appendix A: Variables Description

Table A1: Variables Description

Variable	Description
$Main\ Month_{imt}$	Indicator variable that takes value of one if the current month is the one with highest historical lending volume. Check Section 1.4 for a complete description of the calculation process.
$Selic\ Meta_t(\%)$	Brazilian reference interest rate.
$Ln(Loan\ Volume)_{imt}$	Natural Logarithm of Total Lending Volume negotiated by a branch.
$Size_{imt}$	Natural Logarithm of Total Assets of a branch.
$Market\ Share_{imt}(\%)$	Total Lending Volume as a ratio of the aggregate Total Lending Volume for a given municipality on each time.
$Private_{im}$	Indicator variable that takes value of one if its branch is from one of the private banks from Brazil.
$Public_{im}$	Indicator variable that takes value of one if its branch is from one of the public banks from Brazil.
$Presence_{im}$	It counts the number of months in which a branch is present in the data.
$Branches\ per\ Municipality_{mt}$	The number of branches at each municipality-time.
$Banks\ per\ Municipality_{mt}$	The number of banks at each municipality-time.

Observations: BCB means Brazilian Central Bank. All monetary values are adjusted for inflation by IPCA index and measured as of December 2020. Dataset consists of monthly data from January 2006 to December 2020.

2
Seasonality in Political Lending

Abstract: There is broad evidence showing that political lending is detrimental to the economy and, in particular, to developing economies. I explore publicly available data about bank branches to compute the seasonality faced by each branch in Brazil. Then, I compare branches from government-owned and private branches having their most important month for lending occurring concomitantly to elections. I show that politicians exploit branches' peak in demand to reallocate loans in periods of election. More importantly, politicians seem to take advantage of banks' internal structure to provide loans into politically attractive regions and away from politically unattractive ones. These results underscore the importance of implementing policies aimed at mitigating political interference in credit activities, thus promoting financial stability and economic development.
Keywords: political lending, government-owned banks, seasonality, elections, internal finance markets

2.1 Introduction

Political lending can be defined as the practice in which financial institutions extend credit or loans to politically connected entities for reasons other than financial viability. Agents act mainly through influence in public entities such as government-owned banks[2.1](La Porta *et al.*, 2002). Theory predicts that more loans are directed to places where the political influence is larger and in periods when it is most necessary. In other words, politicians exert pressure during elections to distribute loans to politically attractive areas. Evidence about this phenomenon is large in the literature, and little contribution has been seen in the last years. In this study, I add an important temporal component not yet explored by finance scholars. Thanks to the Brazilian electoral context, I can explore the role that credit highs and lows play in explaining increases in loan volume. Do politicians take advantage of local credit seasonality to drive political lending?

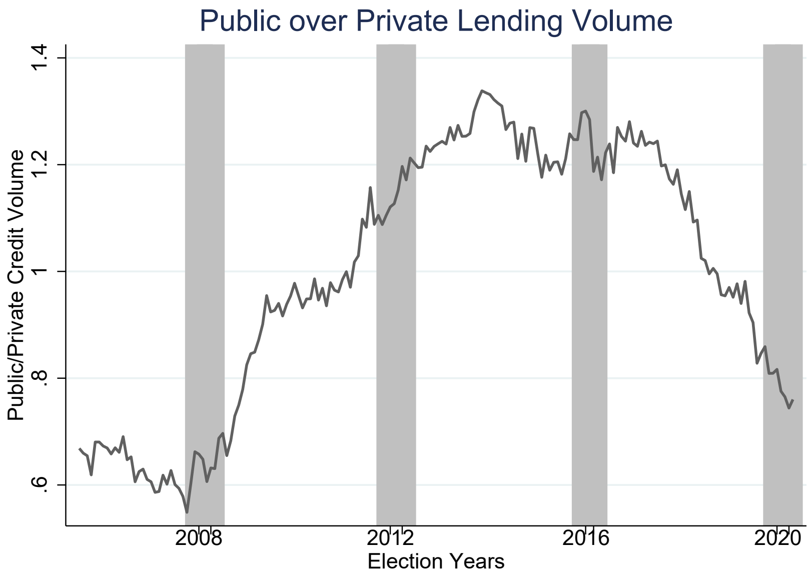
Political lending is detrimental to the economy in several dimensions. Khwaja & Mian (2005) finds that loans misdirected to politically connected firms are substantially more likely to default and Coleman & Feler (2015) provide evidence of politically and inefficiently allocated loans at the onset of the 2007-08 Crisis. Carvalho (2014) finds that politically attractive regions experience higher employment levels to the detriment of less attractive regions near elections. These types of problems can be seen both in emerging countries (Carvalho, 2014; Cole, 2009; Coleman & Feler, 2015; Khwaja & Mian, 2005) and in developed economies (Bertrand *et al.*, 2007; Sapienza, 2004). Some articles find that these inefficiencies are more prevalent in poor countries, where usually the institutions are weaker, the government has more participation in the economy, and the financial sector is less developed (Shleifer & Vishny, 1998; Dinç, 2005).

However, other economic factors might play a role in explaining this sudden rise in public lending. It might be the case that elections generate investment opportunities that require credit, and public banks can strategically supply this capital with subsidized interest rates Sapienza (2004) or to prioritized sectors (Carvalho, 2014). As most articles rely on yearly data, it might be the case that other concomitant factors influence the results obtained. For instance, in September 2008 Lehman Brothers filed for bankruptcy, and in October municipal elections occurred in Brazil. After the 2008 crisis, we witnessed a huge increase in public lending in Brazil, as illustrated in Figure 2.1.

[2.1]In this study, I use state-owned banks and public banks interchangeably, and not as banks stocks being publicly traded in the stock exchange.

During the electoral periods, it is possible to see an increase in the aggregate public-to-private credit ratio, but little can be said about the changes in local credit markets.

Figure 2.1: Lending Volume over Elections



Brazil is a convenient setting for studying this phenomenon for several reasons. First, the banking sector in Brazil is marked by having the second highest interest rate charged to clients in the globe (The Global Economy, 2020). The need for political favors turns out to be more salient when the main source of credit for firms is expensive. Second, Brazil is often associated with corruption scandals. The Lava Jato (Car Wash) operation in Brazil primarily focuses on uncovering corruption and money laundering schemes involving the state-owned petroleum company Petrobras, which is one of the largest oil companies in the world. Colonnelli & Prem (2022) mentions that most municipal corruption schemes occur through the theft of local funds or by bribing and legal disparities in public procurement in Brazil to favor. Corruption is different from political lending but also causes misallocation of funds based on favors rather than efficiency. Third, the Brazilian Central Bank is an important source of public datasets about the banking sector. In their website is possible to obtain data at the branch-level in a considerably high frequency. This permits a deeper look at the timing in which elections occur.

This study utilizes monthly balance sheet data from every bank branch in Brazil. Monthly data allows the econometrician to observe precisely the months in which the lending volume usually increases and match it with the electoral period. Therefore, a second layer of identification can be investigated. I can observe when branches' clients are at the peak of demand and compare their behavior with private branches during the Brazilian Electoral Period. To capture the seasonality in historical loan volume outstanding, I adapt the methodology described by Chang *et al.* (2016) for branches and on a monthly basis. As seasonality is determined by past values, the likelihood of contemporaneous events influencing results is mitigated. Therefore, rather than simply comparing public to private banks' volume of loans, I compare public and private *branches* lending when both have their historical peak of lending occurring contemporaneously with elections.

Results point toward politicians indeed exploiting branches' seasonality in elections. I observe an additional expansion of 2.4 to 8.2 % in loan volume by public branches when its peak in demand happens during elections compared to private branches in the same situation. If borrowers' demand and municipality economic conditions are similar between the two types of branches, we should not see growth in loans happening, which suggests that political lending is likely to occur on the supply side. To provide robustness to my findings, I perform a placebo test considering that elections occur one year before the actual elections. The non-significance of results exhibits that the increase in credit is indeed due to elections and not rollover debt due to branches' portfolios.

To delve deeper into the mechanisms underlying credit redistribution, two analytical exercises are conducted. Firstly, the sample is stratified into municipalities characterized by the mayors in office being from the same party as the president. I find that credit grows by 3.4 to 8.8% in public branches located in non-aligned municipalities when their main month belongs to the electoral period. The point estimates are comparable in magnitude with the main results. Agreeing with this rationale, in municipalities already dominated by the political influence of the president, there is little reason to promote credit growth. A better intervention would be to reduce credit in aligned regions to redirect capital into additional regions. Consonantly, Mian *et al.* (2020) provide evidence that surges in credit supply can lead to more severe recessions by amplifying the business cycle. The results indicate a drop in credit volume in the order of 20.0 to 25.7% for public branches having their peak within the election period. This large and sudden drop in credit suggests that politicians use public banks' borrowers' demand and internal market to reallocate resources from branches in a few aligned municipalities to branches in the majority of other municipalities that are non-aligned.

The second exercise divides the sample into municipalities by varying levels of wealth, delineated by GDP per Capita. As posited by theory, it is suggested that in economically disadvantaged municipalities, the cost of securing electoral support is comparatively lower (Gingerich *et al.*, 2014). Employing a similar framework as the primary analysis, the findings substantiate this rationale, revealing an increase in loan volumes within poor municipalities ranging from approximately 4.6 to 7.0%. Additionally, preliminary evidence indicates a potential small decline in credit supply in rich municipalities. However, further investigation is warranted to offer more conclusive insights. These two analyses give reason to conjecture that politicians are targeting loans to acquire new and cheaper votes.

These findings carry significant political and economic implications. It is imperative to devise mechanisms aimed at curbing political interference in government-owned financial institutions. The observed tendency for politicians to exploit branch seasonality underscores the need for heightened surveillance measures. Colonnelli & Prem (2022) demonstrates that municipal auditing programs in Brazil, intended to combat corruption, have yielded positive outcomes for local economic activity. Moreover, any intervention in this regard should meticulously consider both the source and destination of resources. Given the apparent practice of politicians utilizing branches in aligned municipalities to fund loans in non-aligned ones, monitoring this channel becomes crucial for mitigating the expansion of political lending.

2.2 Theoretical Issues

State-Owned Enterprises (SOEs) are entities owned and operated by the government. There are at least three theories for the existence of SOEs: social, agency, and political views, having distinct predictions for the behavior of public banks. The first theory suggests that SOEs are created to maximize the social benefit, instead of maximizing profits as a usual firm. Examples of sectors often cited under the Social Theory include healthcare, mail services, education, and public transportation. Therefore, this theory emphasizes the social aspect of SOEs, justifying them by promoting equity, accessibility, and social cohesion. Public banks, being a specific type of SOE, can be used to mitigate market failures such as access to credit in poorer regions, offering loans with subsidized interest rates, and engaging in socially profitable projects that private enterprises may neglect.

The Agency Theory adds the incentives of the SOE directors to the equation. While both the social and agency theories consider that public banks emerge to mitigate market failures, the agency theory supposes that managers can exert low effort or misplace resources for personal gains under the premise of maximizing broader social objectives. Hence, public banks can improve social objectives, but also create incentives for managers to divert. One example of such behavior is to supply credit for clients that can provide something in return for the managers, like future professional positions in the private sector, empire-building, and excessive risk-taking prioritizing short-term revenues to increase their compensation. Hence, both the social and agency views consider that government intervention is often justified to correct market failures and promote public welfare.

A third theory disagrees with the previous ones in that SOEs are not used to correct market failures, but to keep politicians in power and exert political influence in economic decisions (Shleifer & Vishny, 1998; La Porta *et al.*, 2002). According to the Political view, politicians are the ones responsible for influencing loan supply in public banks for personal gains. Hence, it creates another problem, by directing loans to the borrowers who by merit would have access to credit. For instance, to favor clientelism, incumbents can put pressure on appointed managers to lend to inefficient projects near elections. Politicians are considered egoistic individuals who want to remain in power and the allocation of resources is a political goal, instead of a problem of unaligned incentives. Therefore, one way to distinguish the agency view from the political view is to observe that more resources are being directed to places where political patronage is more profitable rather than simply a larger portion of loans being offered by public banks (La Porta *et al.*, 2002; Carvalho, 2014).

2.3
Literature Review

This study aims to contribute to both the literature on the consequences of having SOEs and to shed light on a new channel for the literature on Political Lending. Sapienza (2004) presented pioneering empirical evidence on political lending, utilizing firm-level loan data to discern the financing sources for each entity. The study reveals that loans from public banks carry lower interest rates compared to those from private counterparts. The author used firm fixed-effects that enabled the creation of a subset of firms that borrowed both from private and public banks. Thus, the *same* firm borrowed at a lower cost from public banks compared to private banks. This outcome indicates that public banks offer more favorable terms than their private counterparts, a phenomenon attributable to both agency theory and the political theory underpinning the existence of public banks. In addition, Sapienza (2004) explores the political affiliations of bank directors in Italy, linking them to local voting records to gauge the political sway of the directors' parties in each province. The main finding of the study is that the interest rates charged by public banks are lower in regions where the bank director's political party is stronger, favoring the political lending theory.

Khwaja & Mian (2005) finds that politically connected firms (i.e. if its director participates in elections in Pakistan) borrow 45% more and have 50% higher default rates. This effect is observed only in public banks, with private banks not providing political favors. Similarly to Sapienza (2004), the authors can rely on fixed effects to compare the same firm borrowing both from a government-owned bank and a private bank. Therefore, numerous firm characteristics are eliminated as confounders, because the comparison is between the firm's sources of credit while keeping the demand fixed.

Dinç (2005) explores how government-owned banks lend during election years. The author collected data from the largest ten banks from 36 countries and followed them until elections occurred. The first evidence is that both developed economies and emerging markets have the presence of public banks. Additionally, the author shows that government-owned banks increase their lending in election years relative to private banks. Complementarily, Micco *et al.* (2007) expands the dataset by considering 54 countries, the ownership of the countries' banks, and the interest margin charged. They find that, during election years, public banks obtain lower returns on assets while providing more loans at a lower price. The authors argue that this result is driven by supply-side effects, i.e. that politicians intervene by providing more credit during election years. Both Dinç (2005) and Micco *et al.* (2007) find that political lending is more salient in emerging economies.

