COVID-19 and Credit Reallocation: evidence from Brazil

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Abstract

This study examines the reallocation of credit to less risky clients by banks across Brazilian municipalities in response to the COVID-19 pandemic, employing a difference-in-differences (DiD) approach. We leverage the heterogeneous timing and intensity of COVID-19's impact on Brazilian cities to establish causality. Additionally, we investigate bank characteristics associated with a more pronounced credit reallocation, including bank size, control structure, and capital indices. Our findings reveal a bank credit portfolio reallocation toward clients in inland cities, where the impact of the Pandemic was less significant when compared with Brazilian state capitals. Branches of inland cities with highly concentrated local credit markets where large banks dominate, and total outstanding credit is relatively underdeveloped had a more pronounced credit shift. Our results evidence that the bank financing channel did not cushion the effects of COVID-19 in the real economy, potentially becoming a pro-cyclical component.

Keywords: COVID-19, portfolio reallocation, credit growth, banking, econometrics, financial stability.

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1. Introduction

Our study tests whether a banking credit reallocation trend existed from Brazilian state capitals to inland municipalities during the COVID-19 pandemic. Given that COVID-19 initially affected state capitals more severely than inland municipalities in Brazil, this study leverages this distinct timing and intensity of COVID-19's impact. It uses each bank branch's pre-pandemic credit exposure to Brazilian capital cities as a branch-specific measure of COVID-19 exposure. Consequently, the study predicts that the higher the outstanding credit allocated by a bank branch in capital cities during the pre-pandemic period, the greater its exposure to the early adverse effects of COVID-19.

Due to the substantial variations between bank branches, even within the same bank, we can examine how bank branches responded to COVID-19, which initially struck harder in state capitals. This paper uses granular data from data from the Central Bank of Brazil. The main source of data are credit operation information from the Credit Information System (SCR) to identify bank credit operations for individuals and firms above BRL 200 (about US$40). The paper also uses data from the Accounting Plan of the Institutions of the National Financial System (Cosif), the Brazilian Federal Revenue Service (RFB), the Information on Entities of Interest to the Central Bank (Unicad), and IBGE to obtain balance sheet information at the bank branch level, geographical characteristics, and municipal-level economic details.

The empirical strategy employed to test for credit reallocation involves two steps. First, the study analyzes whether branches in inland cities reduce credit to borrowers in state capitals. Subsequently, it examines whether these same bank branches increase credit operations for borrowers in inland municipalities. For that, in our DiD specification, we estimate a panel regression comparing the local outstanding credit of *similar* banks but with *different* exposures to COVID-19 (capital vs inland cities). We take banks within the same municipality to control local demand factors. We use microregion-time fixed effects to all microregion-specific and time-varying differences between banks, including evolving lending opportunities. Our specification also includes branch-fixed effects to absorb any branch-specific time-invariant factors, such as the average quality of the branch's local management.

On the first step (do branches in inland municipalities reduce credit to borrowers in state capitals?), we show that a one-standard-deviation increase in the COVID-19 exposure of bank branches in inland cities results in a 16% reduction in credit issuance to borrowers in capitals compared to branches of the same bank in other municipalities within the same microregion. Similarly, interest rates on this credit issuance increase by 7%. The average maturity of new credit issuance decreases by 78 days (approximately 2.6 months) for each one-standard-deviation increase in the branch's exposure to COVID-19. The decrease in quantity and price increase indicate a negative credit supply shock to state capitals by inland branches that is proportional to their exposure to COVID-19. This negative credit supply also manifests at the extensive margin: more exposed banks reduce the number of clients in the capital. Overall, branches with higher exposure to borrowers in state capitals tightened financial conditions following the COVID-19 outbreak compared to less exposed branches of the same bank in other municipalities within the same microregion.

The second step (do these same bank branches increase credit for borrowers in inland municipalities?) shows that a one-standard-deviation increase in the COVID-19 exposure of bank branches in inland cities causes a 3% increase in credit issuance to borrowers in inland municipalities compared to branches of the same bank within the same microregion with lower exposure levels. Contractual terms remain unchanged: relative interest rates and average maturity differences are not statistically significant across branches of the same bank with different levels of exposure to COVID-19. Provisions decrease, suggesting that credit focuses more on less risky borrowers. The increase in credit issuance does not lead to an increased clientele in inland municipalities, indicating that it occurred for existing clients (intensive margin) of bank branches rather than new clients (extensive margin), supporting the hypothesis of credit pivoting towards less risky borrowers.

This experiment also shows that larger and more financially constrained banks (with lower liquidity coverage ratio - LCR) have a more significant credit *reallocation* to inland clients. Banks that are not financially constrained may be less sensitive to COVID-19, as they have enough capital to withstand the potential increase in losses in Brazilian capital cities while maintaining their minimum capital requirements. We do not find evidence that bank ownership drives this credit reallocation across municipalities. Also, for identification robustness purposes, we employ event studies and show that more and less exposed bank branches did not trend similarly in the absence of the COVID-19 outbreak.

Following our empirical strategy, we investigate whether credit redistribution improved the total outstanding credit in inland municipalities. The previous evidence does not imply an increase in total outstanding credit in inland cities, as competing bank branches could have reduced credit issuance to inland municipalities, offsetting the rise in credit issuance caused by branches with greater COVID-19 exposure. We examine this hypothesis by running regressions at the municipality level rather than the branch level. Therefore, the study investigates whether inland municipalities experience any change in their local aggregate outstanding credit by resorting to *across-city* rather than across-branch comparisons.

As a result, we find that local financial conditions (total outstanding credit) improve in inland municipalities: a one-standard-deviation increase in the inland branches exposure to COVID-19 reduces its total credit issuance by 7% to clients in state capitals, but increases its issuance by 2% to inland clients compared to other less exposed branches in the same microregion. The credit increase is substantial in inland municipalities with highly concentrated local credit markets - particularly by large banks - and with low financial conditions. Reallocating to less financially developed inland municipalities may result from their higher distance to capital cities or the potential room for credit expansion.

Our findings significantly contribute to the literature on crisis propagation channels, particularly studies that detail the transmission of shocks through production networks. As Reischer et al. and Bigio & Jennifer demonstrate, the bank financing channel plays a critical role in the production network's performance, especially during trade credit disruptions, as witnessed during the COVID-19 pandemic (Barrot et al. (2021) and Bodenstein et al.). Our study reveals that banks redirected their credit operations from capital cities to inland regions during the Pandemic. Given that companies in capital cities were the most severely impacted by the Pandemic, we can infer a confluence of factors that disrupted both financing channels for companies: bank financing and trade credit.

Importantly, our regressions shed light on the reallocation of the banking portfolio towards regions less affected by the Pandemic in Brazil, despite government policies aimed at stimulating credit during this period of heightened uncertainty. These results suggest that the bank financing channel did not act as a mitigator of the COVID-19 crisis in the Brazilian economy, a finding with significant implications for future research in this area.

Using a natural experiment, our paper contributes to understanding bank's reactions to significant shocks. We evaluate how banks reallocate their credit portfolio geographically during periods of stress. This understanding is of utmost importance for financial regulators as these shocks may not only harm the economy but also can spread through the financial system, with an increase in nonperforming loans, which would reinforce the adverse shock to the economy (Silva et al., 2018; Silva et al., 2017; Raupach & Memmel, 2021; Park & Shin, 2021).

The forthcoming parts of the paper are structured as follows. Section 2 explains how COVID-19 initially affected state capitals more severely than inland municipalities. Section 3 connects our work with the related literature. Section 4 explores the data sets we used to measure variables and perform the analysis. Section 5 describes and defines our methods. Ultimately, Section 6 contains conclusions.

2. Heterogeneity impact of COVID-19 in Brazil

Beyond health and epidemiological damages, COVID-19 brought substantial economic and financial downturns (Ludvigson et al., 2020; Baker et al., 2020). After the outbreak of the Pandemic, most governments around the world opted for measures like horizontal social distancing, lockdowns, and quarantines[1] to restrict the level of human interactions. Therefore, many economic activities that relied on in-site labor force and consumption suffered.

Brazil had no different pattern (Norden et al., 2021). The first cases in Brazil were reported in São Paulo (the largest city in the country) on February 6th, followed by some isolated cases in other cities. In general, COVID-19 first hit capital cities, which are the most populated areas and host all core airports, to only spread to inland cities more significantly. The left panel of Figure 1 shows the total number of cases per one million of the population in Brazil regarding location (capital vs. inland) and by the regional development level. The right panel of Figure 1 illustrates the number of new deaths per one million of the population regarding location and by the regional development level. The figures show that the timing of the Pandemic was not homogeneous, hitting state capitals first. Regarding deaths, we observe the same timing pattern as total cases except that as advanced age and morbidity groups more vulnerable to the disease die over time, the graph follows an inverted U shape with a convergence of numbers. Thus, in the case of Brazil, state capitals carried a higher burden of the Pandemic. Additionally, as detailed by Norden et al., 2021, in Brazil, the federal, state, and municipal governments have the power to pass laws on public health. It allows local public administrators

[1] Although they seem similar concepts and are frequently used interchangeably, they present different strategies. Social distancing aims to avoid large social gatherings. Quarantine in COVID-19 context means staying alone for at least 14 days. Finally, lockdown is a protocol that stops people from unjustifiably moving out of their houses or accommodation facilities for a specified period (Guzzetta et al., 2020).

to adopt various legislative and administrative measures depending on the Pandemic's progression in respective administrative areas. This characteristic adds a strong heterogeneous effect regarding the strength of the Pandemic's impact per municipality.