Cole (2009) focus on rural loans in India since the majority of the population operates in the agricultural sector. The boom in credit is observed in municipalities in which the majority party won by little, and the targeting is observed in electoral periods only. The author finds higher levels of default in regions where the majority party obtained more votes, and only after elections, indicating that political lending has pervasive and lasting effects on the economy.

Empirical evidence consistent with the political lending theory predictions can also be found in Brazil. Carvalho (2014) shows higher public lending in politically attractive regions. The author merges data from elections and plant-level metrics to identify the channels by which a development bank makes its political intervention. He finds that firms in sectors that are prioritized to obtain loans from this bank, present higher investment levels and create more jobs. Also, this effect is more pronounced in competitive elections and in regions where reelection is possible. More interestingly, the firms that potentially receive these loans grew more in regions with the state executive allied to the president at that time.

Other pervasive effects are demonstrated by Coleman & Feler (2015), who finds that during the 2008-09 crisis, public banks in Brazil compensated for the decline in lending by private banks, but with the credit quality deteriorating for public banks compared to pre-crisis. This effect can be seen both during and after the crisis period, which indicates the long-lasting effects of lending. Furthermore, they find that municipalities with larger share of public branches received more credit when the population voted more for a mayor from the same party as the president in office.

Leão (2011) uses a confidential dataset from the Brazilian Central Bank that contains loan-level data from Brazilian banks. He shows that political alignment affects the allocation of credit by government-owned commercial banks. The research indicates that politically aligned cities receive more credit from federal public banks compared to non-aligned cities, due to the central government's interest in favoring these cities in exchange for political support in Congress or future elections. Since the author knows the type of credit he finds that directed credit, which comes with better conditions, is used as a public policy tool to influence electoral outcomes in highly competitive political areas, while non-directed credit is more likely to be appropriated by local governments to foster economic growth or support the mayor's supporters.

My research contributes to the extensive body of literature on political lending on at least two fronts. Firstly, I contribute methodologically. While prior literature has consistently demonstrated heightened lending activity by public banks during election periods across various contexts, this paper introduces an additional layer of identification by accounting for branches' peak demand during electoral cycles. By leveraging branch-level data, my analysis gains a finer granularity, allowing for the mitigation of potential confounding variables and more precise estimates of supply-side effects. Utilizing seasonality as a proxy for clientele specialization, akin to the approach in Duquerroy *et al.* (2022), I investigate the extent to which political lending internalizes branches' clientele demands when reallocating credit during election cycles.

Secondly, I identify that politicians not only influence public banks to lend more during elections but also that the public branches' seasonality is further explored by politicians. This result is novel in the literature, suggesting that politicians are close to their clientele demands and exploit this vulnerability during electoral periods. Furthermore, politicians take advantage of intrabank markets to transfer credit from less politically attractive regions[2.2]

[2.2] The concept of attractiveness is subject to considerable variation across the literature, with few studies clearly defining it. In this research, I designate poor and non-aligned municipalities as the primary targets that politicians find more appealing to pursue.

to more profitable ones. Therefore, even in the within-country context, we find a substantial difference in the observed effects depending on the municipality.

2.4 Contextual Framework

In the nineties, a wave of privatization diminished the market participation of public branches (Beck *et al.*, 2005; Mariani, 2020). However, they are still responsible for the majority of credit and collection of savings in Brazil. In addition to being an important channel for the transmission of governmental programs, public banks often specialize in certain types of credit. For instance, Banco do Brasil, the largest public bank in the sample, is responsible for 61.66% of total rural credit in Brazil. Public banks, given their broader geographic coverage, also offer savings account access to many remote regions. Caixa Econômica Federal, the second largest public bank in the sample, together with Banco do Brasil collected 52% of the total savings in my sample.

As the largest economy in Latin America, Brazil's banking sector is characterized by a diverse array of financial institutions, ranging from large multinational banks to smaller regional players. These regional banks are often state-owned banks that are reminiscent of the privatization in the recent present of Brazil. Challenges such as high interest rates, regulatory constraints, and economic volatility can impact the availability and cost of credit, influencing borrowing behavior and economic outcomes. Despite having 5,572 municipalities, only 3,363 have at least one physical bank branch. In regions with only one branch, it is common to observe the presence of one branch from a public bank.

In terms of its political structure, Brazil functions as a democratic republic with a presidential system. Elections for federal positions (such as presidents, senators, and deputies) and municipal offices (including mayors and councilors) take place on a four-year cycle. However, these elections are staggered, with federal elections occurring two years apart from municipal ones. As voting is compulsory in Brazil for adults aged between 18 and 70 years old, failure to vote without justification results in a fine imposed by the Electoral Court. Although the fine is nominal, not paying it can have serious consequences, such as hindering the acquisition of a passport or accessing loans from public banks. This electoral setup presents a wide pool of voters susceptible to influence from political figures seeking to sway election outcomes.

Typically the electoral propaganda in Brazil lasts for around three months leading up to election day. This timeframe allows candidates and political parties sufficient time to present their campaigns, communicate their proposals to voters, and mobilize support before the election. During the "Horário Eleitoral Obrigatório" candidates running for public office are granted a specific amount of airtime to present their campaigns, proposals, and messages to the electorate. This is the year period in which elections become more salient in voters' minds and is possible to see candidates actively canvassing for votes. The practice of purchasing votes is commonly observed in more remote regions away from major urban centers. According to Gingerich *et al.* (2014), the occurrence of vote purchasing is associated with a 4 to 6 percent rise in votes secured by the governor in the average municipality within the state of Minas Gerais, Brazil.

2.5 Data

Branch-level data is obtained from the Estatísticas Bancárias (Estban). The Brazilian Central Bank compiles balance sheet data from all bank branches from commercial banks. This panel follows the branches over the month and computes the variables at the branch level. All financial values were adjusted for inflation for December 2020 using the IPCA index. A second dataset is the IFData which contains information on bank ownership over time. I find no changes in ownership from 2006-01 onwards, evidence following Mariani (2020) that lists all bank privatizations in Brazil. Hence, my dataset tracks branches' accounts from 2006-01 to 2020-12[2.3]. I used data from before the crisis to avoid contagion from events unrelated to elections. For example, Norden *et al.* (2021) find that public banks increased lending during the Covid-19 Crisis in Brazil, but this difference is less pronounced than in the 2008 financial crisis.

The National Development Bank of Brazil (BNDES) has been omitted from the government bank sample due to its non-retail nature. The resulting sample comprises 9 public banks, with four federally owned banks, and 135 private banks engaged in commercial lending activities and is closely comparable to the data in Coleman & Feler (2015). Appendix Table B2 illustrates the significant representation of Banco do Brasil and Caixa Econômica Federal in the sample, accounting for 86% of all observations from public banks.

Electoral data are obtained from the Tribunal Superior Eleitoral (TSE). The data contains information from candidates, party affiliation, and voting. As previously mentioned, federal and municipal elections occur in intervals of two years, but never simultaneously. This characteristic of the Brazilian electoral system holds significance for econometric analyses. When a president

[2.3] The quarantine in Brazil occurred on March 17th, but all people had to go vote anyway. Therefore, I opt to keep 2020 in the sample.

is elected, voters must consider whether their mayor aligns with the current president. It is only after two years that voters have the opportunity to elect a new mayor. Table 2.1 demonstrates the electoral dynamics in Brazil. President Dilma Rousseff was impeached and unable to complete her second term and President Jair Bolsonaro departed from the PSL party in November 2019 and joined the PL party in November 2021. Together, all these idiosyncrasies diminish the likelihood of results being contaminated by alternative explanations.

Table 2.1: Electoral Dynamics in Brazil

Presidential Mandate					
Start	Municipal Electoral Period		End	President	Party
2003-01	2008-07	2008-10	2010-12	Lula da Silva	PT
2011-01	2012-07	2012-10	2016-08*	Dilma Roussef	PT
2016-09	2016-08	2016-10	2018-12	Michel Temer	PMDB
2019-01	2020-08	2020-11	2022-12	Jair Bolsonaro	PSL and PL **

* President Dilma Roussef suffered an impeachment and could not finish her second mandate. ** President Jair Bolsonaro left PSL party in November 2019 and ingressed PL party in November 2021. Hence, there is no aligned municipality for the period between these two dates.

I remove some observations to obtain more regular scenarios for my analysis. First, I drop observations from municipalities with only one candidate and cases in which the difference between the first and second candidates is zero or one. In these municipalities, there is no competition for elections, so there is no need for political lending. Second, I drop observations in which the branch has more provisioned capital than lending volume. These values are above the 99 percentile and might indicate that these branches are likely to be in distress. I also drop branches with zero lending volume because this branch is not intended to supply credit for borrowers.

2.5.1 Descriptive Statistics

In Table 2.2 I compare several metrics for public versus private bank branches. The total volume of loans is higher for public banks than for private banks, as seen in several other studies. The t-statistics for loan volume is the larger for the bivariate analysis (diff = -1.647, t = -966.26). Despite the statistical significance in the test comparing the main month in elections for both types of branches, the absolute difference is too small to be considered relevant (diff = 0.001, t = 8.13). The public branches are also larger than the private branches (diff = -0.603, t = -361.22, which is consistent with both the view that public branches lend more and are less efficient. Private branches appear to be more cautious against default. The ratio of provisions over total loans for private branches is almost twice that of the public branches (diff = 0.017, t = 310.25).

Table 2.2: Descriptive Statistics

Variables	Private			Public			Two-tailed T-test	
	Mean	S.D.	Obs.	Mean	S.D.	Obs.	Difference	T-statistic
Log(Loan Volume)	16.189	1.780	1884749	17.836	1.368	1527190	-1.647***	-966.255
Main Month in Election	0.009	0.097	1884749	0.009	0.093	1527190	0.001***	8.125
Branch Size	18.255	1.590	1884749	18.858	1.486	1527190	-0.603***	-361.223
Provisions	0.031	0.067	1884749	0.014	0.028	1527190	0.017***	310.251
Concentration of Loans	0.068	0.203	1884749	0.305	0.350	1527190	-0.236***	-739.07
Concentration of Loans if Public	0.159	0.250	1798745	0.305	0.350	1527190	-0.146***	-429.964
Ln(GDP per Capita)	3.335	0.662	1884749	3.095	0.758	1527166	0.240***	308.283
# Candidates	7.128	4.141	1857132	5.499	3.696	1481369	1.628***	379.056
Aligned to President	0.132	0.339	1884749	0.105	0.307	1527190	0.027***	78.322

The symbols $^+$, *, and **, indicate significance at 10, 5, and 1 % respectively.

Public branches appear to have more market share than private branches, consistent with the volume of loans offered (diff = -0.236, t = -739.07). Coelho *et al.* (2013), however, argues that public banks do not offer so strong competitive pressure on private banks. They mention that both product differentiation and higher costs are responsible for this result. Additionally, Sapienza (2004) mentions that public banks might avoid exploiting their market power due to the benign view that the government could foster private bank's lending. The concentration of loans from public banks that private branches face is also different from the public ones (diff = -0.146, t = -429.96).

Regarding the municipality-level variables, the interpretation should be cautious. The dataset is at the branch level, so variables such as the GDP per Capita are not directly comparable between public and private branches. Therefore, the GDP per capita of observations from private branches is higher than for the public branches' observations (diff = 0.240, t = -373.24). The number of candidates is roughly 7.1 for observations from private branches versus 5.5 for public branches (diff = 1.628, t = -379.06). Also, the percentage of observations of private branches in aligned municipalities is slightly larger than that of private banks (diff = 0.027, t = 78.32).

2.6 Methodology

2.6.1 Main Month in Electoral Period

As previously mentioned, branch seasonality has an important role in determining the credit volume. The $Main\ Month_{imt}$ variable captures this historical pattern and indicates that for branch i the month with the historical highest loan volume. This variable can also be thought of as a proxy for client specialization. For instance, it is possible to observe two branches from the same bank, in the same municipality, with distinct main months. An exemplary case can be observed in Valença, a municipality in Rio de Janeiro. Despite being a town with less than 70.000 citizens, it hosts branches from six different banks. It has two branches from Itaú-Unibanco, situated less than one kilometer from each other. One has June and the other has October as their main month. Duquerroy *et al.* (2022) utilize portfolio data from bank branches to uncover disproportionate lending volumes allocated to specific sectors. Their research illustrates that banks indeed specialize, with branches within the same market with portfolios prioritizing different sectors.

The description to compute this variable can be originally found in Chang *et al.* (2016). I adapt the methodology for branch and monthly data. First, I get a branch and sort its observations from the largest volume of loans observed to the smallest. Then, I attribute a rank for every of observation and compute the monthly average rank. As described in the original study, using rank instead of the monetary value avoids noises due to outliers. The month with the highest monthly average rank becomes the Main Month for a given branch. One branch can have more than one main month, but these cases are not so common. Thus, $Main\ Month_{imt}$ assumes the value of one if the branch is in its main month and zero otherwise.

To finally compute the $Main\ Month\ in\ Election_{imt}$ variable, I simply identify if the variable $Main\ Month_{imt}$ assumes the value of one within the electoral period of municipal elections. In Table 2.1 one can see the Municipal Electoral Period considered to compute the variable. The role of this variable is to identify if this seasonality pattern is present during elections contrasting with non-electoral periods. Table 2.3 demonstrates the number of observations in each scenario. For instance, there are 2,684 observations from public branches that happen to have their Main Month occurring in the elections of November 2020. This loan volume will be compared with the 2,608 observations from private branches at the same moment.