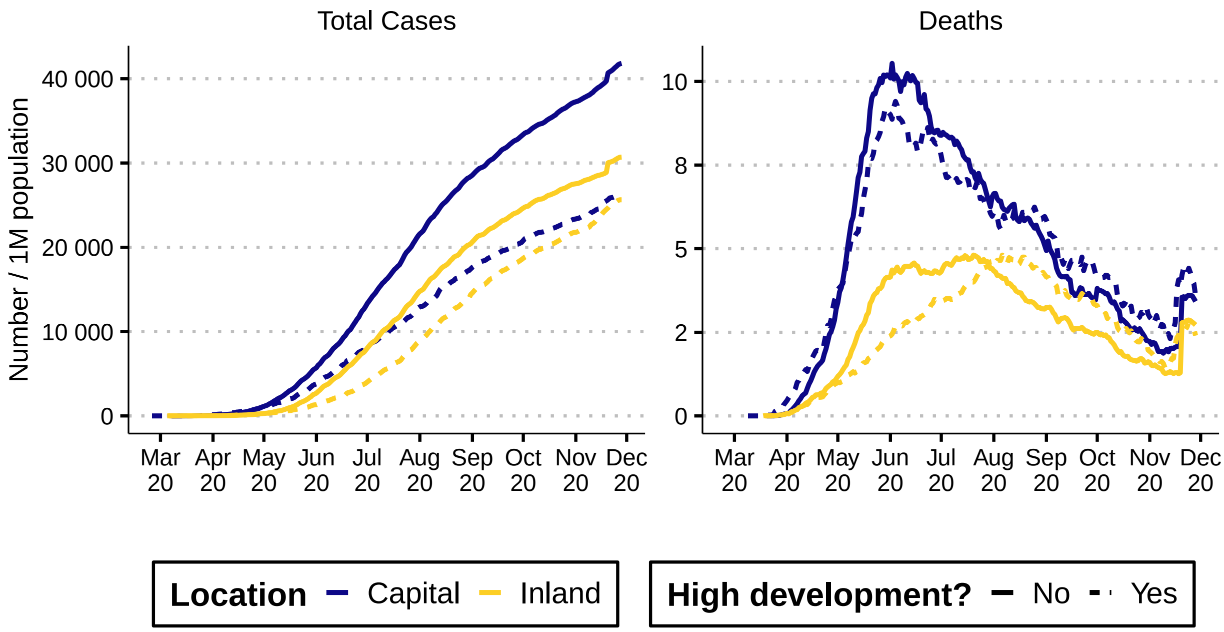


Figure 1: *COVID-19 evolution in Brazil up to November 27th, 2020. The left panel shows the total number of cases per one million population. The right panel shows the number of new deaths per one million population. The right panel graph is smoothed with a two-week moving average filter. We segregate COVID-19 evolution regarding location (capital vs. inland) and the regional development level (high development: Southeast and South regions; low or medium development: North, Northeast, and Midwest).*

This heterogeneity allows us to explore how banks reallocate credit across Brazilian municipalities due to COVID-19 using a difference-in-differences (DiD) approach. To extract causality from our results, we explore the varying timing and strength in which COVID-19 affected Brazilian municipalities—as evidenced in Figure 1—and the pre-determined credit portfolios of Brazilian banks across different cities. This paper also looks at bank characteristics associated with a more pronounced credit reallocation (size, control, and capital indices). Moreover, we investigate which types of inland municipalities receive more credit regarding local credit market concentration.

Regarding the heterogeneity effect, literature evidence suggests that governmental actions influence the size and duration of COVID-19's infection clusters (Kim & Castro, 2020; Yang et al., 2020). However, these contagion contention strategies imply that a restriction on human interaction has caused adverse effects on many economic activities. Using such strategies, part of the labor force cannot perform their tasks. Lockdown policies tend to be age- and sector-specific due to risk groups and the nature of each economic activity. Considering that different economic activities have different possibilities of being performed remotely or without gathering groups of people, whether in their production process or in the way demand consumes it, they were unevenly affected by public health policies enacted to detain COVID-19 spread. Some activities, such as performance artists, waitpersons, and cookers, tend to be overly affected by these measures, while accountants, software developers, and writers are only marginally affected. Therefore, the economic structure of a region or city can influence the intensity with which such policies may hit the economy.[2]

Brazilian state capital cities have a larger share of their economic structure, relying on more vulnerable sectors to implement lockdown measures. Figure 2 shows the sectorial average percentage of value-added and employment grouped by social interaction intensiveness and its propensity to flexibility for capitals and inland municipalities. Capital cities' economic structure has a more significant portion of their value-added and employment level from highly social-intensive sectors and with low flexibility. The share of essential sectors, whose activities cannot be performed remotely, is also higher in capitals than inland municipalities. On the other hand, inland cities tend to have a higher share of activities that are better performed when workers are in contact with customers or other workers but can also be done remotely and of activities that mostly require labor's presence but still allow for social distancing.

As a result of the more intense contagion contention restrictions, we can affirm that capital cities in Brazil were more exposed to the economic impact arising from the Pandemic. Therefore, as banks have noticed this information, they are more willing to perform portfolio reallocation from state capitals to inland cities. Consequently, expected total outstanding credit substantially deteriorated in these cities[3].

In a context where banks operate under oligopoly circumstances[4] on both credit and deposits, they evaluate and decide whether to lend or not to one market based on the cost of lending (Klein, 1971; Hannan, 1991). Since a higher default risk increases lending costs, thereby affecting profitability, banks may be willing to reallocate their portfolio toward customers, firms, and locations less exposed to the Pandemic (De Jonghe et al., 2020; Liberti & Sturgess, 2018; DeYoung et al., 2015). This paper empirically corroborates such theory: banks more exposed to state capitals, and hence to COVID-19, *increase* their total outstanding credit to inland municipalities, where the economic effects of the Pandemic were less pronounced. In other words, as banks estimated lower expected returns and higher risk in state capitals, they would instead seek the same expected returns but at a lower default risk in inland cities.

[2]Evidence from Colombia suggests that sectors such as accommodation and food services, administrative services, and real estate are the most affected, and regions such as Antioquia, Boyacá, San Andrés, Santander, and Valle delCauca had a higher vulnerability to these restrictions. Estimated monthly economic losses represented 0.5 and 6.1 percent of national GDP, depending on the severity of the contagion contention measures (Bonet-Morón et al., 2020).

[3]Haddad et al., 2022 calculated a regional index of economic activity for the state of São Paulo from March 29th to August 1st. In that index, they divided the sample of municipalities into Regional Health Departments (DRS in Portuguese), and one of them was São Paulo's state capital. They found that on March 29th, the economic activity there was between 50 and 55 percentage points below the pre-crisis level, and it was the most affected among all departments.

[4]The share of assets held by the five largest banks in Brazil in 2016 was 85% (Joaquim et al., 2019).

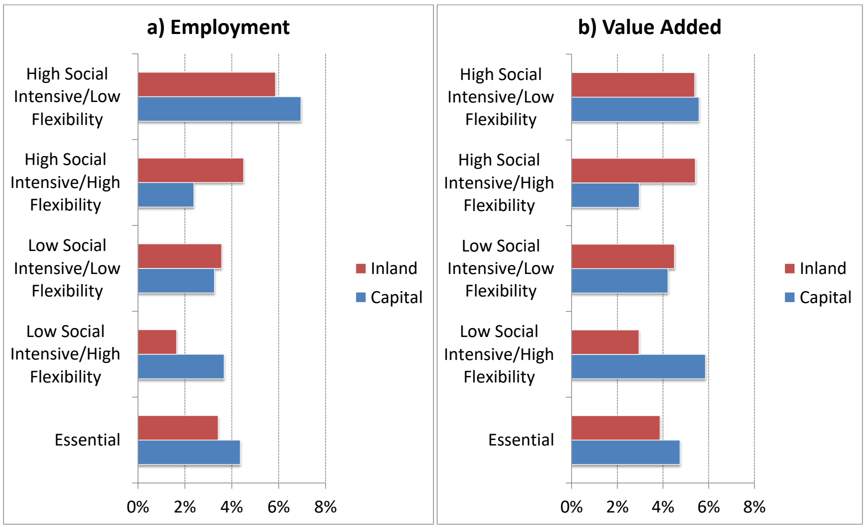


Figure 2: *Average share of value-added and employment grouped by social interaction characteristics, sector, and region. Figure (a) shows the average total sectorial men/year employment percentage of inland cities and state capital for each social interaction classification. Figure (b) illustrates the same idea but with regard to the added value. The database we used to compute these values was the Inter-regional Input-Output Matrices elaborated by* **?**, **?**. *Those matrices are composed of 22 sectors and four regions (State capitals, capital´s adjacent municipalities, inland cities, and the rest of Brazil) for 11 different population arrangements (Belém, Belo Horizonte, Brasília, Curitiba, Fortaleza, Goiania, Porto Alegre, Recife, Rio de Janeiro, Salvador, and São Paulo).To group the economic sectors according to the social interaction intensiveness, we considered the share of each sector when producing the goods based on the 2015 Input-Output matrix for Brazil.*

3. Literature Review

The banking activity study has addressed how banks respond to credit crunches and how they affect the depth and duration of recessions (Campello et al., 2010; Jordà et al., 2013; Reinhart & Rogoff, 2009). Also, it has investigated the real effects of liquidity shocks from banks to firms (Amiti & Weinstein, 2011; Carvalho et al., 2015; Chodorow-Reich, 2014). Our paper contributes to the banking literature by studying the specifics of geographic portfolio reallocation when a negative shock occurs in the real economy.

The literature substantiates the fundamentals of our analysis of the theory of portfolio reallocation in the context of banks, which sheds light on how banking firms choose how much lending to perform. Diamond (1984) developed a model in which banking firms minimize the costs of monitoring information to solve asymmetries between borrowers and lenders. He finds that lending diversification is crucial to banking activity because, depending on agents' risk aversion, it increases the probability that they will be able to repay depositors (risk-neutral) or increase their risk tolerance toward each loan (risk aversion). Boyd & Prescott (1986) use a similar framework but also elaborate that banks have information asymmetries before lending. It leads to adverse selection problems on the public information production issue and financial penalties. They find that banks maximize efforts to diversify both sides of their balance sheets, and they tend to produce information about potential and case claims with different state-contingent payoffs than those of ultimate borrowers. Besides that, Winton (1999) modeled the dichotomy of diversifying across other regions and industry sectors or specializing in some of them and argued that the choice between the two depends on the downside risk faced by the bank. If the downside risk is high, specialization is the choice, while if it is limited, diversification plays some role.

The efforts to put some of this body of theoretical propositions to the test have been taken. Our work is related to papers that consider the geographical lending reallocation. By using loan-level data since the 1980s, which includes 1,913 different bank-country pairs and 2,326 bank-firm pairs, De Haas & Van Horen (2013), provide evidence that, internationally, banks tend to lend more to borrowers from closer countries. Still in the international realm, with data on borrowers, lenders, and loan price and non-pricing terms at origination from 1997 to 2009 for banks from several countries, Giannetti & Laeven (2012) show the called flight home effect, in which banks reallocate their portfolio towards domestic borrowers due to a higher cost of negotiating and monitoring loans from foreigners, to the fact that by lending to government and government-owned firms they are more likely to be bailed out in case of distress, and to the increasing of risk aversion caused by the increased uncertainty regarding their ability to meet their capital requirements. We differ from these papers because we use multiple regions within the same country to investigate portfolio reallocation in different places with many institutional environments similar to those previously done.

A particular case is that sometimes the reallocation occurs not due to a bank's lending strategy change but due to exogenous adverse shocks. Our work also contributes to the literature on shock propagation. The most recent systemic negative shock, the 2008 financial crisis, is frequently used to study how these shocks affect portfolio reallocation (DeYoung et al., 2015; Liberti & Sturgess, 2018; De Jonghe et al., 2020). Since the financial crisis was an event that started in the financial sector, these papers analyze how banks reacted to an almost immediate shock on their balance sheets, meaning that the real sector of the economy served as a propagation channel to the financial economy. Their analysis found evidence that small and big multinational banks reduced their credit lending due to increased risk effects. Also, the reduced loan supply elasticities suggest credit rationing and heterogeneous banking relationships. Our paper differs from these in using COVID-19 as the negative shock. We investigate the effects on the many regions, in the municipality and individual levels, of a specific country (Brazil[5]).

Regarding the Pandemic, its uniqueness allowed a series of research to explore what the impacts were on the financial system and real economy (Berger & Demirgüç-Kunt, 2021). Consequently, considering the Pandemic as a tail event (Raupach & Memmel, 2021), our work will contribute to economic literature through the use of a detailed credit database which, combined with bank statistics by branches and municipality, allow mapping the allocation of credits among Brazilian municipalities as a result of the Pandemic. Authors such as Seelye &

[5]Our paper contributes to many other articles that analyzed shock propagation for Brazil in the context of housing collateralization for banking operations and of public-private supply chain relationships (Fazio et al., 2020; Cortes et al., 2019).

Ziegler, 2020, Beck & Keil, 2021, and Park & Shin, 2021, studied changes in loans and loss allocations by banks. However, our study innovates by aggregating the municipality's view and allowing the reallocation effect to be desegregated at the level of bank branches and cities. Furthermore, we introduce elements to control the role of geography in loans, as well as made by several authors, such as Petersen & Rajan, 2002, Burtch et al., 2014 and Herpfer et al., 2023.

Additionally, it is worth mentioning that, by monitoring the effect that the Pandemic caused in terms of credit allocation, our study highlights, with an empirical approach, the impact of an unprecedented crisis brought to the Brazilian credit market, quantifying this channel of economic friction propagation. Similarly to the study done by Berger & Udell, 2002, we also considered a wide variety of characteristics of municipalities. In line with the study by Cottarelli & Kourelis, 1994, the dimensions controlled in this study include structural characteristics of the Brazilian financial system, such as the competitive and the ownership structures of each bank (state-owned or private).

This research will also shed light on the possible breakdown of lending relationships in times of crisis, as already noted by some authors, such as Sette & Gobbi, 2015, who state that the lending relationship effect is weaker if the relational creditor is more exposed to the financial crisis, especially when lending to more vulnerable borrowers (in our study, it would be those borrowers in capital cities, meaning the more exposed to COVID-19). Studying the effects of the Pandemic on US bank lending, Berger & Demirgüç-Kunt, 2021 finds evidence that borrowers with relationships fared worse during the COVID-19 crisis than borrowers without connections. In our case, the experiment on cities most exposed to the Pandemic allows us to show the effect on borrowers in the intensive margin most exposed to the crisis.

Still in the literature on economic impacts arising from the Pandemic, Colak & Öztekin, 2021 used a sample of banks from 125 countries, applying difference in differences (DiD) and concluded that bank loans decreased in countries most affected by the health crisis. According to the authors, this effect would depend on the bank's financial conditions, the market structure, and the public health sector's response to the crisis, among other factors. Similarly, in our regressions, we apply DiD and controls related to the financial market structure to show that a similar conclusion can be made when analyzing data disaggregated by Brazilian municipalities.

In fact, in terms of using DiD to assess the impact of the Pandemic on the economy, it was possible because there was a lot of heterogeneity in terms of the varying timing and strength of COVID-19 between countries and, as shown in our study, between Brazilian municipalities. As previously mentioned, Colak & Öztekin, 2021 used this heterogeneity of impacts on a sample of banks from 125 countries, in which the treated banks were those located in countries with higher infection rates (above the median). The control group are the banks in countries with lower infection rates (below the median). The authors concluded that the Pandemic led to a decline in credit growth despite unprecedented government stimulus and cash injection measures aimed at avoiding disruptions to the supply of credit. Similarly, we conclude that the Pandemic led banks to pivot credit operations to less risky borrowers of their portfolio (intensive margin), shifting to borrowers in cities other than capital cities, despite Brazilian government credit stimulus[6].

Our work is closer to the study done by Norden et al., 2021, in which the authors evaluate, applying DiD to the heterogeneity of the Pandemic's scope among Brazilian municipalities, the impact on local credit. The authors innovate and create a database to register the different sanitary measures adopted by each city. Our work differs - and brings new findings - because we monitor credit allocation and use proprietary data from the Central Bank of Brazil to obtain data at the individual and firm levels, comparing the impact on the bank's portfolio for each Brazilian municipality, including those related to interest rates and maturity, allowing us to map credit allocation more desegregated. In other words, we gauge the effect on both intensive and extensive margins of bank operations, controlling for geographical effects (region and microregion).

Finally, it must be in mind that, as a scenario to understand the behavior of banks during the Pandemic, even though initially there was an increase in general levels of deposits arising from the precautionary effect and a reduction in family spending due to mobility restrictions (Dursun-de Neef & Schandlbauer, 2022), loan decisions are taken by banks following the current prudential regulatory framework, i.e., they kept following the suitability of borrowers to institution's risk policy in the face of the Pandemic. Under these conditions, uncovering the reallocation of credits resulting from this impact allows us to contribute to the understanding of viable strategies available to financial institutions to mitigate the risks arising from a significant crisis. This finding is vital information for financial regulators.

4. Data

We use the credit operation's detailed information from the Credit Information System (SCR), a proprietary dataset maintained by the Central Bank of Brazil. This dataset allows us to identify each bank credit operation for individuals and firms above R$ 200 (about US$ 40). The SCR comprises information about the amount of credit granted, the interest rate charged by the bank, and the credit maturity. The dataset also has borrower information, which allows us to identify the municipality where the credit was granted.

While SCR provides information from the clientele side, the Accounting Plan of the Institutions of the National Financial System (Cosif) has granular banks' balance sheet information. Cosif is also a proprietary data maintained by the Central Bank of Brazil. Although Cosif is a rich database, it only contains information at the bank level. This paper considers credit operations made by banks from January 2019 to December 2020 (quarterly aggregated), which were used for our estimations strategy.

We merge proprietary data from the Brazilian Federal Revenue Service (RFB) to obtain individual and firm information. We also use bank-level meta-information from the Information on Entities of Interest to the Central Bank (Unicad), a proprietary dataset maintained by the Central Bank of Brazil.

To observe geographical characteristics and obtain municipal-level economic information, we use data from IBGE (Instituto Brasileiro de Geografia e Estatística), the official public

[6] More information in KPMG, accessed in November 2023

agency responsible for generating, organizing, and publishing a vast range of datasets in Brazil. IBGE records information on geography and socio-economic aspects for aggregation (e.g., the participation of industrial and agricultural activity), including all municipalities, states, and the nation.

Table 1 presents descriptive statistics for the variables we used in our analysis. We estimated municipality and bank-specific models to have a more than one-dimensional view of the topic. We used data from 3190 significant cities and from 8941 state and private oened bank branches operating nationwide.

Table 1: *Summary statistics of the variables employed in our baseline regressions.*

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Step 1 – Branches in inland and borrowers in capitals								
Dependent variables (variation: bank-municipality-time)								
Credit Issuances	244,295	1.901	58.514	0.000	0.015	0.074	0.328	5,960.128
Average Interest Rate (%)	244,295	80.899	170.238	0.000	18.773	28.890	68.221	1,355.000
Average Maturity (days)	244,277	1,409.398	1,494.457	0.000	365.000	1,084.411	2,109.998	47,788.000
Provisions (% outstanding credit)	244,295	3.626	7.627	0.000	0.538	1.393	3.724	100.000
Quantity of Clients	244,295	729.832	53,897.940	1	4	15	68	7,865,893
Independent variables (variation: bank-municipality, fixed with December 2019 values)								
Branch Distance to Capital (km)	17,667	237.578	163.961	1.497	103.728	210.624	345.624	1,474.873
Branch Exposure to COVID-19	17,667	5.810	10.859	0.000	0.713	2.247	5.821	100.000
Population (thous. habitants)	17,667	70.113	129.730	0.836	12.107	26.363	66.680	1,365.899
Branch Credit Market Share (%)	17,667	27.095	30.392	0.00002	3.964	15.759	36.425	100.000
Per Capita GDP (thous. R$/habitant)	17,667	28.598	25.241	4.970	13.916	23.290	35.805	583.172
Step 2 – Branches and borrowers in inland and borrowers in capitals								
Dependent variables (variation: bank-municipality-time)								
Credit Issuances	302,469	13.134	91.705	0.000	0.419	3.028	9.051	8,985.599
Average Interest Rate (%)	302,469	65.274	154.218	0.000	18.308	24.713	48.952	981.855
Average Maturity (days)	302,468	1,448.417	1,073.184	0.000	657.639	1,242.909	2,029.888	11,023.000
Provisions (% outstanding credit)	302,469	2.721	3.300	0.000	0.808	2.012	3.638	100.000
Quantity of Clients	302,469	3,391.312	82,590.180	1	67	306	1,800	12,986,986
Independent variables (variation: bank-municipality, fixed with December 2019 values)								
Branch Distance to Capital (km)	21,429	243.532	163.304	1.497	110.343	218.691	350.680	1,474.873
Branch Exposure to COVID-19 (%)	21,429	4.538	8.903	0.000	0.071	1.481	4.588	100.000
Population (thous. habitants)	21,429	67.679	130.030	0.786	10.370	23.886	62.854	1,365.899
Branch Credit Market Share (%)	21,429	24.951	30.881	0.00000	1.425	12.540	33.578	100.000
Per Capita GDP (thous. R$/habitant)	21,429	29.048	25.179	4.903	14.276	23.773	36.311	583.172

Note: Data from January 2019 to December 2020, quarterly aggregated. We used data from 3190 significant municipalities for the data sources to compute information and from 8941 state-owned and private bank branches operating nationwide. There is evidence of heterogeneity among them. Some have drastically reduced, and others have significantly increased the amount of credit from Jan 2019 to Dec 2020. However, from the 25 percentile upwards, the value was positive. The majority had positive variations, meaning that credit may go from a small number of municipalities (we argue it would be state capitals) to a larger number (inland cities).