I do not particularly address first- and second-turn elections differently, thus I consider the whole electoral period as the period in which the mayors can exert influence on public branches' officers to increase lending. Despite the

Table 2.3: Observations in which the Main Month belongs to the Electoral Period

Main Month	2008		2012		2016		2020		Total	
in Elections	Public	Private	Public	Private	Public	Private	Public	Private	Public	Private
July	235	490	399	667	0	0	0	0	634	1,157
August	373	619	585	971	753	944	605	719	2,316	3,253
September	550	780	845	1,188	1,064	1,171	898	893	3,357	4,032
October	713	1,359	1,101	2,090	1,321	1,818	1,082	1,560	4,217	6,827
November	0	0	0	0	0	0	2,684	2,608	2,684	2,608
Total	1,871	3,248	2,930	4,916	3,138	3,933	5,269	5,780	13,208	17,877

lockdown due to the COVID-19 pandemic that occurred in 2020, I chose to include 2020 as a fourth municipal election during my sample coverage. Since I am comparing the same branch in and out of the main month during elections, it is not expected to change any results. Additionally, by considering 2020 in the sample, I have a larger time frame to compute the main month variable.

2.6.2 Econometric Specification

This section describes the econometric specification used to capture the desired effect. I regress the total loan volume for branch i, in municipality m, at the month-year t. The Equation 2.1 below expresses this relation.

$$\begin{aligned} Log(Loan\ Volume)_{imt} = \ & \beta_1 Main\ Month\ in\ Elections_{imt} \\ & + \beta_2 Public_{im} \times Main\ Month\ in\ Elections_{imt} \\ & + \Gamma' X_{imt} + \Psi' Z_{mt} + \theta_{i(t)} + \varepsilon_{imt} \end{aligned} \tag{2.1}$$

Despite politicians being able to exert pressure on branches' managers, the *timing* in which they do it is relevant for the theory. Therefore, the coefficient β_1 captures if private banks in their main month lend more during elections. Although the theory does not offer a clear prediction about political lending in private branches, I kept the variable in the model to allow for a cleaner effect for public branches. Moreover, the coefficient β_2 for $Public_{im} \times Main\ Month\ in\ Elections_{imt}$ examines whether public branches demonstrate a greater lending volume when their seasonal peak coincides with electoral periods, compared to private branches experiencing similar demand peaks. Therefore, I proxy the type of clientele that both private and public branches face, allowing β_2 to be less likely to be contaminated by omitted variables in the error term.

Existing literature anticipates an increase in lending by public branches during electoral periods, indicative of political lending practices. However, this analysis delves further by considering the influence of seasonality. Recall that we are *not* interested in verifying whether public banks lend more in elections since this is largely evidenced in the literature. Instead, I hypothesize that public branches lend more when their main months belong to the Electoral Period interval.

Control variables should be considered in a regression analysis when there is reason to believe that they may have a confounding effect on the relationship between the independent and dependent variables being studied. $\Gamma' X_{imt}$ is a vector of control variables at the branch-level. The first control is the Branch Size because public banks are expected to be larger than private branches. Also, larger banks have more capital available to offer as credit. Another control added is the ratio between capital provisioned for credit defaults over total loan volume. This variable is used to capture the portion of preventive capital used by each branch. Branches with higher values provisioned might avoid lending due to the risk faced. The concentration of loans for each branch and only for public branches in a given municipality is also used as control. This aims to control for competitive factors that might inhibit the capacity of lending in a given period and that might predetermine client specialization captured by the main month.

Finally, $\Psi' Z_{mt}$ is a vector of controls at the municipality level. The degree of economic development in a municipality is an important factor related to both the loan volume and the presence of public branches. The number of candidates in the last election controls for electoral competition. Together with the credit market competition, I hope to rule out both forms of competition as possible explanations.

Khwaja & Mian (2005) suggest using local fixed effects to control for possible confounders. I interact branch and month $\theta_{i(t)}$ fixed-effects for at least three main reasons. First, the two fixed effects saturate the model and control for a large setting of possible confounders. This can be noticed by the higher levels of R^2 observed even without controls. Second, given the seasonal nature of my main explanatory variable $Main\ Month\ in\ Election$, month-fixed ($\theta_{i(t)}$) effects subtract from the results any other seasonal patterns related to credit supplied by the branches. Third, by using this setting of fixed effects, I can still observe the coefficients for the control variables employed in Sapienza (2004) and adapted for municipality level from Dinç (2005). This helps by allowing a closer comparability between estimates in other studies.

2.7 Results

2.7.1 Seasonality and Political Lending during Elections

In column (1) of Table 2.4 we observe the simplest specification in which I am using only branches fixed-effects. The main month of private branches in elections appears to be relevant but becomes indistinguishable from zero when other branch characteristics are used as controls. It can be interpreted as evidence that the main month in elections for private branches is not as relevant as it is for public branches. The coefficient for the interaction term points that public banks do lend more when their main month occurs during the electoral period. In column (3), I add month fixed-effects interacting with branch fixed-effects to clean the specification for other seasonal patterns that account for any systematic variations in loan volume that are not related to the electoral period. This adds 264,659 coefficients to be estimated in the regression, helping to saturate the model. The coefficient for the interaction is still positive and in a similar magnitude. In columns (4), (5), and (6), I add branch and municipality controls that were used in other studies. The coefficient falls but remains statistically significant at 1%. Overall, the disproportional increase in lending by public branches during their peak in demand coinciding with the electoral period ranges from 2.4 to 8.2% compared to private branches in the same context.

The control variables also corroborate findings from existing literature. Larger branch sizes show a positive correlation, indicating that larger branches tend to lend more. Conversely, branches allocating more capital to provisions tend to lend less, likely to mitigate risk exposure. Higher market share levels are linked to increased credit supply, suggesting that private banks exert competitive pressures within their local markets. Conversely, in markets with a higher concentration of public banks, branches tend to offer smaller lending volumes, aligning with the notion that state-owned enterprises (SOEs) avoid competing with private banks. In terms of municipal controls, a positive coefficient for GDP per capita suggests that wealthier municipalities tend to have higher lending volumes, and municipalities with a greater number of candidates, indicative of more politically competitive environments, tend to experience reduced credit supply.

The findings thus far suggest a discernible political dimension in the volume of loans extended by banks, a phenomenon actively leveraged by politicians. Given that the $Main\ Month_{imt}$ corresponds to the period of heightened credit demand, branches become particularly instrumental for politicians seeking electoral support during such periods. Specifically, the results underscore the heightened significance of certain months, particularly

Table 2.4: Public Lending in Electoral Periods

The dependent variable is the logarithm of the loan volume of branch i in municipality m at time t. $Public_{im}$ is a dummy variable equal to one if branch i is a state-owned bank. I measure the size of the branch by logarithm of total assets. The provision for loans is the ratio of provisions scaled by total loans. I measure market concentration by the market share at the branch level on total municipal lending. The GDP per capita is measured at the municipality level. The number of candidates in the absolute number of the candidates for the last mayor elections. Standard errors are clustered at the municipality level and reported in parenthesis. Singletons are dropped to avoid underestimation of standard errors. The symbols $^{+}$, *, and **, indicate significance at 10, 5, and 1% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Log(Loan Volume)			
Main Month in Election	0.147**	0.132**	0.084**	-0.017+	0.030**	-0.009
	(0.005)	(0.005)	(0.006)	(0.009)	(0.009)	(0.007)
Public × Main Month in Election	0.054**	0.054**	0.082**	0.033**	0.050**	0.024**
	(0.008)	(0.008)	(0.010)	(0.010)	(0.009)	(0.008)
Branch Size				0.757**		0.739**
				(0.007)		(0.008)
Provisions				-2.351**		-2.450**
				(0.066)		(0.056)
Concentration of Loans				1.944**		2.033**
				(0.058)		(0.060)
Concentration of Loans if Public				-0.317**		-0.319**
				(0.017)		(0.017)
Ln(GDP per Capita)					0.647**	0.104**
					(0.016)	(0.028)
# Candidates					-0.005	-0.016**
					(0.005)	(0.006)
Observations	3411936	3411936	3411773	3325758	3338310	3252944
Adjusted R-squared	0.844	0.844	0.835	0.910	0.851	0.912
Branch	Yes	Yes	No	No	No	No
Month	No	Yes	No	No	No	No
Branch x Month	No	No	Yes	Yes	Yes	Yes

the main month, for public branches, implying politicians' adept exploitation of this temporal pattern. Conversely, it can be interpreted that candidates exploit borrowers' demands to secure their allegiance through political patronage. Politicians strategically target public branches experiencing peak demand to garner additional electoral support in exchange for facilitating lending. Given the observed increase in lending during electoral cycles and at the peak of public branches' demand, the evidence leans towards a narrative of political lending rather than being attributable to alternative theories.

2.8 Mechanisms

So far, I have shown evidence that politicians use public branches' clientele seasonality to provide more loans during elections in contrast with private banks. The natural next step is to identify the flow of this capital. In other words, in which types of municipalities the candidates are more eager to exert pressure in public banks during elections? The ongoing analysis delves into the nuanced dynamics of political influence on lending behavior by dividing the data into distinct subsamples. By disaggregating the sample along these dimensions, the study aims to provide a nuanced understanding of the interplay between political alignment, socio-economic conditions, and lending dynamics.

In this section, I investigate the dynamics of capital flow during electoral periods. In instances where branches are unable to access additional resources externally, they resort to intrabank transfers to acquire surplus capital from other branches that are not experiencing peak demand. Bustos *et al.* (2020) examine the challenges within the Brazilian interbank market, highlighting that a significant portion of collected deposits face difficulty in being allocated to high-demand regions. In contrast to interbank markets, intrabank markets are anticipated to exhibit lower levels of turbulence due to the simpler transfer of capital within banks. Consequently, I explore the potential for politicians to exploit the intrabank structure to redistribute loans to strategic regions.

2.8.1 Aligned versus Non-aligned Municipalities

The political view of SOEs indicates that candidates should lend more in regions where they can extract more rent if elected. Carvalho (2014) finds an increase in employment in politically attractive regions and a decline in less attractive regions. Thus, regions already dominated by political influence possibly provide less return or are more costly to enter than other regions. Leão (2011) finds that lending volume increased in regions where the political alignment is higher and decreased where alignment is lower. The author classified an aligned municipality if the mayor's party has a member of the President's Cabinet. I adopted a more restrictive approach, classifying a municipality as aligned if the mayor of that municipality, in that municipal election, is from the same party as the president in office. Notably, the same candidate might be aligned in one election but non-aligned in another one.

In this section, I check if the effect we already captured varies according to the political alignment of the municipality's mayor. I divide the sample according to aligned and non-aligned municipalities belonging to the same party of the president to check whether the increase in lending is heterogeneous between the two groups of municipalities.

Table 2.5 presents the findings of the analysis. It is observed that loans extended by public banks, coinciding with their peak demand periods aligning with the electoral cycle, exhibit an increase in municipalities where the mayor does not share party affiliation with the president, while a decrease is noted in aligned municipalities. The coefficients in columns (1) to (3) demonstrate positive and economically significant effects, indicating a rise in lending activity by public branches during electoral periods by 3.4 to 8.8%. Conversely, columns (4) to (6) display larger coefficients with an inverse sign. The dimension in reduction of loans is from 20 to 25.7% depending on the specification. These results suggest that political pressure is exerted to curtail lending activities in regions governed by the dominant party. The magnitude of the effects underscores the substantial scale of credit misallocation by public banks during municipal elections, with a preference shown towards regions potentially amenable to political capture.

Table 2.5: Public Lending in Aligned and Non-aligned municipalities.

Aligned municipalities are those in which the mayor is from the same party as the president. The dependent variable is the logarithm of the loan volume of branch i in municipality m at time t. $Public_{im}$ is a dummy variable equal to one if branch i is a state-owned bank. I measure the size of the branch by logarithm of total assets. The provision for loans is the ratio of provisions scaled by total loans. I measure market concentration by the market share at the branch level on total municipal lending. The GDP per capita is measured at the municipality level. The number of candidates in the absolute number of the candidates for the last mayor elections. Standard errors are clustered at the municipality level and reported in parenthesis. Singletons are dropped to avoid underestimation of standard errors. The symbols $^+$, *, and **, indicate significance at 10, 5, and 1 % respectively.

	Non-aligned			Aligned		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Loan Volume)			Log(Loan Volume)		
Main Month in Election	0.132**	0.085**	-0.010	0.054*	0.026	0.117**
	(0.006)	(0.007)	(0.008)	(0.022)	(0.040)	(0.030)
Public × Main Month in Election	0.053**	0.088**	0.034**	-0.200**	-0.257**	-0.203**
	(0.008)	(0.012)	(0.009)	(0.024)	(0.045)	(0.051)
Branch Size			0.729**			0.728**
			(0.008)			(0.033)
Provisions			-2.480**			-1.929**
			(0.070)			(0.241)
Concentration of Loans			1.996**			2.526**
			(0.062)			(0.217)
Concentration of Loans if Public			-0.307**			-0.184**
			(0.017)			(0.035)
Ln(GDP per Capita)			0.096**			0.321**
			(0.031)			(0.047)
Candidates			-0.018**			-0.025+
			(0.004)			(0.015)
Observations	3002117	3000923	2847762	409793	406039	400422
Adjusted R-squared	0.850	0.840	0.913	0.907	0.895	0.951
Branch	Yes	No	No	Yes	No	No
Month	Yes	No	No	Yes	No	No
Branch x Month	No	Yes	Yes	No	Yes	Yes

My results go in the opposite direction to studies like Khwaja & Mian (2005) and Leão (2011). Authors argue that politicians will provide more credit to politically aligned players/regions. My results are more in line with Cole

(2009) that finds a strategic redistribution of credit in swing districts. In other words, in municipalities in which candidates have a similar chance of winning the pool, politicians direct credit to obtain an advantage at the last moment and win the elections.

The significant decrease in credit for non-aligned municipalities may be viewed through the lens of politicians' strategic incentives. Diminishing credit access in areas where political support is already secured can serve as a tactical maneuver for politicians. By doing so, politicians aim to mitigate economic downturns during their tenure, thus reducing the volatility of the business cycle. Mian *et al.* (2020) posit that the business cycle tends to exacerbate when credit expansion occurs, leading to increased investment by firms and heightened consumption by households. Therefore, by curtailing lending activities in regions where political dominance is established, politicians can divert resources toward other areas, *

2.8.2
Rich versus Poor Municipalities

In this section, I try to mimic the separation into emerging markets and developing economies that drive the findings of Dinç (2005) and Micco *et al.* (2007). The authors performed a cross-country analysis and found that only in developing economies the political lending can be observed. In their study, the coefficient that captures public lending in elections is positive only in countries from emerging markets, such as Brazil. However, public banks from one country are unlikely to affect public banks from another one. In a within-country context, as we explore here, it is possible to transfer resources from one locality to another. Politicians might strive to succeed in one region, thus influencing a redistribution of credit to another location. If the internal market of the public banks is fluid, portions of credit can be reduced and allocated in more lucrative markets. This channel is precisely what we explore in this analysis.