Regarding municipality-specific, summary statistics show evidence of heterogeneity among them. Some have drastically reduced, and others have significantly increased the amount of credit from Jan 2019 to Dec 2020. However, from the 25 percentile upwards, the value was positive. The majority had positive variations, meaning that credit may go from a small number of municipalities (we argue it would be state capitals) to a more significant number (inland cities). Also, they are exposed to COVID-19 in varying degrees since the extreme values are very close to the upper and lower bounds of the index, and there are a significant number of municipalities in the interval of less than a standard deviation difference from the 25 percentile to the 75 percentile. Thus, banks have reasons to respond differently towards risk depending on their location.

All other variables illustrate the heterogeneity as well. In terms of financial development captured by the Credit to GDP ratio, by looking at the 75 percentile, we observe that a considerable number of municipalities may have room to improve in financial terms. On the other hand, the common ground among most cities is that large banks tend to occupy a significant market share.

Now, considering bank-specific aspects, summary statistics show similar heterogeneous patterns for the variation of credit and for exposure to COVID-19. Some banks drastically reduced, and others increased the amount of credit, indicating portfolio reallocation. The exposition to the novel coronavirus was also heterogeneous because while some banks were unexposed, others held assets that made them more susceptible to adverse shocks, denoting heterogeneous portfolio settings among them.

Considering that control variables for the two situations differ, we look closely at the bank-specific ones. Bank size (in terms of total assets) generally varies substantially. However, after the 25 percentile, we can observe a predominance of big banks in the Brazilian economy. The capacity to fund their operations also indicates the concentration of the banking system. Regarding solvency, banks perform close to the mean, which suggests that despite much heterogeneity, as shown before, portfolio management produced quite close results among them (and, probably, the relatively homogeneous profit to total assets ratio).

5. Empirical results

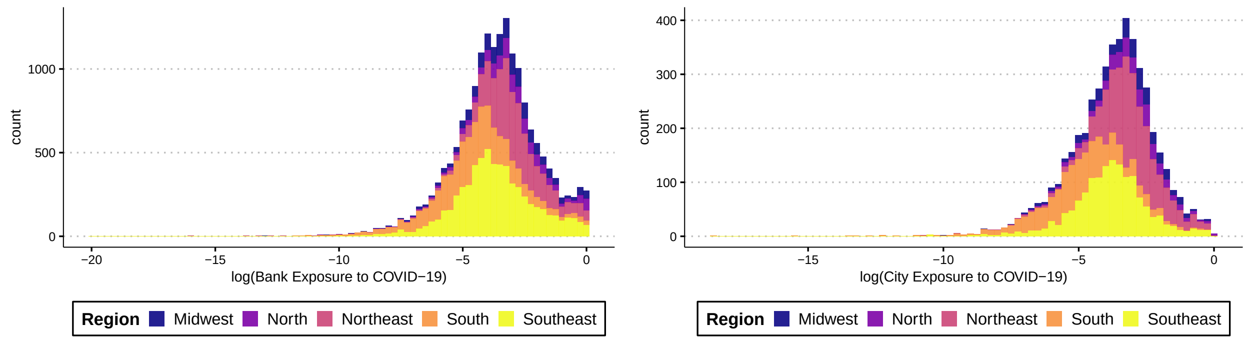
This section explains the empirical methodology and the main results of the paper.

5.1. Do inland bank branches more exposed to capital cities (i.e., more exposed to COVID-19) increase credit to inland municipalities?

This section analyzes whether banks with credit portfolios more concentrated in Brazilian capital cities increased their outstanding credit to inland municipalities. To extract causality from our results, we explore the heterogeneous timing and strength with which COVID-19 affected Brazilian municipalities and the pre-determined credit portfolios of Brazilian bank branches across different municipalities. Given that COVID-19 affected first and more strongly state capitals than inland municipalities, we use each bank branch's *ex-ante* credit exposure to Brazilian capital cities as a branch-specific measure of COVID-19 exposure. Thus, we predict that the higher the outstanding credit that a bank branch allocated in capital cities during the pre-pandemic period, the greater its exposure to the early adverse effects of COVID-19. Mathematically, the exposure of bank b located in municipality m—or the branch bm—to COVID-19 is given by:

$$\text{Branch Exposure to COVID-19}_{bm} = \frac{\sum_{c \in \mathscr{M}_{capital}} \text{Bank Credit}_{bmc}}{\sum_{j \in \mathscr{M}_{capital} \cup \mathscr{M}_{inland}} \text{Bank Credit}_{bmj}}, \tag{1}$$

in which $\mathscr{M}_{capital}$ and $\mathscr{M}_{inland}$ are sets of capital and inland municipalities, respectively. The term Bank Credit$_{bmj}$ refers to the amount of outstanding credit that the branch of bank b in municipality m grants to borrowers in municipality j (two values: either capital or inland) at the end of the pre-pandemic period (end-of-month December of 2019). The range of our measure falls within the unity interval. Higher values (≈ 1) indicate that bank branch bm is highly exposed to state capitals, making it susceptible to sudden financial and economic downturns in these locations, such as COVID-19. Figure 3a shows a histogram of the exposures to COVID-19 of each Brazilian bank branch located in inland municipalities. There are substantial differences between bank branches, even between branches of the same bank. This heterogeneity allows us to examine how branches in inland municipalities reacted to COVID-19, which initially hit harder in state capitals.



***(a)** Bank-Specific Exposure to COVID-19*

***(b)** Municipality-Specific Exposure to COVID-19*

***Figure 3:** Histogram of bank- and city-specific exposure to COVID-19, evaluated using (1) and (6), respectively. The exposure to COVID-19 is proportional to the banks' outstanding credit to borrowers in Brazilian capitals, which were the first and most affected by COVID-19 in Brazil. Exposures are taken immediately before COVID-19 reaches Brazil (end-of-month December 2019).*

Because of the possibility of potential omitted variables, it is challenging to show that COVID-19 caused a credit reallocation in inland bank branches. One critical variable that must be considered is banks' lending opportunities. Following Drechsler et al. (2017), we control for bank-specific lending opportunities by comparing branches of the same bank operating across localities. Since banks can raise deposits at one branch and lend them at another, the decisions on how many deposits and loans a branch holds are unrelated.[7] Thus, as an identifying assumption, we examine how variations in the branches' exposures to COVID-19, independent of banks' lending opportunities, affect their financial outcomes.

Another critical factor is the bank branch's distance from the capital. Unlike hard information conveyed through online systems, the amount of soft information is inversely proportional

[7]Empirical evidence shows that banks allocate funds internally across branches to equalize the marginal return on lending. The banks' profit-maximizing motive rationalizes this behavior. For instance, Gilje et al. (2016) shows that banks export liquidity across banks by channeling deposits to areas with high loan demand. Bustos et al. (2020) show that branches in areas more financially integrated with soy-producing areas increase lending in other areas.

to the branch's distance from the borrower. Therefore, we expect the branch's lending volume to decay with its distance to the borrower, especially for credit modalities that require constant monitoring, becoming another crucial omitted variable that within-bank analysis does not capture and could drive our results: bank branches near capital cities have less flexibility to reallocate credit away from their surroundings because most of the soft information regarding borrowers is located at nearby capitals. We account for this geographical selection by comparing branches of the same bank within the same microregion (the immediate geographic regions). Microregions are sets of adjacent municipalities sharing strong socio-economic ties[8]. Because cities in the same microregion are close to each other, this empirical strategy also controls for differences in how far away the branches are from the capital. We operationalize this within-bank estimation of branches in the same microregion by introducing bank-microregion-time fixed effects into our specifications.

Our empirical strategy to test for credit reallocation from capitals to inland municipalities has two steps. First, we analyze whether branches in inland cities reduce credit to borrowers in state capitals. We then examine if these same bank branches increase credit for borrowers in inland municipalities (intensive or extensive margin). We accomplish this by estimating the following panel regression:

$$y_{b,m,i,t} = \alpha_{b,\text{microregion}(m),t} + \gamma_{m,t} + \delta_{b,m} + \beta \ \text{Post}_t \cdot \text{Branch Exposure to COVID-19}_{b,m} + \varepsilon_{b,m,i,t}, \qquad (2)$$

in which b, m, i, and t index banks, bank branches' municipalities (capitals are excluded), borrowers' location (binary variable: state capital or inland municipality), and time (January 2019 to December 2020, quarterly), respectively. The dimension bm denotes a bank branch, i.e., a bank within a municipality. The dependent variable $y_{b,m,i,t}$ represents financial outcomes of bank b in municipality m to borrowers located in capital cities or inland municipalities (index i) during quarter t: volume of credit issuance (in log), average interest rates, average maturity, and quantity of clients (in log). The variable Branch Exposure to COVID-19$_{b,m}$ is our branch-specific *continuous* treatment variable and follows (1). The dummy Post$_t$ represents the onset of the COVID-19 crisis in Brazil and equals 1 when $t \geq$ March 2020, and 0, otherwise. The terms $\alpha_{b,\text{microregion}(m),t}$, $\gamma_{m,t}$, $\delta_{b,m}$ represent bank-microregion-time, municipality-time, and bank branch (bank-municipality) fixed effects. Following Abadie et al. (2020), we cluster errors at the bank branch level, which matches the level of variation of our continuous treatment variable Branch Exposure to COVID-19$_{b,m}$. We standardize all numeric variables. $\varepsilon_{b,m,i,t}$ is the usual error term.

The critical set of controls is the bank-microregion-time fixed effects $\alpha_{b,\text{microregion}(m),t}$, which account for all microregion-specific and time-varying differences between banks, including evolving lending opportunities. Intuitively, the introduction of these fixed effects permits us

[8]According to IBGE, the Immediate Geographic Regions have their main reference element in the urban network. These regions are structured based on nearby urban centers to satisfy the immediate needs of populations, such as purchasing consumer goods, working and job opportunities and seeking health and education services, and providing public services (e.g., National Institute of Social Security (INSS), the Ministry of Labor and judicial services, among others).

to interpret our results as comparing branches of the *same* bank operating in *different* inland municipalities within the *same* microregion and asking, following COVID-19 outbreak, whether bank branches with more outstanding credit channeled to borrowers in state capitals experience any changes in their credit portfolios relative to other branches of the same bank (in the same microregion) with less concentrated credit portfolios toward state capitals.

The remaining fixed effects are additional controls. Bank branch fixed effects $\delta_{b,m}$ absorb any branch-specific time-invariant factors, such as the average quality of the branch's local management (Drechsler et al., 2017). The municipality-time fixed effects $\gamma_{m,t}$ absorb any municipality-specific shocks, which is a crucial component in our analysis because of the COVID-19 outbreak. There was a substantial injection of resources into the Brazilian economy to mitigate the economic effects of COVID-19[9], such as emergency aid support for individuals and numerous credit lines for firms. The volume of resources received by recipients of these programs varied across Brazilian municipalities, besides being enacted at different times. Finally, we must highlight that the emergency credit lines backed by government guarantees launched during the Pandemic did not change the banks' credit policies. In other words, notwithstanding the public policy conducted by the Brazilian Government, it was mandatory to the banks to maintain their risk policy in lending operations, not impacting our hypothesis of credit pivoting to less riskier borrowers. Thus, the municipality-time fixed effects can absorb these time-varying and municipality-specific events. The within-bank analysis operationalized by the bank-microregion-time fixed effects also mitigates concerns about changes in the regulatory framework that banks experienced during the COVID-19 outbreak.

In the first step, we show that inland bank branches reduce credit to borrowers located in capitals ($i =$ capital). In the second step, we show that the same inland bank branches increase credit issuance for borrowers in inland municipalities ($i =$ inland), following the hypothesis of credit reallocation. Our coefficient of interest in (2) is β, which measures the effect of a one-standard-deviation increase in the bank branch's exposure to COVID-19 on its outstanding credit (and other branch-level outcomes) to borrowers in capitals (step 1) or inland municipalities (step 2) compared to other bank branches of the same bank operating in other municipalities within the same microregion.

Table 2 reports our coefficient estimates of Equation (2) for borrowers located in state capitals (Step 1, Specs. I–V) and inland municipalities (Step 2, Specs. VI–X). We use the following dependent variables: log of the volume of credit issuance (Specs. I and VI), average interest rates in percentage terms (Specs. II and VII), average maturity in days (Specs. III and VIII), provisions as a percentage of the outstanding credit (Specs. IV and IX) and the log of the number of distinct clients (Specs. V and X).

Step 1: inland branches reduce lending in state capitals. A one-standard-deviation increase in the exposure to COVID-19 of bank branches in inland municipalities causes a 16% reduction in credit issuance to borrowers in capital cities compared to branches of the same bank in other municipalities of the same microregion. Similarly, interest rates of these credit issuance increase by 7%. The average maturity of new credit issuance decreases by 78 days (ap-

[9]For more information, in the KPMG website the credit lines in Brazil during the Pandemic are enumerated.

proximately 2.6 months) for each one-standard-deviation increase in the branch's exposure to COVID-19. The decrease in quantity and price increase indicate a negative credit supply shock to state capitals by inland branches that is proportional to their exposure to COVID-19. The negative credit supply also works at the extensive margin: more exposed banks reduce the number of clients in the capital. Overall, branches that are more exposed to borrowers in state capitals tightened financial conditions following the COVID-19 outbreak than less exposed branches of the same bank in other municipalities within the same microregion.

Table 2: *Baseline results (within-bank, across-locality analysis): How do inland bank branches more exposed to COVID-19 reallocate credit across municipalities during COVID-19?*

Sample (borrower's location i):	State Capitals (Step 1)					Inland Municipalities (Step 2)				
Dependent variables:	$\log(Credit)$	$Int.Rate$	$Maturity$	$\%Provisions$	$\log(Clients)$	$\log(Credit)$	$Int.Rate$	$Maturity$	$\%Provisions$	$\log(Clients)$
(Jan 2019–Dec 2020, quarterly)	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables										
Post_t ·										
Branch Exposure to COVID-19$_{bm}$	-0.1630***	6.992***	-78.22***	0.1475	-0.0340***	0.0334***	0.3122	-3.727	-0.0471*	0.0078
	(0.0168)	(0.6086)	(12.35)	(0.0964)	(0.0067)	(0.0083)	(0.3282)	(4.458)	(0.0254)	(0.0056)
Fixed Effects										
Time · Bank · Bank Microregion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank · Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics										
Observations	244,295	244,295	244,277	244,295	244,295	302,469	302,469	302,468	302,469	302,469
R^2	0.9450	0.9865	0.8061	0.7723	0.9889	0.9877	0.9967	0.9598	0.8091	0.9943

Note: This table reports changes in inland bank branches' financial outcomes to borrowers in state capitals (Specs. I–V) and inland municipalities (Specs. VI–X) around the beginning of COVID-19 crisis in Brazil (March 2020) using Specification (2) at the bank (b) $\times$ municipality (m) $\times$ borrower's locality (i) $\times$ time (t) level. The borrower's locality dimension takes two values: state capitals (Specs. I–V) and inland municipalities (Specs. VI–X). Data is aggregated quarterly from January 2019 to December 2020. We use the following dependent variables: log of the volume of credit issuance (Specs. I, VI), average interest rates in percentage terms (Specs. II, VII), average maturity in days (Specs. III, VIII), provisions as a percentage of the outstanding credit (Specs. IV, IX), and the log of the number of distinct clients (Specs. V, X). The variable Branch Exposure to COVID-19$_{b,m}$ is our branch-specific *continuous* treatment variable and follows Equation (1). The dummy Post_t represents the onset of the COVID-19 crisis in Brazil and equals 1 when $t \geq$ March 2020, and 0 otherwise. We add bank-microregion-time, municipality-time, and bank branch (bank-municipality) fixed effects. One-way (bank branch) standard errors are in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Step 2: reallocation effect. Inland branches increase lending toward inland (non-capital) cities. A one-standard deviation increase in the exposure to COVID-19 of bank branches in inland municipalities causes a rise of 3% in credit issuance to borrowers in inland municipalities compared to branches of the same bank within the same microregion with lower exposure levels. Contractual terms seem not to change: relative interest rates and average maturity differences are not statistically significant across branches of the same bank with different levels of exposure to COVID-19. Provisions decrease, suggesting that credit operations focused more on less risky borrowers. The increase in credit issuance does not lead to an increased *clientele* in inland municipalities, suggesting that the growth took place for existing clients (intensive margin) of bank branches and not for new clients (extensive margin), reinforcing the hypothesis of credit pivoting to less risky borrowers[10].

[10]Must be highlighted that, at the end of the second quarter of 2020, the Brazilian Federal Government

Event study: one identifying assumption of the DiD setup is that the branch-specific outcomes of more and less exposed bank branches would have trended similarly in the absence of the COVID-19 outbreak. While we cannot directly measure the exact counterfactual, we investigate potential pre-trends in our empirical specification using an event-study analysis. The event study also enables us to examine the time-varying effects of the COVID-19 outbreak on credit reallocation. Empirically, we replace the dummy $Post_t$ in Specification (2) with monthly pulse dummies as follows:

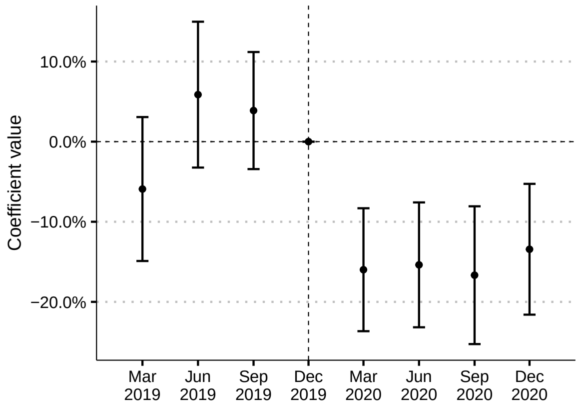
$$y_{b,m,i,t} = \alpha_{b,\text{microregion}(m),t} + \gamma_{m,t} + \delta_{b,m} + \sum_{k \in \mathscr{T}} \beta_k \text{ Branch Exposure to COVID-19}_{b,m} \cdot \mathbb{1}_{\{k=t\}} + \varepsilon_{b,m,i,t}, \tag{3}$$

in which b, m, i, and t index banks, bank branches' municipalities (capital cities are excluded), borrowers' location (binary variable: state capital or inland municipality), and time (January 2019 to December 2020, quarterly), respectively. The term $\mathbb{1}_{\{argument\}}$ is the pulse function that equals one when the $argument$ is true and zero otherwise. The set $\mathscr{T}$ represents time points with a quarterly frequency between the beginning of 2019 and the end of 2020, except for the last quarter in 2019, which we use as a reference for our point estimates. All the remaining setup follows our baseline specifications in Equation (2). Figure 4 portrays the coefficient estimates of β_k for Step 1 (left panel) and Step 2 (right panel). We use all dependent variables analyzed in our baseline specifications. We do not observe pre-trends between more and less exposed branches as $\beta_k = 0$ for all k on the pre-pandemic period. Only after the COVID-19 outbreak did we observe abrupt changes in the β_k estimates for some dependent variables, consistent with our baseline results.