Sub-setting the sample into above and below median GDP per Capita, I find that politicians seem to take advantage of branches' seasonality for patronage and it possibly goes in both directions. In Table 2.6 the coefficients reported in columns (1) through (3) show a positive and large coefficient for the interaction term. The estimates show a disproportionate increase in lending by public branches with their main month during elections in poor municipalities. In columns (4) and (5) for the rich municipalities, we cannot distinguish the estimates from zero at the usual significance levels. The coefficient of 3.1% observed in column (6) comes with caution, because in addition to the nonsignificant interaction coefficient in columns (4) and (5), the estimates are close to zero. Therefore, I find suggestive evidence that public banks coordinate reductions in lending in municipalities where they are in the peak of demand to distribute in poor municipalities.

Table 2.6: Public Lending in Electoral Periods: poor and rich municipalities

High GDP per Capita is defined as above median GDP per Capita, and Low GDP per Capita the the opposite. The dependent variable is the logarithm of the loan volume of branch i in municipality m at time t. $Public_{im}$ is a dummy variable equal to one if branch i is a state-owned bank. I measure the size of the branch by logarithm of total assets. The provision for loans is the ratio of provisions scaled by total loans. I measure market concentration by the market share at the branch level on total municipal lending. The GDP per capita is measured at the municipality level. The number of candidates in the absolute number of the candidates for the last mayor elections. Standard errors are clustered at the municipality level and reported in parenthesis. Singletons are dropped to avoid underestimation of standard errors. The symbols $^+$, *, and **, indicate significance at 10, 5, and 1% respectively.

	Low GDP per Capita			High GDP per Capita		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Loan Volume)			Log(Loan Volume)		
Main Month in Election	0.102**	0.045**	-0.033**	0.131**	0.091**	0.021**
	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.006)
Public × Main Month in Election	0.070**	0.112**	0.046**	-0.018+	-0.007	-0.031**
	(0.008)	(0.010)	(0.009)	(0.009)	(0.013)	(0.010)
Branch Size			0.652**			0.786**
			(0.017)			(0.009)
Provisions			-2.568**			-1.932**
			(0.128)			(0.061)
Concentration of Loans			1.956**			2.412**
			(0.063)			(0.164)
Concentration of Loans if Public			-0.247**			-0.286**
			(0.022)			(0.024)
Ln(GDP per Capita)			0.338**			-0.287**
			(0.022)			(0.035)
Candidates			-0.015**			-0.017**
			(0.005)			(0.006)
Observations	1698934	1673484	1590404	1712931	1704520	1629179
Adjusted R-squared	0.868	0.856	0.925	0.865	0.853	0.920
Branch	Yes	No	No	Yes	No	No
Month	Yes	No	No	Yes	No	No
Branch x Month	No	Yes	Yes	No	Yes	Yes

Collectively, the estimates indicate the presence of political lending intersecting with seasonality across both categories of municipalities. In affluent municipalities, a decline in loan volume during elections is observed if public banks coincide with their peak demand periods. This phenomenon suggests potential challenges in garnering political support through lending in wealthier areas, possibly due to the availability of alternative sources of financing for borrowers. Conversely, in economically disadvantaged municipalities, a clearer pattern emerges where public banks exploit the synchronicity between demand and electoral cycles to increase lending. The ability to influence electoral dynamics in impoverished regions appears more pronounced and cost-effective, as supported by empirical findings. Hunter & Power (2007) explore President Lula's reelection in 2006 amidst numerous corruption scandals, highlighting his administration's strategic utilization of social programs to secure voter support, particularly in Brazil's poorer regions. Additionally, Gingerich *et al.* (2014) note that municipalities in Brazil under the control of local bosses, who engage in vote buying, tend to be smaller, less educated, economically disadvantaged, and exhibit poorer performance across various indicators compared to those without such local influence.

2.9 Robustness

2.9.1 Pre-Electoral Periods

This section explores the timing in which the increase in lending occurs. Public banks may roll over their debt for longer periods instead of offering credit in the months comprised by the election. If this is the case, we would see an increase in lending outstanding not driven by elections, but by the duration of debt. To avoid this alternative explanation, I drop observations from the actual election years and compute a variable called $Main\ Month\ in\ Fake\ Election_{imt}$. It takes the value of one whether the main month belongs to a Fake Electoral Period. For this fake period, I consider that the election occurred one year before the real elections to capture the seasonal lending patterns outside the electoral period. This placebo test is applied to check if the coefficient for the interaction term appears significant even in periods without elections. If it happens, it might suggest that the duration of the branches' portfolio is driving the results. In Table 2.7 one can see that the results are not in line with this explanation.

This table replicates the first econometric analysis of the study in Table 2.4. Despite in columns (3) and (4) the coefficient for the interaction term appears as significant, they are comparatively small and become indistinguishable from zero when controls are added. This provides evidence that the increase in lending volume did not originate from seasonal monthly patterns unrelated to the Electoral Period. In other words, it is unlikely that end-of-the-year events are responsible for the increase in lending by public banks, giving more reason to believe that elections play a fundamental role in the results.

Table 2.7: Public Lending before the Electoral Periods

This table considers that the elections occurred 12 months before the actual elections to replicate Table 2.4. For this test, I dropped the years with real elections to avoid the intertemporal contagion of estimates[2.4]. The dependent variable is the logarithm of the loan volume of branch i in municipality m at time t. $Public_{im}$ is a dummy variable equal to one if branch i is a state-owned bank. I measure the size of the branch by logarithm of total assets. The provision for loans is the ratio of provisions scaled by total loans. I measure market concentration by the market share at the branch level on total municipal lending. The GDP per capita is measured at the municipality level. The number of candidates in the absolute number of the candidates for the last mayor elections. Standard errors are clustered at the municipality level and reported in parenthesis. Singletons are dropped to avoid underestimation of standard errors. The symbols $^{+}$, *, and **, indicate significance at 10, 5, and 1 % respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Log(Loan Volume)			
Main Month in Fake Election	0.138**	0.120**	0.079**	0.006	0.022**	-0.004
	(0.005)	(0.005)	(0.007)	(0.004)	(0.007)	(0.005)
Public × Main Month in Fake Election	0.013+	0.012+	0.031**	0.013*	0.014	0.008
	(0.007)	(0.007)	(0.009)	(0.005)	(0.009)	(0.005)
Branch Size				0.756**		0.721**
				(0.008)		(0.011)
Provisions				-2.636**		-2.811**
				(0.107)		(0.119)
Concentration of Loans				1.936**		2.098**
				(0.059)		(0.063)
Concentration of Loans if Public				-0.318**		-0.323**
				(0.017)		(0.018)
Ln(GDP per Capita)					0.681**	0.171**
					(0.016)	(0.029)
Candidates					-0.007	-0.011
					(0.006)	(0.008)
Observations	2498754	2498754	2498515	2435680	2443205	2380911
Adjusted R-squared	0.843	0.843	0.831	0.906	0.849	0.908
Branch	Yes	Yes	No	No	No	No
Month	No	Yes	No	No	No	No
Branch x Month	No	No	Yes	Yes	Yes	Yes

2.10 Conclusion

This study presents compelling evidence indicating that politicians exploit the unique seasonality patterns of public bank branches to manipulate loan distribution during electoral periods. These findings align with existing theories on political lending, particularly concerning the behavior of state-owned enterprises. By comparing public and private branches with lending peaks coinciding with municipal elections in Brazil, this research adds a novel layer of identification to the literature, employing a methodological approach akin to the fixed effects utilized by Sapienza (2004) and Khwaja & Mian (2005). Specifically, the study contrasts branches with similar clientele characteristics, as proxied by historically higher loan months.

Through this comparative analysis of branches within the same electoral period, the study controls for various local factors that could potentially confound the results. Moreover, concerns regarding alternative explanations such as political and credit market competition are addressed through the inclusion of appropriate controls. A placebo test further substantiates the findings by demonstrating that loans do not exhibit a similar increase in the absence of elections.

The key takeaway from this investigation is the evidence of politicians leveraging the seasonality of public bank branches to augment lending activity during elections, with a discernible preference for directing loans towards politically attractive municipalities while shrinking credit in politically unattractive ones. This phenomenon suggests that the intrabank structure - due to having fewer frictions - serves as a conduit for politicians to reallocate capital strategically. Specifically, borrowers from economically disadvantaged and politically non-aligned municipalities experience heightened loan supply from public banks during election months.

Other takeaways relate to the policy implication of my results. The role of public banks in mitigating financing frictions should be considered when designing policies to reduce politicians' influence in the credit market. Both the origin and the destination of resources can be used to track the flow of credit increasing the likelihood of identifying the responsible politicians, firms, and bank officers. The use of internal credit markets also suggests a closer target for finding traces of political lending. I hope that with these results we observe improvement in designed policies that mitigate the problems caused by the interplay between politics and credit.

Appendix A: Variables Description

Table B1: Variables Description

Variables	Description
$Main\ Month\ in\ Election_{imt}$	Indicator variable that takes the value of one if the current month is the one with the highest historical lending volume and belongs to the Election Period. Check Section 2.6.1 for a complete description of the calculation process.
$Ln(Loan\ Volume)_{imt}$	Natural Logarithm of Total Lending Volume negotiated by a branch.
$Public_{im}$	Assume value 1 if the bank is a Government-Owned bank and zero if Private. There is no change in ownership status for any bank in the period studied.
$Branch\ Size_{imt}$	Natural Logarithm of Total Assets from a branch.
$Provisions\ _{imt}$	Ratio of Provision for Credit Defaults over Total Lending Volume.
$Concentration\ of\ Loans_{mt}$	Total Loan Volume of branch i divided by the Sum of Total Loan Volume in a municipality m.
$Concentration\ of\ Loans\ if\ Public_{mt}$	Total Loan Volume of branch i, if branch i is a branch from a Public Bank, divided by the Sum of Total Loan Volume in a municipality m.
$Ln(GDP\ per\ Capita)_{mt}$	Natural Logarithm of Municipality m Gross Domestic Product divided by its Population.
$\#\ Candidates_{mt}$	Number of Candidates for the last Mayoral Election.
$Aligned_{mt}$	Assume value 1 if the municipality has a mayor that is from the same party as the current president.

All monetary values are adjusted for inflation by IPCA index and measured as of December 2020. The dataset consists of monthly data from January 2006 to December 2020.

Appendix B: Public Banks List

Table B2: Public Banks in Brazil

Bank Name	Ownership	Observations	Percentage	Cumulative
Banco do Brasil S.A.	Federal	829,538	54.32	54.32
Caixa Econômica Federal	Federal	493,415	32.31	86.63
Banco do Estado do Rio Grande do Sul S.A.	State	82,824	5.42	92.05
Banco do Nordeste do Brasil S.A.	Federal	41,353	2.71	94.76
Banco Banestes S.A.	State	22,321	1.46	96.22
Banco da Amazônia S.A.	Federal	20,143	1.32	97.54
BRB - Banco de Brasília S.A.	State	15,908	1.04	98.58
Banco do Estado do Sergipe S.A.	State	11,038	0.72	99.3
Banco do Estado do Pará	State	10,650	0.7	100
Total		1,527,190	100	

3
Predicting Branch Seasonality using Machine Learning

Abstract: Lending seasonality might have important consequences for the economy. The network of banks might deter developments in some regions. In this study, I compute the month with the peak in lending volume for each bank branch in Brazil and geographically observe its dispersion. I use data from the five banks with the higher number of branches and find that, within banks, we see a large dispersion in the demand for lending at the branch level. Using machine learning models, we identify the Random Forest as the best model for predicting branches' main month. I also identify which balance-sheet accounts are more relevant for predicting the lending seasonality. A very distinct pattern between public and private banks can be found in the data. Both the geographical presence of branches and the variables that appear as large predictors vary substantially. Thus, both spatial and seasonal aspects of the banking sector should be taken into consideration by authorities to avoid unintended consequences.
Keywords: seasonality, lending, prediction, variable importance, banking

3.1 Introduction

As previously noted in the literature, seasonality has important explanatory power, In this study, I expanded the methodology of Chang *et al.* (2016) to banks and demonstrated the relevance of the branch-level seasonality in lending activity. This seasonal component is important both at the macro level and at the branch level, being intrinsically linked to local activity. Branches within the same market can present distinct specialization in their clientele captured by the month with the highest credit demand. Other studies have investigated the effect on credit from the timing of monetary shocks (Olivei & Tenreyro, 2007) and the geographical distribution of bank branches (Degryse & Ongena, 2005; Nguyen, 2019). However, it remains to be investigated whether this seasonal component can be predicted using the branches' accounts and financing structure.

This article shows that this seasonality can be explained by the branch's local activity, captured by the composition of its balance sheet accounts. Using machine learning techniques, it is possible to identify the determinants of each branch's main month and obtain a model with high predictive capacity. Despite having more geographical coverage than private banks, public banks are easier to predict their main months. Possibly, because public banks are expected to follow a strict agenda to achieve governmental goals, the models offer an almost perfect prediction. More importantly, the relevant features used in the prediction are in line with the core business of each bank and with its presence in specific regions.

The analysis is conducted using the five largest banks in Brazil, which represent 74.81% of total lending. I define the largest banks based on the number of branches in the sample for these banks. Thus, the sample of 3.4 million observations was split into five subgroups. This was necessary due to the computational power required to estimate some of the models employed. This large number of observations is obtained because the dataset tracks the branches' balance sheets for a long period. In my sample, I used data from January 2006 up to December 2020. However, this large number of observations still returns a small number of interesting cases - i.e. when the branch faces its main month.

I applied the SMOTE technique to address the underrepresentation of the main month category. In most cases branches have only one month as their main month, leaving eleven months assuming a value of zero. Thus, SMOTE artificially creates observations while avoiding the risk of having a model that works only in that subset of data. I tested several models to predict when a branch faces its main month: logit regression, logit regression with lasso penalization, XGBoost, and Random Forests. In all analyses, the accuracy of the Random Forest was substantially higher, with several variables having a small but still relevant importance for the prediction. This suggests two complementary interpretations. First, a large set of branches' characteristics matter for explaining seasonality in lending, rather than just a few features, indicating the complexity of this task. Second, both accounts from the asset side and liabilities side are relevant to explain the branches' activity. In particular, the triad of savings, term, and government deposits often appears as candidates that explain lending seasonality.

Chang *et al.* (2016) demonstrates that stocks from firms susceptible to seasonality present higher than expected returns during these periods. Adapting their methodology of computing these main months to bank branches, I compute which months are the ones with higher demand. The large heterogeneity obtained agrees with other studies about branch specialization. For instance, Duquerroy *et al.* (2022) relies on branches' loan data and identifies that branches from the same bank, in the same municipality, offer most of their credit for firms in different sectors. This suggests that branches within the same market and banks do specialize in different types of clientele. In my study, I explore another dimension of such heterogeneity, seasonality.

This study also contributes to the literature on distance and lending. I plot the main monthly data from banks into the Brazilian map to both identify banks spread over the country and their heterogeneity in lending seasonality. According to research by Degryse & Ongena (2005) and Nguyen (2019), the proximity between borrowers and banks remains a significant factor in determining the strength of their relationship, despite technological advancements. The studies suggest that borrowers who are geographically closer to their banks tend to establish stronger connections. This phenomenon can be attributed to lower transportation costs, which facilitate the acquisition of soft information. For Brazil, it is particularly relevant due to its continental dimensions.

Agriculture is recognized as highly competitive and a significant source of employment, wealth, food, fibers, and bioenergy for Brazil. It is one of the sectors that contributes the most to the growth of the national GDP, accounting for 21% of the total wealth produced, a fifth of all jobs, and 43.2% of Brazilian exports, reaching $96.7 billion in 2019 (EMBRAPA, 2020). However, most private banks only operate in large economic centers and far from productive regions in the north. IBGE (2022) classify the soil regarding its quality and their map suggests that the north has regions to be explored for agriculture. Banks can help provide financing for entrepreneurial activities in these regions. However, this should be made cautiously, since credit has been found to have an impact on deforestation in the Brazilian Amazon. Assunção & Gandour (2013) found that a rural credit policy with stricter requirements implemented in 2008 led to a substantial reduction in deforestation in the following years.

The findings in this study hold significant implications for credit analysis and the formulation of monetary policy. Specifically, given that certain regions are more heavily serviced by bank branches, fluctuations in interest rates may have varying impacts on local credit. As such, policymakers should consider these differences when crafting strategies.

3.2 Contextual Framework

The Brazilian Credit Market is composed of 134 financial institutions that offer a large variety of credit products. From 5572 municipalities in Brazil, we observe at least one bank branch in 3,613 of them. However, it does not mean the remaining municipalities are excluded from the credit market. The presence of *correspondentes bancários* plays an important role in supplying credit in these regions (Assunção, 2013b). The main source of external financing for firms is bank credit, therefore we focus on this type of lending activity.

In 1990, Brazil experienced a significant upheaval when the president implemented a policy to freeze withdrawals from bank accounts for one and a half years. This measure was taken in response to soaring inflation rates, aiming to stabilize the economy. However, this decision resulted in unforeseen and severe consequences for savers, precipitating a crisis of trust in financial institutions. Advertising campaigns aimed at promoting financial education and encouraging savings were observed in the following years in an attempt to revitalize the population's confidence in the banking market. Yet, the nineties were also a period of large privatization of banks in Brazil. Mariani (2020) cites that with public banks being bought by private banks, the competition decreased, which led to a reduction in lending and an increase in branch closure. Furthermore, the Brazilian spread (difference between lending interest and deposit interest) increased and nowadays is the second largest worldwide (The Global Economy, 2020).

Albeit public banks also have objectives that go beyond maximizing profit (Coelho *et al.*, 2013; Sapienza, 2004), Banco do Brasil is a public bank with shares traded in the Brazilian Stock Exchange. On the other hand, Caixa

Econômica is also a public bank, but without stocks traded. In this study, I explore the idiosyncrasies of Brazilian banks such as their funding and allocation of lending to explain the loan seasonality. For instance, Caixa has the largest share of savings deposits (liabilities side), whereas Banco do Brasil is the main lender of rural credit (assets side). Thus, I try to identify if such idiosyncracies help determine the main months of the branches belonging to these banks.

3.2.1 The largest five banks in Brazil

Banco do Brasil, a state-owned bank with shares traded on the Brazilian stock exchange, was established in 1808 and remains the oldest active bank in Brazil. With 5388 branches nationwide, it plays a pivotal role in implementing numerous government programs. It was not until 1905 that the government assumed control of bank ownership. Since then, Banco do Brasil has been entrusted with managing various governmental initiatives, particularly in recent years, focusing on rural credit logistics, leveraging its extensive nationwide network. The extent of rural credit offered by the bank calls for attention. According to the data, 61.66% of total rural credit in Brazil comes from Banco do Brasil. Thus, having incentives that go beyond maximizing profits, even in poorer and remote areas there are branches offering products for the population, in particular to more distant regions.

The second bank with the most branches (4594), Bradesco is also the second bank in the total volume of Loans and Discounted Accounts Receivable, which consists mostly of working capital and short-term credit for small and medium enterprises (SMEs). This is one of the goals of Bradesco in a country in which SME's main source of financing is loan credit. There is broad evidence that banking markets are located near SMEs even in countries with more alternatives of funding such as the US (e.g. Garmaise & Moskowitz 2006). Bradesco is the private bank with the largest market share in total credit (11.69%). Due to data limitations, the econometrician is unable to distinguish consumer from firm capital. However, both the participation in this market and spread over the territory suggest that Bradesco focuses on serving firms.

Itaú-Unibanco Bank typically caters to a clientele with higher income levels and firms. Its 3900 branches are mainly in the most developed regions of the country, namely the south, and southeast. Joaquim *et al.* (2019) extensively discusses the process of merging between Itaú bank and Unibanco bank in 2008. The merger between Itaú and Unibanco was a milestone in the history of the Brazilian banking sector. The union of the two banks, already market leaders, created an even stronger and more competitive institution. At the time, Itaú was the 3rd and Unibanco the 6th largest bank in the country. Despite the large concentration, the merger was approved and the banks adopted a common brand name, becoming one of the top 20 banks in the world. Naturally, it decreased even more the competition in the Brazilian banking sector, but the banks could take advantage of economies of scale, complementarity in products, and synergies to become more competitive. Despite the merger, the bank holds the last position for our five banks in total lending volume (9.83%). However, is the private bank with the highest amount in savings deposits.

The biggest responsible for saving deposits in Brazil is another public bank: Caixa Econômica Federal. Contrary to Banco do Brasil, it is strategically advantageous that its ownership is fully from the government. For instance, it takes on the important role of managing subsidized real estate credit initiatives. Notably, the Minha Casa Minha Vida program, initiated in 2009, has successfully provided homes to 3.5 million recipients by 2017 (Chagas & Rocha, 2019). Through a lottery system, eligible candidates gain the chance to secure financing for a home at significantly reduced interest rates.

Also, Caixa is the bank responsible for payments regarding *Bolsa Família.*. *Bolsa Família.* is recognized as the largest Conditional Cash Transfer program in the globe affecting (Paiva *et al.*, 2019). According to the authors, the program affected 14 million households with an average payment of U$74.16, calculated based on the PPP conversion factor for private consumption, updated as of January 2018.

Additionally, Caixa is responsible for payments regarding employment rights (e.g. unemployment insurance, Government Severance Indemnity Fund for Employees (FGTS), etc). And even the Federal Lottery is managed by the bank. Likely, because of these governmental programs, Caixa is the bank with the highest number of clients (Banco Central do Brasil, 2024), despite being only the third in the number of branches (3,389). Also, Caixa's main funding comes from governmental transfers and savings accounts from the general public (37.16%).

Originating from Spain, Santander Bank boasts a network of 2,694 branches across Brazil, yet its coverage extends to only 771 municipalities within the nation. Despite its private status, Santander has earned commendation in Brazil for its unwavering dedication to social responsibility and sustainability initiatives. Through a multifaceted approach encompassing education, culture, entrepreneurship, and social inclusion, Santander significantly contributes to societal progress.

Noteworthy examples of its educational initiatives include the Santander

Universidades grant and the Santander Universitário card. The former provides grants to academically exceptional students seeking to pursue a semester abroad at a foreign university. Covering tuition fees and living expenses, this program facilitates international academic experiences for deserving scholars. Meanwhile, the latter initiative endeavors to be the premier credit card option for burgeoning adult students navigating financial independence. In collaboration with various universities, Santander sets up stands to educate students on financial literacy, offering the Cartão Santander Universitário card with a modest credit limit of approximately R\$250.00 ($50.00 USD$). Serving as a foundational financial tool, this card often marks the initial foray into financial independence for many students.

3.3 Methodology

3.3.1 Data

The data used in this study comes from the Banking Statistics System (Estban) and comprises monthly branch-level data about all the financial institutions operating in Brazil. The window of analysis starts in January 2006 and goes until December 2020 (180 months).

As previously noted, branch seasonality significantly influences credit volume. The variable $Main\ Month_{imt}$ captures this historical pattern by identifying the month with the highest historical loan volume for branch i. The methodology to compute this variable is originally detailed in Chang *et al.* (2016), with adaptations made here for branch and monthly data. Initially, observations for a branch are sorted from the largest to the smallest loan volume. Subsequently, each observation is assigned a rank, and the monthly average rank is computed. Using ranks instead of monetary values, as suggested in the original study, mitigates noise from outliers. The month with the highest monthly average rank is designated as the Main Month for the branch. While it's possible for a branch to have more than one main month, such cases are infrequent. Consequently, $Main\ Month_{imt}$ equals one if the branch is in its main month and zero otherwise.

I use a more agnostic approach, in which the data is taken as given, letting computations of other variables (such as returns and leverage) for future analysis. I discard some variables that are a combination of others to avoid perfect multicollinearity (e.g. Total Assets, Other Credit Operations) remaining 25 continuous variables to be used as predictors. Notice that all variables are on the branch level, thus, variables such as ownership (bank-level) or municipality (municipal level) are not used in the predictive models.

The analyses focus exclusively on the top five largest banks in Brazil for three practical reasons. Firstly, the dataset encompasses approximately 3.4 million observations, making employing complex models across such a vast dataset impractical. A more manageable dataset is obtained by segregating the data into five subsamples, each corresponding to a specific bank. Secondly, the objective of this study is to pinpoint distinctive bank characteristics that can predict their main month. Incorporating data from other banks into the analysis may yield more generalized outcomes, which do not align with the unique market practices adopted by individual banks. Thirdly, as explained in the next section, I use SMOTE to compute synthetic observations about the main month. Since the method creates newer observations using branches' characteristics, it is useful to rely on comparable units of analysis.

The volume of lending (operações de crédito) should be an expected predictor because the main month variable is computed (non-linearly) based on this variable. Hence, if the models are capturing well these non-linearities, is indicative of a good fit. In unreported results, I included this variable to identify if Random Forest is capable of attributing a large weight for it. For all five banks, the volume of credit is either the first or second variable with largest importance, suggesting it is an obvious candidate captured by the model.

Lastly, the data exhibits a panel structure, wherein the primary month is represented by a dummy variable that takes a value of one if the observation corresponds to a primary month. While it is possible for a branch to have more than one main month, such instances are relatively uncommon. Consequently, the number of observations not from primary months outweighs those from primary months, highlighting the classical issue of class under-representation. In the subsequent section, I elucidate the methodology employed in this study to address this challenge.

3.3.2
SMOTE - Synthetic Minority Over-sampling Technique

Class imbalance occurs when one class (the minority class) is significantly underrepresented compared to another class (the majority class) in the dataset. This can lead to biased models that perform poorly in predicting the minority class. In this context, the main month is roughly one month, leaving eleven months as the majority class. Therefore, SMOTE works by creating observations in the space of minority class to improve classification tasks.

SMOTE was initially presented in Chawla *et al.* (2002), where the authors show their algorithm helps to improve the classification of minority classes in nine different datasets. SMOTE can be used for a vast range of empirical problems and is often combined with other techniques. For instance, SMOTE can be used for predicting credit scores (Tian *et al.*, 2020; Harding & Vasconcelos, 2022), for predicting credit card frauds in purchases (Ileberi *et al.*, 2021), and to predict car insurance frauds (Padmaja *et al.*, 2007).

As previously mentioned, the number of main months is substantially smaller compared to the number of the remaining months. Since discarding observations from the non-main months might lead to missing aspects that might drive the seasonality present in the banks, I opt for a widely used technique used to deal with class imbalance. On the other hand, heavily forcing the algorithm to generate a larger number of observations might lead to artificial conclusions or overfitting. Thus, I opt for a conservative measure in which I use smote to double the number of observations in which the main month is labeled as one.

The SMOTE uses a K-nearest neighbor to compute the distance between one datapoint and others near. Then, the data is created in the midway of these k-distances. A n-dimensional vector (in which n represents all variables) is used to compute these distances. For my analysis, I choose to select four (K = 4) nearest neighbors to compute the synthetic observation. Empirically, the distance will be taken from the four closest observations, from the same bank, to return the majority class of these observations. The other parameter that should be decided is the number of times the SMOTE algorithm will run through the existing ones in the data. I select $dup\_size = 1$, indicating that the number of main months will double, consequently roughly reducing the ratio of ones to zeroes by half. Table B1 contains the results.