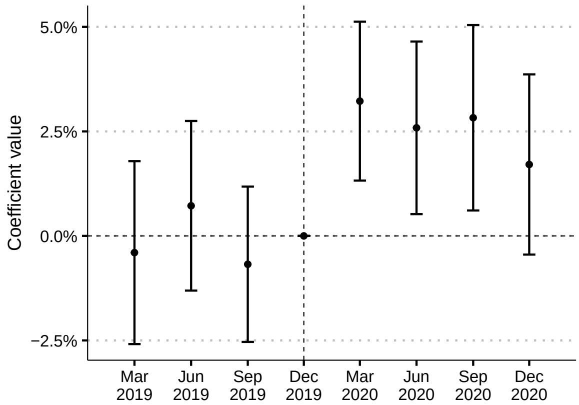
Heterogeneous effects: We now examine the heterogeneous effects of the relative reduction in credit issuance to borrowers in state capital cities. We investigate how bank-specific observables attenuate or amplify the credit reallocation from capitals to inland municipalities suggested in our baseline results. We augment our baseline specification in Equation (2) by introducing triple interactions between Branch Exposure to COVID-19$_{b,m}$, Post$_t$, and these features as follows:

$$\begin{aligned} y_{b,m,i,t} = \alpha_{b,\text{microregion}(m),t} + \gamma_{m,t} + \delta_{b,m} + \beta \text{ Post}_t \cdot \text{Branch Exposure to COVID-19}_{b,m} + \\ + \rho \text{ Post}_t \cdot \text{Branch Exposure to COVID-19}_{b,m} \cdot \text{Feature}_b + \\ + \lambda \text{ Lower-Order Interactions} + \varepsilon_{b,m,i,t}, \end{aligned} \tag{4}$$

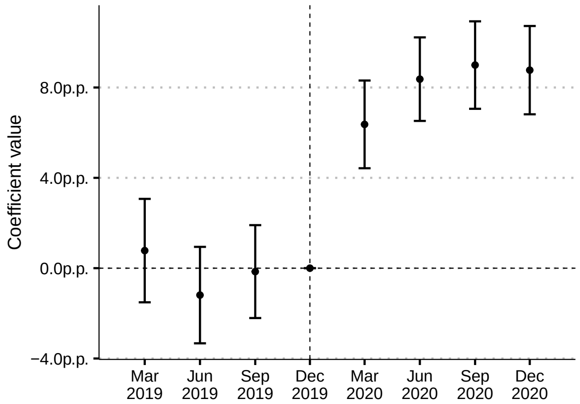
launched two programs to guarantee, with resources from the National Treasury, loans to small and medium companies. The first one was the Emergency Credit Access Program, operated by BNDES, along the lines of the Investment Guarantee Fund (FGI). The second was the National Support Program for Micro Enterprises and Small Companies (Pronampe), using the Operations Guarantee Fund (FGO). In both programs, the financial institutions needed to follow their ordinary risk policy in credit loans under these programs, which contributed to the reallocation to less risky borrowers under study



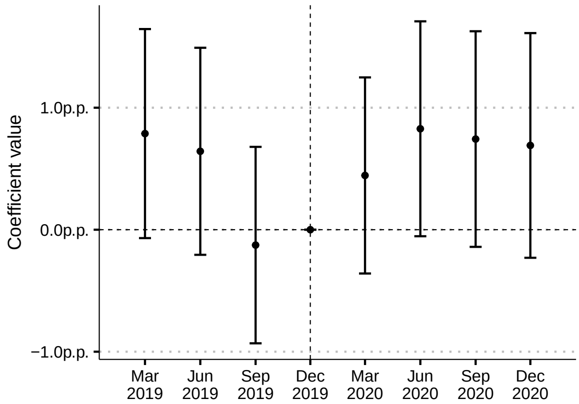
***(a)** Step 1: Outstanding credit*



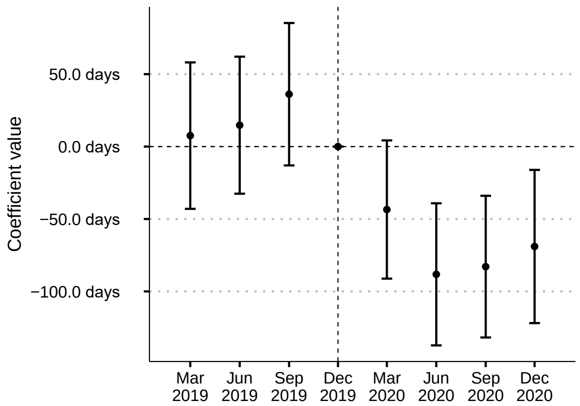
***(b)** Step 2: Outstanding credit*



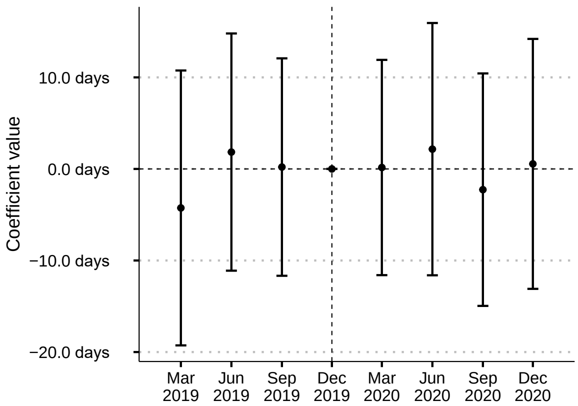
***(c)** Step 1: Interest rate*



***(d)** Step 2: Interest rate*

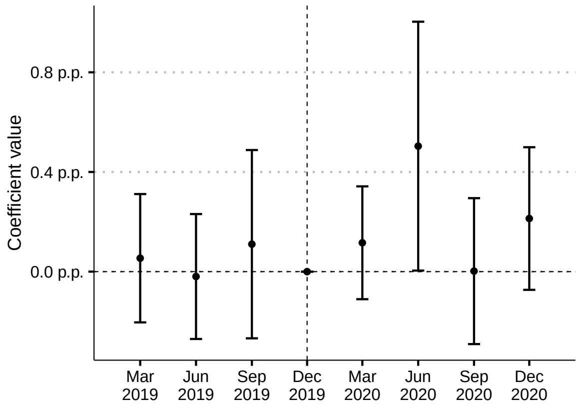


***(e)** Step 1: Credit Maturity*

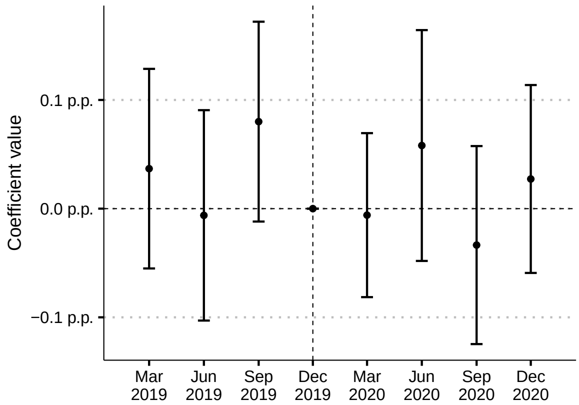


***(f)** Step 2: Credit Maturity*

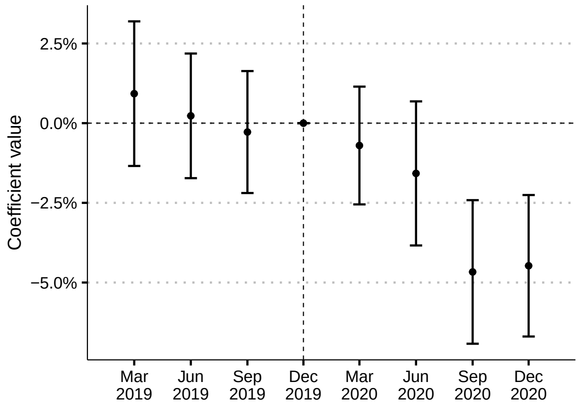
in which b, m, i, and t index banks, bank branches' municipalities (capitals are excluded), borrowers' location (binary variable: state capital or inland municipality), and time (January 2019 to December 2020, quarterly). We standardize the numerical variable Feature_b. The vector



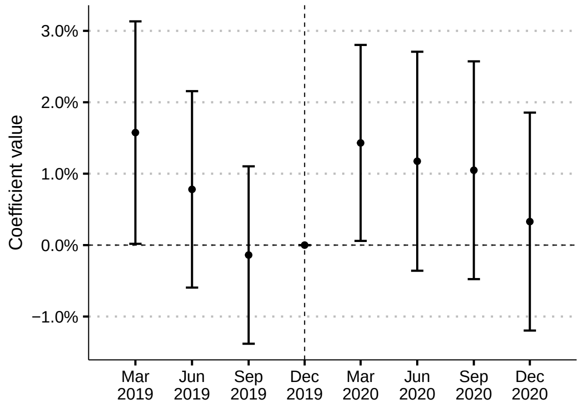
***(g)** Step 1: Provision (% outstanding credit)*



***(h)** Step 2: Provision (% outstanding credit)*



***(i)** Step 1: Number of distinct clients*



***(j)** Step 2: Number of distinct clients*

***Figure 4:** Event study using the within-bank, across-localities analysis defined in Equation (3). We report Step 1 (inland branches lending to borrowers in state capitals) in the left panel and Step 2 (inland branches lending to borrowers in inland municipalities) in the right panel. The vertical axis encodes the coefficient estimates of β_k in Equation (3) (solid points) and the associated 95% confidence interval (vertical bars), all relative to December 2019. The horizontal axis is the absolute time in quarterly frequency. We use the following dependent variables (a) and (b) log of credit issuance (vertical axis is the percentage change for a one-standard-deviation increase in the bank branch's exposure to COVID-19 relative to branches less exposed to COVID-19 of the same bank in other municipalities within the same microregion); (c) and (d) interest rates (percentage points); (e) and (f) credit maturity (days); (g) and (h) provisions as a percentage of the outstanding credit (percentage points); and (i) and (j) log of the number of distinct clients (percentage change).*

Low-Order Interactions contains all lower-order interactions between Branch Exposure to COVID-19$_{b,m}$, Post$_t$, and Feature$_b$ that are not collinear with the fixed effects. All the remaining empirical steps follow those in our baseline specifications described above. Our coefficient of interest is ρ, which measures any heterogeneous effects on our baseline results absorbed by the coefficient β.

Table 3 reports bank-specific heterogeneous effects of inland bank branches' credit reallocation from state capitals (Specs. I–V) to inland municipalities (Specs. VI–X). We analyze potential heterogeneous effects using the following broad bank-specific observables (Feature$_b$): liquidity index proxied by the Liquidity Coverage Ratio (LCR) as defined by Basel III (Specs. I and VI), capitalization level proxied by the net worth as a share of the bank's total assets (Specs. II and VII), size measured regarding total assets (Specs. III and VIII), dummies for the bank segment—commercial, investment, or credit union—taken commercial banks as the reference (Specs. IV and IX), a dummy for bank control— state-owned or private held—taken as the reference private owned banks (Specs. V and X).