Table B1: Sample Size

		Banco do Brasil	Bradesco	Itaú-Unibanco	Caixa Econômica	Santander
Original	Main = 0	749498	632253	517077	442090	350697
	Main = 1	94747	70071	62477	55546	44491
	Ratio	7.91	9.02	8.28	7.96	7.88
SMOTE	Main = 0	749498	632253	517077	442090	350697
	Main = 1	189494	140142	124954	111092	88982
	Ratio	3.96	4.51	4.14	3.98	3.94

3.3.3 Random Forest

Initially proposed by Breiman (2001), the Random Forest model consists of estimating the same model B times on samples with replacement but for a different subset of variables. This subset of variables is randomly selected to define each split rule guaranteeing that models have large differences, which benefits bagging estimates (Breiman, 1996). Thus, the algorithm uses both random selection of independent variables and bootstrap (random selection of observations in the sample) to achieve an uncorrelated forest of decision trees. Together, these two aspects ensure a low correlation among decision trees that makes the predictions more accurate (Breiman, 2001). Also, it reduces overfitting and improves the model's generalization performance.

Decision trees seek to find the best split to subset the data, and they are typically trained through the Classification and Regression Tree (CART) algorithm. Growing a CART (Classification and Regression Trees) model involves an iterative process that commences at the root node and progressively expands the tree until reaching terminal nodes. At each step, a new split is introduced in a node. This split entails determining the variable j and splitting point c_j to employ. The optimal split is identified by minimizing a loss function, such as the Gini index or quadratic loss. The tree-building process ceases upon reaching a specified criterion, such as the minimum number of observations per terminal node or a maximum depth.

Three important parameters should be set in advance: the node size, the number of trees, and the number of features sampled. To avoid researchers' degrees of freedom all parameters were set to default. For this study, I used the `ranger` package (Wright *et al.*, 2017) in R to estimate the Random Forests. The tree size was controlled by the minimum number of observations allowed in each terminal node, which was 5 and the number of trees in the Random Forest was 500. The number of candidate variables for each split was the square root of the total number of variables (25 independent variables), chosen randomly in each split.

To assess the predictive performance, I employed three measures for in-sample prediction evaluation. Accuracy represents the percentage of correct predictions made by the model. Sensitivity measures the percentage of main month predictions that accurately correspond to the main month observations. Specificity quantifies the percentage of non-main month predictions that correctly correspond to non-main month observations. I also briefly mention the incorrect predictions to identify any pattern, but none is observed.

In addition to Random Forest, three other models were utilized in an attempt to predict the main month. These included Logit, Logit with Lasso penalization, and Gradient Boosting (XGBoost). However, none of these models yielded satisfactory predictions. They frequently excelled at predicting non-main months but performed poorly in identifying main months accurately. Notably, the Logit with Lasso penalization often selected none or only one feature. With the pertinent variables identified, the next step is to determine which ones are most influential.

3.3.4 Variable Importance

In machine learning models, it is usual to have a measure of the relative importance of each variable for the prediction. In this study, I compute the variable importance of each variable by permutation. Permutation is a technique to estimate the importance of each variable by measuring the change in the model's performance when the feature's values are randomly shuffled. To identify how much a variable is relevant to the model, I compute the variable importance using the Gini Impurity Index. To compute variable importance using the Gini impurity index, the decrease in Gini impurity attributed to each variable is calculated. Variables with higher decreases in Gini impurity are considered more important.

For each class C we have a probability $p(i)$ that an observation belongs to class $i = 1, ..., C$. Hence, for each node η the Gini Impurity Index is as follows:

$$GI_\eta = \sum_{i=1}^{C} p(i)(1 - p(i)) \tag{3.1}$$

To obtain this metric we compute the decrease in impurity for each node of the tree. Then, we compute the total decrease for each variable, considering the nodes split by that variable. This total decrease is obtained by summing the decrease for each variable, weighted by the number of samples in each node. Within the context of Random Forest for classification, we simply count the number of correct predictions of the model. Variable importance will tell us the rank of each variable based on the decrease of impurity. For simplicity, I will discuss deeply only the variables with larger importance for each bank in the next section.

3.4 Results

In this section, I will discuss the results of my analyses in the following order for each of the largest five banks in Brazil. First, I plot a map to highlight the geographical spread of each bank and the heterogeneity in the main month for each municipality. To numerically interpret the maps, Table B2 provides the dispersion of the main months belonging to a bank. Next, I show the Confusion Matrix for each bank's prediction emphasizing the accuracy of the Random Forest model that was superior to all other models. To check for the Confusion Matrices of other models please check Appendix 3.5.

Table B2: Municipalities' Main Month Distribution for the Top 5 Banks

	Banco do Brasil	Bradesco	Itaú-Unibanco	Caixa Econômica	Santander
January	39	188	5	17	16
February	11	233	21	6	7
March	12	208	27	4	38
April	26	258	60	9	103
May	43	109	62	16	48
June	246	151	49	46	75
July	100	79	40	41	33
August	114	159	91	42	32
September	134	199	61	123	65
October	175	272	164	117	99
November	693	325	535	291	194
December	1,324	80	73	917	61
Total	2917	2261	1188	1629	771
Std. Dev.	388.54	77.03	143.17	259.28	50.67

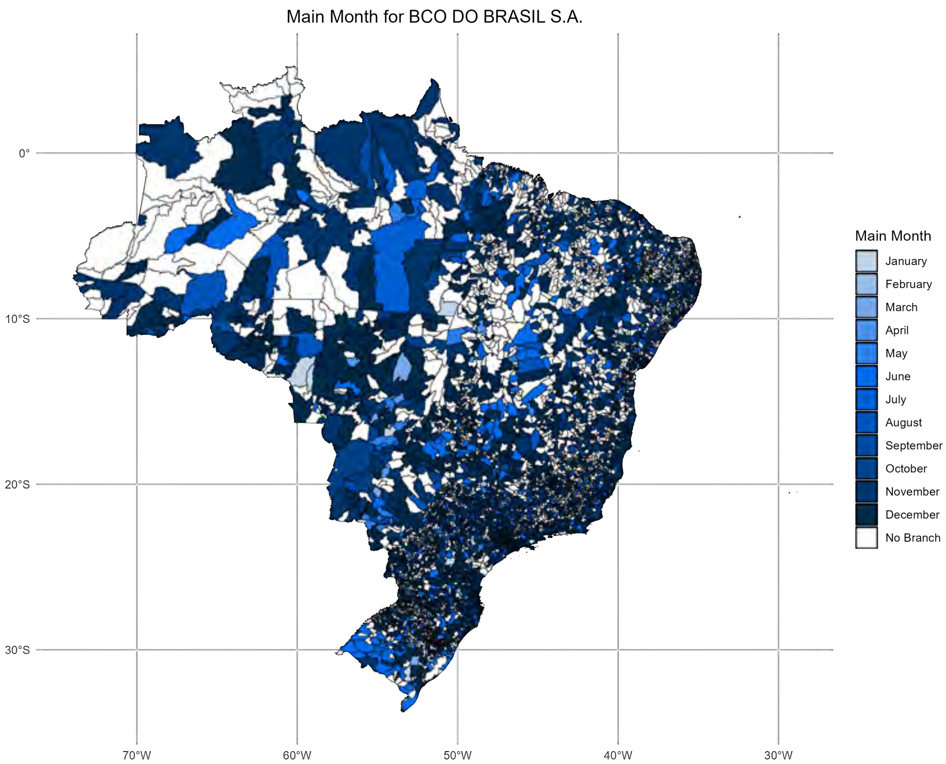
Lastly, I report the variable importance, which measures the impact of removing a given variable will have on the prediction. This measures the average decrease in impurity (e.g., Gini impurity) across all decision trees in the forest when a particular feature is used for splitting. In all bar graphs, the same scale is used to allow direct comparability of variable importance. Furthermore, the variables have an A) or L) indicating if this is an account from the assets or liabilities side, respectively. The order of the results will be decreasing from the bank with the largest number of branches.

3.4.1 Banco do Brasil

Banco do Brasil is the bank with the highest spread over the Brazilian territory. As can be seen in Figure 3.1, Banco do Brasil has the largest territorial coverage and heterogeneity of main months over the municipalities. Compared to other banks, it presents the highest number of branches and standard deviation of main months, according to B2. In very few municipalities we see main months in the first semester, leaving November and December as the two months with the most concentration of main months. The dispersion of

Banco do Brasil branches' in Brazilian territory, together with the prevalence of November and December as Banco do Brasil's main months, suggests that shocks in these months might affect differently the regions the bank has coverage. For example, an increase in interest rates can disproportionately affect the rural loans of the north of the country, where Banco do Brasil has a large coverage and share of rural credit.

Figure 3.1: Branch Dispersion of Banco do Brasil in Brazil



Despite the large dispersion in the data for Banco do Brasil, the percentage of correct predictions using the Random Forest is 96.53%. There is one case in which the model predicted the main month but the true value is zero. However, a small number of predictions indicated zero when the real outcome is one, as can be observed by the Sensitivity of 0.8278. From the group of wrong predictions, 24,489 are from the original observations, and 8,134 are from synthetic observations generated by SMOTE. Perhaps surprisingly, the model has a good prediction of the main months for the bank with the most variation in the main months. As a public bank having a larger coverage is expected, but the model is capable of capturing such variation and providing useful results.

The variable which represents events related to relationships between financial institutions across various branches of an institution (Interfinancial Relations and Interdependency), suggests that most of these transactions involve a debit balance, as it is a liability-side account. This implies that the

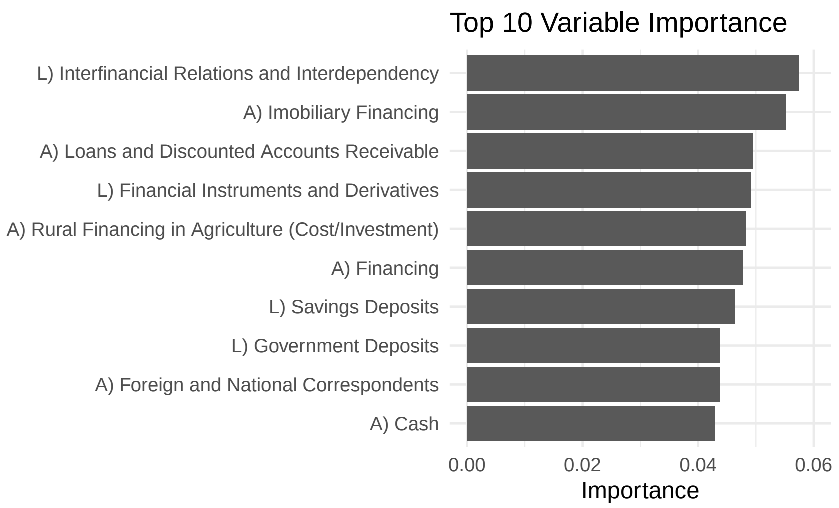
Table B3: Confusion Matrix with Random Forest predictions for Banco do Brasil

Random Forest		BCO DO BRASIL S.A. Reference			
		0	1	Accuracy	0.9653
Prediction	0	749497	32622	Sensitivity	0.8278
	1	1	156872	Specificity	1.0000

agency utilizes its internal markets to finance its credit activity. Being the bank with the largest geographical dispersion, relying on its network seems to be important in terms of predicting the seasonality of lending. As the second most significant variable, we identify real estate financing, which involves loans for the acquisition of properties, often using the property itself as collateral. Loans and Discounted Accounts Receivable and Financial Instruments and Derivatives also play an important role. Discounts of future revenues and use of derivatives to mitigate risk are mainly made by entrepreneurs, and both appear with a weight of (0.044).

Rural credit emerges as the fifth most influential factor in forecasting the main month (0.044). As previously noted, Banco do Brasil plays a pivotal role in disseminating government programs nationwide. It's worth highlighting that Brazil holds the title of the world's largest producer of soybeans. The period between October and December marks the planting season for soy, aimed at maximizing harvest yields. During this time, farmers engage in land preparation, invest in machinery, and undertake various costly activities. This pattern together with the vast presence of bank branches may help explain why Banco do Brasil's main lending month typically falls towards the year's end.

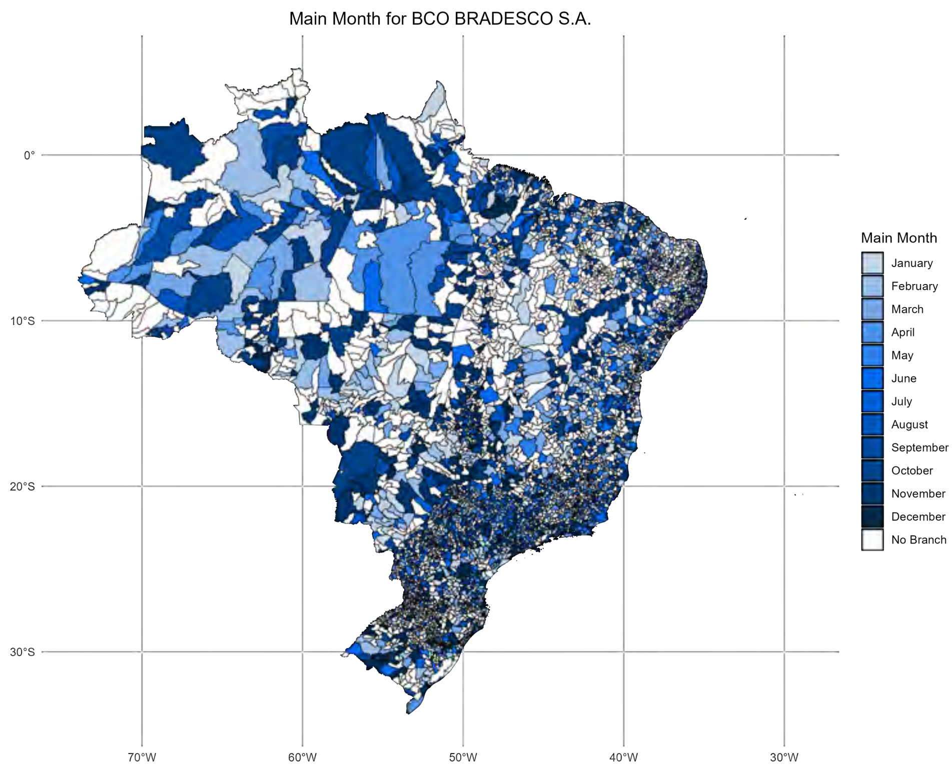
Figure 3.2: Variable Importance for Banco do Brasil



3.4.2 Bradesco

The Bradesco bank presents the second largest coverage in the Brazilian territory, being the largest among the private banks. Although operating in 2261 of the 5572 municipalities, it has one of the smallest standard deviations for the main month. According to Table B2, November is the month with more concentration of municipalities in the main month, but for other months the values are evenly distributed. If the months every evenly distributed, there would be roughly 188 branches in each month, that is precisely the month of January.

Figure 3.3: Branch Dispersion of Bradesco in Brazil



Despite the small standard deviation, Bradesco presents the lowest Accuracy value for all banks analyzed. Table B4 shows 82.20% of correct predictions, which is a still high value. However, such a high prediction is followed by a low Sensitivity (0.0189), indicating that the model is predicting many zeroes when the true observations are one. This might suggest that Bradesco is so focused on *local* clientele that is hard to find a general rule for prediction in the trees. From the wrong predictions, 69,897 are from original data whereas 67,595 are from synthetically generated data.

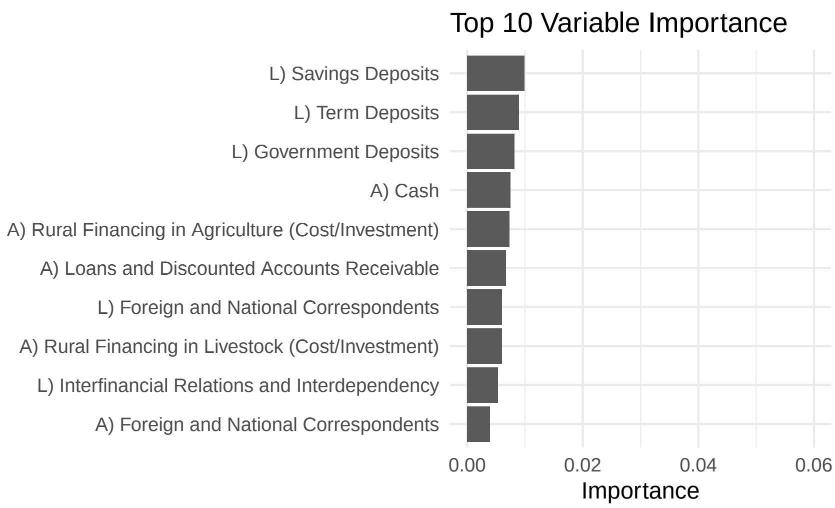
Table 3.4 reports variable importance for Bradesco. Notice that all variables have a quite small value. Savings, Term, and Government deposits

Table B4: Confusion Matrix with Random Forest predictions for Bradesco

BCO BRADESCO S.A.					
Random Forest		Reference			
		0	1	Accuracy	0.8220
Prediction	0	632253	137492	Sensitivity	0.0189
	1	0	2650	Specificity	1.0000

occupy the first three positions as the main source of funding. Perhaps taking advantage of the widespread structure, Bradesco plays an important role in providing savings for the population. In fourth place is Cash, suggesting that Bradesco can use cash for financing in periods of high demand. In sum, given the low accuracy and variable importance, little can be concluded about the seasonality of Bradesco's lending.

Figure 3.4: Variable Importance for Bradesco



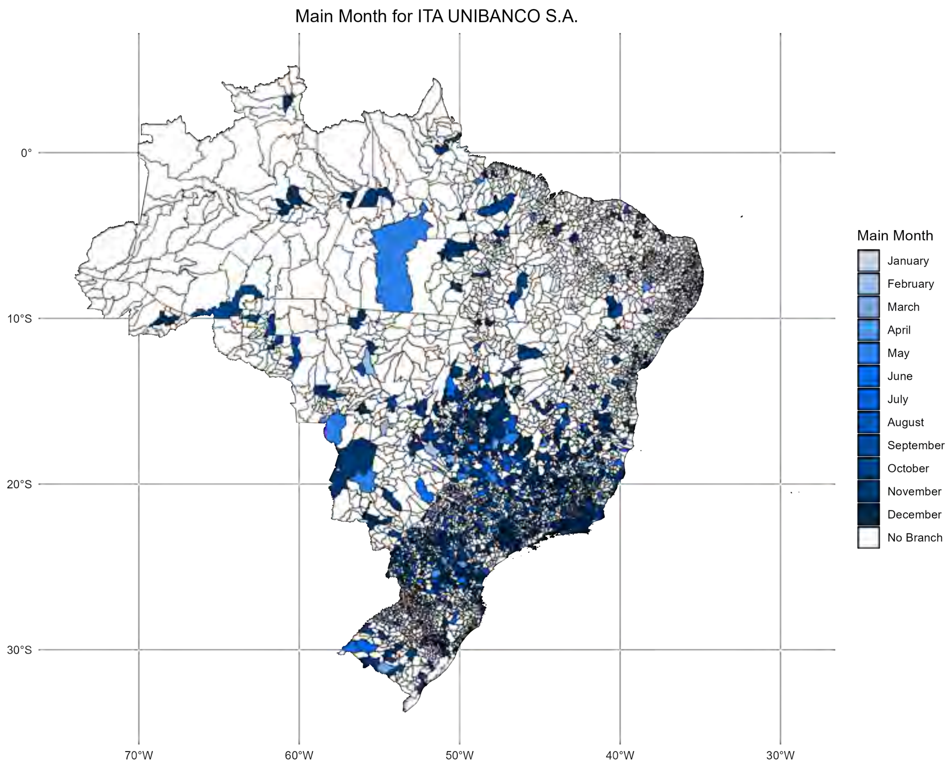
3.4.3 Itaú-Unibanco

In Figure 3.5 it is clear that the coverage of Itaú-Unibanco is mainly concentrated in the south and south-east portion of the country. These regions are the most economically developed regions of the country and these inequalities can be traced back to the colonization of Brazil with the Treaty of Tordesillas in 1494 (Laudares & Caicedo, 2022). The high concentration of municipalities with their main months in November suggests that the bank is more specialized in clients that demand more at the end of the year. Individuals and firms can take advantage of tax discounts if paid in anticipation of the new year. On the other hand, firms demand capital to pay the thirteenth salary[3.1]

[3.1] In Brazil, salaries are paid every month and in December firms have to pay an additional salary for their employees according to the Employment Law.

and two important festive dates occur for Brazilians in December, namely the Christmas and New Year. Anecdotal evidence suggests that individuals do anticipate these events.

Figure 3.5: Branch Dispersion of Itaú-Unibanco in Brazil



Regarding model prediction the overall Accuracy is 81.67%. As in the previous case, the model fails to adequately predict the ones. The high accuracy comes from the correct prediction of zeroes. Hence, the proportion of correct predictions of ones when the true value is one is low, with a Sensitivity of 0.0584. The number of incorrect predictions from SMOTE is 57,163 and from non-SMOTE observations is 60,500.

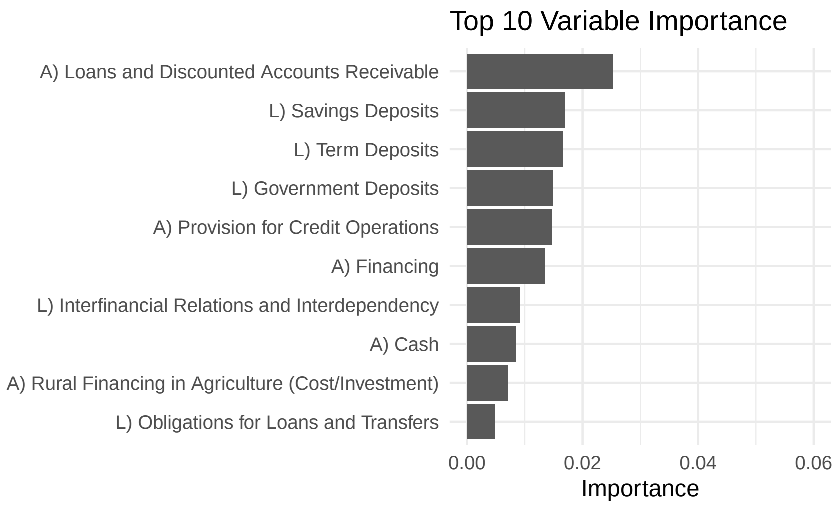
Table B5: Confusion Matrix with Random Forest predictions for Itaú-Unibanco

		ITA UNIBANCO S.A.			
Random Forest		Reference			
		0	1	Accuracy	0.8167
Prediction	0	517077	117663	Sensitivity	0.0584
	1	0	7291	Specificity	1.0000

The variable importance indicates the Loans and Discounted Accounts Receivable as the main predictor with an importance of 0.023. As previously mentioned, the bank aims to attend firms in the more economically developed regions. Itaú-Unibanco is the private bank with largest amount of savings in Brazil. With an importance lower than 0.02 we observe Savings, Term, and

Government deposits appear as the main determinants of main months. The provision for credit defaults, mainly registering credit operations that are likely to default, appears as the fifth main determinant. This suggests that previous loans might drive current-period loan volume depending on the default rate of the borrowers. Recall that this bank faced a merger in 2008, so it is expected that its activity might be more dispersed as for the other banks. From the private banks, it is the one with the highest standard deviation in the main months, as shown in table B2.

Figure 3.6: Variable Importance for Itaú-Unibanco



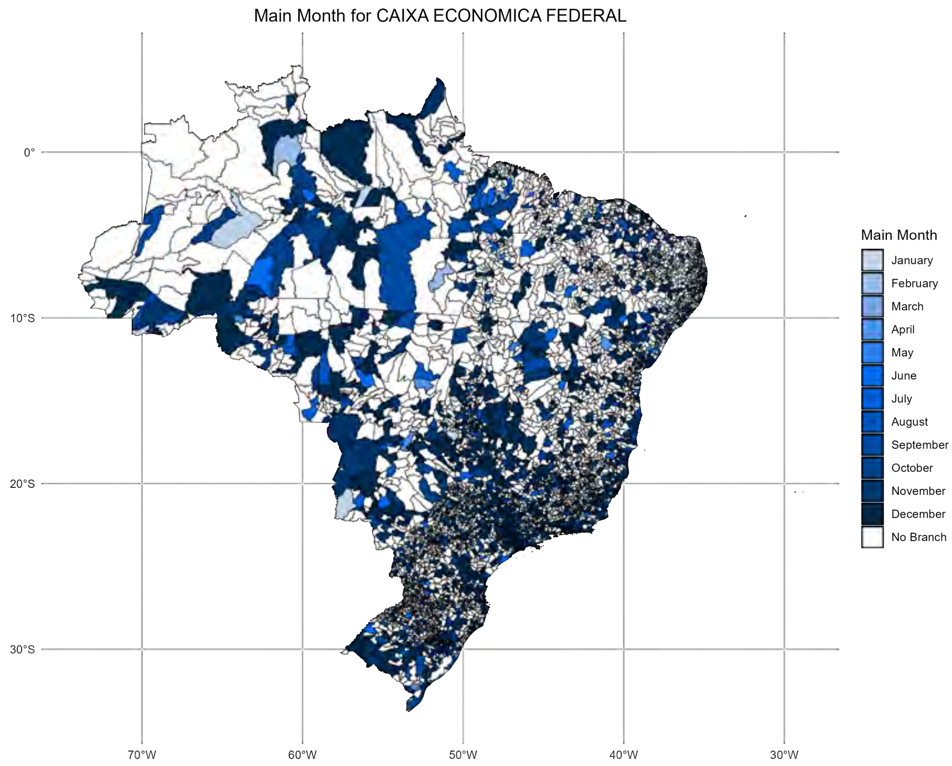
3.4.4
Caixa Econômica

The large prevalence of December as the main month for Caixa Econômica can be checked in Table B2. Of the 1629 municipalities in which the bank has a branch, 917 (56.3%) of them are in December. As above-mentioned, the festive dates and taxing incentives might also explain it. In particular, because Caixa is the bank responsible for Bolsa Família, many clients are poor and financially uneducated. To illustrate, Klapper & Lusardi (2020) cite that 32% of adults in Brazil have a credit card although only 35% can be considered financially literate in a 2014 survey[3.2]. Therefore, their loans may be used for short-term consumption.

The predictive accuracy of Caixa Econômica's model is demonstrated to be surprisingly high. According to Table B6, it achieved a 99.81% accuracy rate, with only 1,078 instances incorrectly predicted as zero when they were

[3.2] Klapper & Lusardi (2020) consider financially literate those that can answer correctly at least three of the four concepts explored in their study: Risk Diversification, Inflation, Numeracy Interest, and Interest Compounding.

Figure 3.7: Branch Dispersion of Caixa Econômica in Brazil



one. Of those, 827 are from original data and 251 are from synthetic observations. This asymmetry can be attributed to the small number of cases. The sensitivity reached 99.03%, and the specificity approached 100%, marking the highest levels observed in this study.