Financially constrained banks are more sensitive to COVID-19 shock: less liquid banks reduce credit to a more significant extent to borrowers in state capitals. State-owned banks also reduce credit more in state capitals. However, this reduction was more significant in private-owned banks. Additionally, the size of a bank also matters. We uncovered that the larger a bank is, the more pronounced the portfolio shift. One interesting fact is that credit unions (also called in Brazil credit cooperatives) branches had less reallocating effect compared to the commercial banks, showing that the ties presented in credit cooperatives' business model (which is to encourage both the economic well-being of its associates and the need for the self-sufficiency of the cooperative) mitigated the propagation effect through portfolio rearrangements.

Further tests: one potential concern in our baseline results is that more exposed inland banks could have improved time-varying lending opportunities than less exposed inland branches, allowing them to reallocate credit to borrowers in localities to which less exposed branches have no access. If these localities are precisely inland municipalities, these could explain our results and would be unrelated to the branches' exposure to the capital. Despite introducing our branch fixed effects in the main specifications, they only capture the average lending opportunity over time. If it substantially changes during COVID-19, these fixed effects would not be able to capture this behavior. One robustness test to examine whether this is the case is to compare similar branches—i.e., in the same microregion—lending to borrowers in *similar* localities. Analogous to our empirical strategy on the bank side, we compare aggregate lending to borrowers in municipalities in the same microregion.

$$\begin{aligned} y_{b,m,l,t} = \alpha_{b,\text{microregion}(m),\text{microregion}(l),t} + \gamma_{m,t} + \rho_{l,t} + \delta_{b,m} + \\ + \beta \text{ Post}_t \cdot \text{Branch Exposure to COVID-19}_{b,m} + \varepsilon_{b,m,l,t}, \end{aligned} \tag{5}$$

in which b, m, l, and t index the bank, bank's municipality, borrower's municipality, and time (2019–2020, quarterly). Equation (5) differs from our baseline specification in Equation (2) in three critical ways. First, instead of composing an aggregate financial outcome to borrowers in *all* state capitals or *all* inland municipalities (the subscript i with binary values in Equation (2)), we now consider the precise city of the borrower, which we denote with the subscript l to avoid confusion. There are 27 state capitals and 5,543 inland municipalities in Brazil. Each observation represents the aggregate financial outcome of a bank branch b in municipality m to borrowers in municipality l during quarter t. Second, we introduce time $\times$ bank's microregion $\times$ borrower's microregion fixed effects, $\alpha_{b,\text{microregion}(m),\text{microregion}(l),t}$, allowing us to interpret our estimates as comparing financial outcomes of branches of the *same* bank in

Table 3: *Within-bank, across-locality analysis: Heterogeneous effects of the credit reallocation of inland bank branches*

Dependent variable:	$\log(Credit_{bmit})$									
Sample (borrower's location i):	Capital (Step 1)					Inland Municipalities (Step 2)				
(Jan 2019–Dec 2020, quarterly)	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables										
Post_t · Branch Exposure to COVID-19_{bm}	-0.1514***	-0.1630***	-0.1636***	-0.1622***	-0.1431***	0.0365***	0.0345***	0.0365***	0.0301***	0.0252***
	(0.0180)	(0.0168)	(0.0173)	(0.0182)	(0.0171)	(0.0100)	(0.0084)	(0.0088)	(0.0089)	(0.0083)
Post_t · Branch Exposure to COVID-19_{bm} ·										
Liquidity Index_b	0.0159*					-0.0170**				
	(0.0086)					(0.0086)				
Capitalization Level_m		-0.0003					0.0085			
		(0.0130)					(0.0094)			
Total Assets_b			0.0055					-0.0179**		
			(0.0155)					(0.0085)		
Investment Bank_b				0.2030***					0.1264*	
				(0.0520)					(0.0701)	
Credit Union_b				-0.0785					0.0064	
				(0.0515)					(0.0236)	
Public Bank_b					-0.0881**					0.0443**
					(0.0371)					(0.0197)
Fixed Effects										
Time · Bank · Bank Microregion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank · Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics										
Observations	203,950	244,295	244,295	244,295	244,295	242,577	302,469	302,469	302,469	302,469
R^2	0.9502	0.9450	0.9450	0.9450	0.9450	0.9898	0.9877	0.9877	0.9877	0.9877

Note: This table reports bank-specific heterogeneous effects of inland bank branches' credit reallocation from state capitals (Specs. I–V) to inland municipalities (Specs. VI–X) around the beginning of COVID-19 crisis in Brazil (March 2020) using Specification (4) at the bank (b) $\times$ municipality (m) $\times$ borrower's locality (i) $\times$ time (t) level. The borrower's locality dimension takes two values: state capitals (Specs. I–V) and inland municipalities (Specs. VI–X). Data is aggregated quarterly from January 2019 to December 2020. We use the log of the volume of credit issuances in all specifications as the dependent variable. We analyze potential heterogeneous effects using the following broad bank-specific observables (Feature_b): liquidity index proxied by the Liquidity Coverage Ratio (LCR) as defined by Basel III (Specs. I and VI), capitalization level proxied by the net worth as a share of the bank's total assets (Specs. II and VII), size measured regarding total assets (Specs. III and VIII), dummies for the bank segment—commercial, investment, or credit union—taken commercial banks as the reference (Specs. IV and IX), a dummy for bank control—publicly-held or private-owned—taken as the reference private-owned banks (Specs. V and X). The variable Branch Exposure to COVID-$19_{b,m}$ is our branch-specific *continuous* treatment variable and follows Equation (1). The dummy Post_t represents the onset of the COVID-19 crisis in Brazil and equals 1 when $t \geq$ March 2020, and 0 otherwise. We add bank-microregion-time, municipality-time, and bank branch (bank-municipality) fixed effects. One-way (bank branch) standard errors are in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

the *same* microregion to borrowers in the *same* microregion. Our variation comes from different branches in the same microregion lending to borrowers in municipalities in the same microregion. Third, we further introduce additional controls in the form of fixed effects. We also include time $\times$ borrower's municipality fixed effects, $\rho_{l,t}$, to absorb any municipality-level shock at the borrower side, which is essential to control for different local measures to prevent the spread of COVID-19 in Brazil.

Table 4 shows the results when we employ as the dependent variable the log of the volume of credit issuances (Specs. I, VI), average interest rates in percentage terms (Specs. II, VII), average maturity in days (Specs. III, VIII), provisions as a percentage of the outstanding credit (Specs. IV, IX), and the log of the number of distinct clients (Specs. V, X). We consider borrowers in state capitals (27 municipalities) in Specs. I–V and in inland cities (5,543 municipalities) in Specs. VI–X. Our results remain qualitatively the same as our baseline findings if we also account for the borrower's physical location.

Table 4: *Robustness test (within-bank, across-locality analysis): Does credit reallocation from inland branches still hold when considering the borrower's locality?*

Sample (borrower's location i):	State Capitals (Step 1)					Inland Municipalities (Step 2)				
Dependent variables:	$\log(Credit)$	$Int.Rate$	$Maturity$	$\%Provisions$	$\log(Clients)$	$\log(Credit)$	$Int.Rate$	$Maturity$	$\%Provisions$	$\log(Clients)$
(Jan 2019–Dec 2020, quarterly)	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables										
Post_t · Branch Exposure to COVID-19_{bm}	-0.0396**	8.157***	-20.79*	0.0640	-0.0133**	0.0249***	7.658***	9.177*	0.0648*	-0.0098
	(0.0192)	(1.354)	(11.16)	(0.0887)	(0.0063)	(0.0084)	(1.239)	(5.118)	(0.0357)	(0.0102)
Fixed-effects										
Time · Bank · Bank Microregion · Borrower Microregion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank · Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Borrower Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	590,459	590,459	590,373	590,459	590,459	8,558,392	8,558,392	8,557,306	8,558,392	8,558,392
R^2	0.7978	0.9092	0.6907	0.6104	0.9006	0.5388	0.7770	0.4908	0.3620	0.5886

Note: This table reports changes in inland bank branches' financial outcomes to borrowers in state capitals (Specs. I–V) and inland municipalities (Specs. VI–X) around the beginning of COVID-19 crisis in Brazil (March 2020) using Specification (2) at the bank (b) $\times$ municipality (m) $\times$ borrower's municipality (l) $\times$ time (t) level. The borrower's locality l is now the precise borrower's municipality: 27 state capitals (Specs. I–V) and 5,543 inland municipalities (Specs. VI–X), for 5,570 municipalities. Data is aggregated quarterly from January 2019 to December 2020. Each observation represents the aggregate financial outcome of a bank branch b in municipality m to borrowers in municipality l during quarter t. We use the following dependent variables: log of the volume of credit issuances (Specs. I, VI), average interest rates in percentage terms (Specs. II, VII), average maturity in days (Specs. III, VIII), provisions as a percentage of the outstanding credit (Specs. IV, IX), and the log of the number of distinct clients (Specs. V, X). The variable Branch Exposure to COVID-$19_{b,m}$ is our branch-specific *continuous* treatment variable and follows Equation (1). The dummy Post_t represents the onset of the COVID-19 crisis in Brazil and equals 1 when $t \geq$ March 2020, and 0 otherwise. We add bank-microregion-time, municipality-time, and bank branch (bank-municipality) fixed effects. One-way (bank branch) standard errors are in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

5.2. Do local financial conditions of inland municipalities more exposed to COVID-19 improve?

The previous section established that branches with credit portfolios more concentrated in Brazilian capitals *ex-ante* to the COVID-19 outbreak decreased credit issuance to borrowers in capital cities and increased them to those in inland municipalities when compared to other branches of the same bank in the same microregion. This section examines whether the redistribution of credit improved the total outstanding credit for inland cities. Our previous evidence does not imply this increase in total outstanding credit in inland municipalities, as competing bank branches could have reduced credit issuance to inland municipalities, offsetting the rise in credit issuance caused by branches with greater COVID-19 exposure.