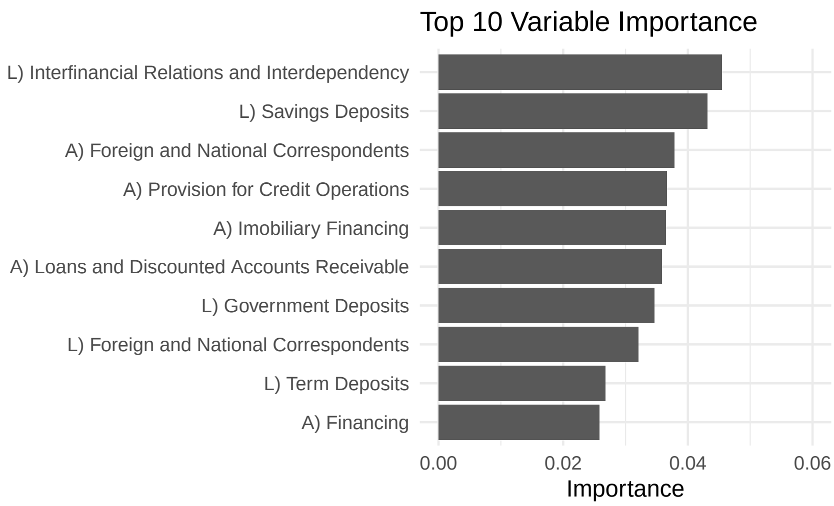
Table B6: Confusion Matrix with Random Forest predictions for Caixa Econômica

Random Forest		CAIXA ECONOMICA FEDERAL Reference			
		0	1	Accuracy	0.9981
Prediction	0	442090	1078	Sensitivity	0.9903
	1	0	110014	Specificity	1.0000

The variable with higher importance for Caixa is the one regarding intra- and inter-relations. Broadly speaking, this account deals with compensations within the bank (between branches), and between the bank and other banks. Notably, this variable was also the one with higher importance for Banco do Brasil, the other public bank in the sample. The Savings Deposits account from Caixa deserves a detailed description because the Brazilian population widely uses it. According to the data in this study, Caixa concentrates the largest share of savings deposits in the country (37.16% of total savings) followed by Banco do Brasil (22.81%) in that savings also appear as having a high importance for prediction. Also, historically public banks, in particular Caixa with advertising campaigns, are responsible for incentives savings (Marchesoni, 2012).

Foreign and National Correspondents also indicate the spread of Caixa's branches and correspondents. Both its Assets side and Liability side appear as relevant. This account is published mixing the national banking correspondents and the foreign bank correspondents, which makes it hard to go beyond mere conjecture. Provisions for Credit Operations also suggest that public banks are leading with more risky clients, and appear as the fourth determinant. Housing financing appears as the fifth most important variable when predicting the main month for Caixa. Recall that Caixa is responsible for financing the Minha Casa Minha program, which focuses on increasing the supply of habitation for the low-income population in Brazil. Over the years, the default rate in contracts from Minha Casa Minha Vida achieved alarming values. For instance, for 2022, the number of contracts in default for more than a year, for the lowest tier of credit, was 45% (Folha de São Paulo, 2023). In sixth place Loans and Discounted Accounts Receivable appear once again, in particular, an activity mainly made by firms. Finally, government deposits also matter, which is expected for a public bank.

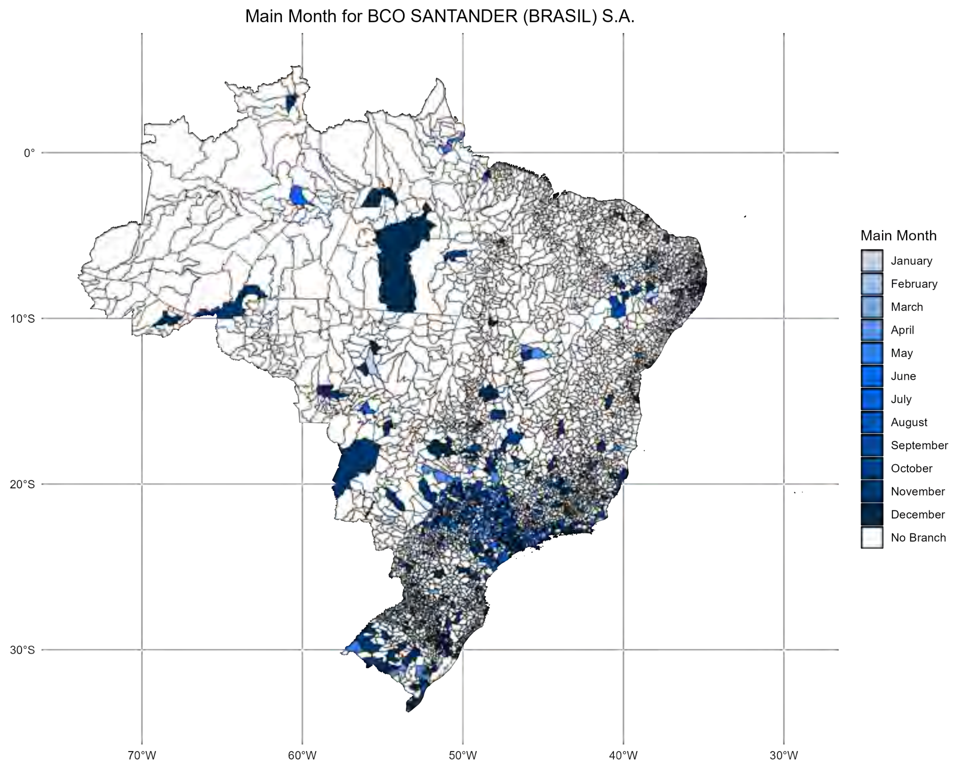
Figure 3.8: Variable Importance for Caixa Econômica



3.4.5 Santander

Santander stands out as the bank in my sample with the lowest standard deviation of main months, as indicated in Table B2. The number of municipalities where Santander's main month falls in December (194) is slightly more than three times the average (64.25). Moreover, there is minimal clustering of municipalities in the initial months of the year, making it challenging to discern a pattern. Additionally, Santander has the smallest coverage across the Brazilian territory among the sampled banks. Its presence is predominantly limited to the southeast and southern regions, which are the wealthiest regions of the country. Outside these regions, one can see branches mostly located in state capitals.

Figure 3.9: Branch Dispersion of Santander in Brazil



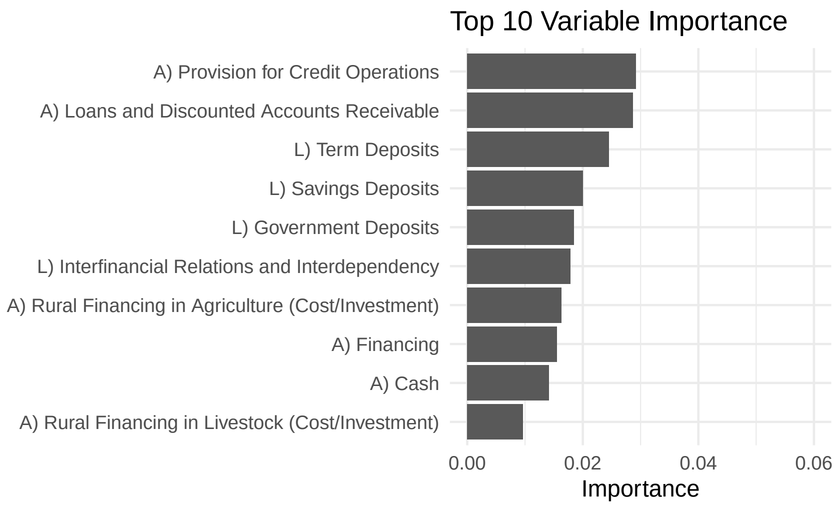
Similarly to other private banks, the model for Santander provides a large portion of wrong predictions of zeroes when the true value is 1 (Sensitivity = 11.25%). Thus, it reduces the accuracy for Santander to 82.04%. However, this value is still high, because the model is good in predicting correctly the non-main months (Specificity = 1). From the wrong predictions, 41,947 are from original data, and 37,028 are from synthetic data.

Table B7: Confusion Matrix with Random Forest predictions for Santander

		BCO SANTANDER (BRASIL) S.A.			
Random Forest		Reference			
		0	1	Accuracy	0.8204
Prediction	0	350696	78973	Sensitivity	0.1125
	1	0	10009	Specificity	1.0000

The Variable Importance in Figure 3.10 shows that Santander's most important variable for predicting seasonality is the Provision for Credit Operations, which registers losses with credit operations. It is an asset-side account

Figure 3.10: Variable Importance for Santander



with negative values, expressing the capital the branch expects to lose in its creditor activity. Interestingly, Santander Bank seems to be more concerned than other banks with possible defaults. This might be explained by its narrow geographical activity or its clientele of students having its first account. The discount on trade bills is the feature with the second highest importance, followed by term, savings, and government deposits.

3.5 Conclusion

This study aimed to uncover patterns in predicting the seasonality of lending among bank branches. Leveraging balance-sheet data from banks to identify the factors influencing total outstanding lending volume, machine learning models achieved high accuracy in forecasting the month with the highest loan volume. The analysis further revealed that branches within the same bank experience varying demands depending on their location.

Overall, the geographical spread of private branches is wider than the public banks in the sample. Private banks tended to concentrate their branches in more developed regions of the country, particularly in the south and southeast, corroborating findings by Mariani (2020), which reported a 21% increase in branch closures following bank privatization in the nineties, when the concentration was larger in these regions. Notably, the maps in this study revealed large areas in the northwest with only Banco do Brasil branches, raising concerns given the bank's significant role in rural credit provision in Brazil.

The prediction exercise provided substantially better results for public banks than for private banks. The Random Forest models often predict nonmonths which are the main months in the data. Therefore, the proportion of correct predictions of private banks deteriorated, whereas public banks obtained almost perfect predictions. This might suggest that the public banks do not directly compete with private banks. This result agrees with other findings in the literature in which public banks might not compete directly with private banks (Coelho *et al.*, 2013) or at least not in the same markets by having different maximizing functions. This difference agrees with the geographic dispersion of both types of banks. While more incipient markets (north) have the presence of a single public bank, in richer regions (south and southeast) there is a large variety of banks competing.

Regarding the variable importance, the triad of savings, term, and government deposits are important predictors for all banks, but assume the highest positions for private banks. Banco do Brasil plays a significant role in providing rural credit in Brazil, with findings indicating that the volume of rural credit reflected in its balance sheet serves as a predictor for its peak in total lending. In contrast, Bradesco, Itaú-Unibanco, and Santander, which operate primarily in more developed regions, report the discount on accounts receivable as a strong predictor of their main lending month. Additionally, they rely heavily on savings and term deposits for financing. As for Caixa, the other public bank responsible for various social programs, its funding situation is heavily reliant on transactions within and between banks. Moreover, the account representing loans associated with housing finance emerges as a significant predictor of peak demand for Caixa, which is the main conductor of Minha Casa Minha Vida.

Taken together the result in this study underscores the importance of both spatial and seasonal variations in ensuring a sufficient supply of credit. In particular, when branches face the borrowers' peak in demand (i.e. its main month). Authorities should take these results cautiously while considering that policies could disproportionately affect regions and banks and have unintended economic consequences.

Appendix B: Confusion Matrices with all models

Table C1: Confusion Matrices for Banco do Brasil

Banco do Brasil					
Logit		Reference			
		0	1	Accuracy	0.7982
Prediction	0	749459	189466	Sensitivity	0.0001
	1	39	28	Specificity	0.9999
Lasso Logit		Reference			
		0	1	Accuracy	0.7982
Prediction	0	749492	189493	Sensitivity	0.0000
	1	6	1	Specificity	1.0000
XGBoost		Reference			
		0	1	Accuracy	0.8038
Prediction	0	749101	183828	Sensitivity	0.0299
	1	397	5666	Specificity	0.9995
Random Forest		Reference			
		0	1	Accuracy	0.9653
Prediction	0	749497	32622	Sensitivity	0.8278
	1	1	156872	Specificity	1.0000

Table C2: Confusion Matrices for Bradesco

Bradesco Logit		Reference			
		0	1	Accuracy	0.8186
Prediction	0	632251	140138	Sensitivity	0.0000
	1	2	4	Specificity	1.0000

Lasso Logit		Reference			
		0	1	Accuracy	0.8186
Prediction	0	632253	140142	Sensitivity	0.0000
	1	0	0	Specificity	1.0000

XGBoost		Reference			
		0	1	Accuracy	0.8189
Prediction	0	632227	139961	Sensitivity	0.0013
	1	26	181	Specificity	1.0000

Random Forest		Reference			
		0	1	Accuracy	0.8220
Prediction	0	632253	137492	Sensitivity	0.0189
	1	0	2650	Specificity	1.0000

Table C3: Confusion Matrices for Itaú-Unibanco

Itaú-Unibanco Logit		Reference			
		0	1	Accuracy	0.8054
Prediction	0	517061	124946	Sensitivity	0.0001
	1	16	8	Specificity	1.0000

Lasso Logit		Reference			
		0	1	Accuracy	0.8054
Prediction	0	517077	124954	Sensitivity	0.0000
	1	0	0	Specificity	1.0000

XGBoost		Reference			
		0	1	Accuracy	0.8055
Prediction	0	517073	124896	Sensitivity	0.0005
	1	4	58	Specificity	1.0000

Random Forest		Reference			
		0	1	Accuracy	0.8167
Prediction	0	517077	117663	Sensitivity	0.0584
	1	0	7291	Specificity	1.0000

Table C4: Confusion Matrices for Caixa Econômica

Caixa Econômica Logit		Reference			
		0	1	Accuracy	0.7991
Prediction	0	441999	111050	Sensitivity	0.0004
	1	91	42	Specificity	0.9998
Lasso Logit		**Reference**			
		0	1	Accuracy	0.7992
Prediction	0	442090	111092	Sensitivity	0.0000
	1	0	0	Specificity	1.0000
XGBoost		**Reference**			
		0	1	Accuracy	0.8020
Prediction	0	441999	109429	Sensitivity	0.0150
	1	91	1663	Specificity	0.9998
Random Forest		**Reference**			
		0	1	Accuracy	0.9981
Prediction	0	442090	1078	Sensitivity	0.9903
	1	0	110014	Specificity	1.0000

Table C5: Confusion Matrices for Santander

Santander Logit		Reference			
		0	1	Accuracy	0.7976
Prediction	0	350691	88974	Sensitivity	0.5000
	1	6	8	Specificity	1.0000
Lasso Logit		**Reference**			
		0	1	Accuracy	0.7976
Prediction	0	350697	88982	Sensitivity	0.0001
	1	0	0	Specificity	1.0000
XGBoost		**Reference**			
		0	1	Accuracy	0.7977
Prediction	0	350697	88945	Sensitivity	0.0004
	1	0	37	Specificity	1.0000
Random Forest		**Reference**			
		0	1	Accuracy	0.8204
Prediction	0	350696	78973	Sensitivity	0.1125
	1	0	10009	Specificity	1.0000

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