We can examine this hypothesis by running regressions at the municipality level rather than the branch level. Therefore, we determine if inland municipalities experience any change in their local aggregate outstanding credit by resorting to *across-city* rather than across-branch comparisons. This strategy enables us to compare municipality-level financial outcomes (total credit issuance of all branches in a specific municipality) of *different* municipalities. To mitigate potential omitted-variable biases, we consider nearby cities within the same microregion but with varying levels of COVID-19 exposure. Following our branch-specific measure of exposure to COVID-19 in Equation (1), we define the municipality's vulnerability to COVID-19 by averaging the exposures of local bank branches to COVID-19 in that municipality. Mathematically:

$$\begin{aligned}\text{Municipality Exposure to COVID-19}_m &= \sum_{b \in \mathscr{B}_m} w_{bm} \cdot \text{Branch Exposure to COVID-19}_b \\ &= \frac{\sum_{b \in \mathscr{B}_m} \text{Bank Credit}_{bm} \cdot \text{Branch Exposure to COVID-19}_b}{\sum_{j \in \mathscr{B}_m} \text{Bank Credit}_{jm}},\end{aligned} \tag{6}$$

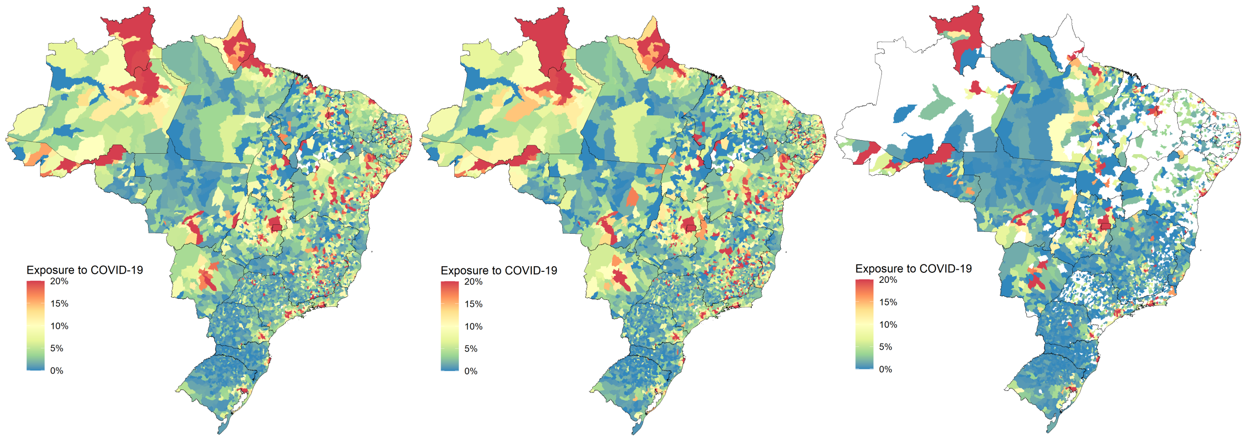
in which $\mathscr{B}_m$ is the set of bank branches in municipality m, Branch Exposure to COVID-19$_b$ follows Equation (1), and $w_{bm} = \frac{\text{Bank Credit}_{bm}}{\sum_{j \in \mathscr{B}_m} \text{Bank Credit}_{jm}}$ is the local outstanding credit share of bank b in municipality m in the end of 2019. The term w_{bm} permits us to weigh each branch's exposure to COVID-19 by its corresponding local credit representativeness (weighted average).

Figure 3b portrays the histogram of our municipality-level exposure measure segmented by the municipality's region. Again, we find substantial variation, even within the same Brazilian region. Figure 5 displays a map of exposures to COVID-19 in each Brazilian municipality in December 2019. There is a substantial variation even within neighboring cities. Figures 5b and 5c exhibit the municipality's exposure to COVID-19 when we consider only large financial institutions (S1 prudential segment) and other financial institutions (S2 to S5 prudential segments). Large financial institutions extended more credit to borrowers in capitals, becoming more exposed to COVID-19 than non-large financial institutions. The exposure to COVID-19 in many municipalities in the Northeast originates exclusively from large financial institutions due to the absence of non-large financial institutions.

Similar to our branch-specific specifications, we employ the following econometric specification to evaluate municipality-level outcomes:

$$\begin{aligned} y_{m,i,t} = \alpha_{\text{microregion}(m),t} + \gamma_m + \beta \ \text{Post}_t \cdot \text{Municipality Exposure to COVID-19}_m + \\ + \tau \ \text{Post}_t \cdot \text{Controls}_m + \varepsilon_{m,i,t}, \end{aligned} \tag{7}$$

in which m, i, and t index inland municipalities (capital cities are excluded), borrower's locality (binary variable: state capital or inland municipality), and time (January 2019 to December 2020, quarterly), respectively. The dependent variables y_{mit} are municipality-specific outcomes constructed by aggregating financial outcomes of all branches in municipality m at time t for borrowers in state capitals or inland cities. Our analysis includes several dependent variables: total credit issuance (which is the sum of credit issuance across branches in a specific municipality), average interest rate (expressed in average annual percentage rates), maturity (measured in average days), and percentage of provisions to the total outstanding credit. Interest rates and maturity are weighted by branch-specific credit issuance. Additionally, we consider the number of distinct clients of all branches in a specific municipality as a



(a) Overall Average (b) S1 Segment Average (c) S2-S5 Segment Average

Figure 5: *Map of municipalities' exposures to COVID-19, evaluated using Equation (6). We calculate the exposure by considering various bank branches $\mathscr{B}_m$ in the summation term of Equation (6). These sets include (a) all branches within the municipality, (b) only large financial institutions belonging to the S1 prudential segment, and (c) only non-large financial institutions belonging to the S2 to S5 prudential segments. Warmer colors indicate high exposure to COVID-19, while colder colors indicate low exposure. In cases where there are no bank branches present in the municipality (or a specific segment, in the case of maps (b) and (c)), blank colors are used.*

dependent variable in our study. The variable Municipality Exposure to COVID-19$_m$ is our *continuous* treatment variable and follows Equation (6). The dummy Post$_t$ represents the onset of the COVID-19 crisis in Brazil and equals 1 when $t \geq$ March 2020 and 0, otherwise.

We include the following municipality-specific controls in the vector Controls$_m$: population (in 2019), *per capita* GDP (in 2019), distance to the capital, average Herfindahl-Hirschman Index (HHI)[11] evaluated from the outstanding credit across branches in the same municipality (in December 2019), dummy variables indicating whether the preponderant local activity is agriculture or industry (in 2019), and the percentage of the local population receiving emergency aid programs in 2020 to combat the economic effects of COVID-19.[12] ε_{mit} is the usual error term. We cluster errors at the municipality level, which coincides with the level of variation in the municipality's exposure to COVID-19. All numeric covariates are standardized.

The term γ_m represents municipality-fixed effects, absorbing any municipality-specific unobservable and time-invariant features. The term microregion-time fixed effects, $\alpha_{\text{microregion}(m),t}$,

[11] The Herfindahl-Hirschman Index (HHI) is a common measure of market concentration. The index measures the size of companies relative to the size of the industry they are in and the amount of competitiveness. The HHI is calculated by squaring the market share of each firm competing in a market and then summing the resulting numbers. It can range from close to 0 to 10,000, with lower values indicating a less concentrated market.

[12] Our baseline specifications with branch-specific data in Equations (2)–(5) accounted for these potential municipality-level concerns with the introduction of the time × bank's municipality fixed effects (and also borrower's municipality in the case of Equation (5)). However, we can no longer add these fixed effects because our data is now at the municipality × time level, not bank × municipality × time level. Therefore, we resort to controls to control for municipality-specific factors that could drive credit reallocation by inland branches across municipalities. For instance, we capture the intensity of government programs during COVID-19, which could drive credit-taking behavior and local credit issuance.

absorb time-varying microregion-specific shocks. Introducing these fixed effects enables us to interpret our results as comparing municipalities within the same microregion and asking if cities more exposed to COVID-19 face changes in their financial outcomes relative to less exposed municipalities.

Table 5 reports our coefficient estimates of Equation (7) for borrowers located in state capitals (Step 1, Specs. I–V) and inland municipalities (Step 2, Specs. VI–X) for the same dependent variables as in our branch-level analysis. We find that a one-standard-deviation increase in the inland municipality's exposure to COVID-19 reduces its total branches credit issuance by 7% to state capital clients and increases them by 2% to inland cities clients compared to other less exposed municipalities in the same microregion. For the same variation in the municipality's exposure to COVID-19, interest rates also increase by three percentage points for clients in state capitals and one percentage point for those in inland cities. Credit maturity shortens by 15 days for clients in state capitals. We find no changes in the branch's *clientele* (extensive margin) in capital cities and inland municipalities. Combining our branch-level and municipality-level findings, we conclude that there was a more pronounced reallocating effect in inland cities more exposed to COVID-19, highlighting the strategy of banks to mitigate the risks arising from the Pandemic. However, the cost of credit increased overall.

We also examine heterogeneous effects at the municipality level. We use the following econometric specifications:

$$\begin{aligned} y_{m,i,t} = \alpha_{\text{microregion}(m),t} + \gamma_m + \beta\ \text{Post}_t \cdot \text{Municipality Exposure to COVID-19}_m + \\ + \rho\ \text{Post}_t \cdot \text{Municipality Exposure to COVID-19}_m \cdot \text{Feature}_m + \\ + \tau\ \text{Post}_t \cdot \text{Controls}_m + \lambda\ \text{Lower-Order Interactions} + \varepsilon_{m,i,t}, \end{aligned} \tag{8}$$

in which m, i, and t index inland municipalities (capitals are excluded), borrower's locality (binary variable: state capital or inland municipality), and time (January 2019 to December 2020, quarterly), respectively. Table 6 lists the coefficient estimates of Equation (8) when we examine the log of credit issuances to borrowers in state capitals (Specs. I–V) and inland municipalities (Specs. VI–X) for the following municipality-level features (Feature_b): population (Spec. II), *per capita* GDP (Spec. III), HHI of the outstanding credit originated by branches in the municipality (Spec. IV), and distance to the capital (Spec. V). We also include all features in the same regression (Specs. V and X).

By focusing on the most saturated regressions (Specs. V and X), we find that bank branches in inland municipalities with more concentrated local credit (a proxy for market power) reduce to a lesser degree credit issuance to state capitals, suggesting branches in these inland municipalities perceived as less attractive to diminish credit for state capital clients due to the higher local competition. Likewise, the credit concentration mitigates the increase in credit issuance for inland clients. The size of the inland city (population) and its wealth (*per capita* GDP) are mitigators of the reallocating effect, suggesting that this effect was more prominent in small and poor cities. One possible explanation for this finding is that those small and poor municipalities may have a greater demand for credit, and banks may be more willing to allocate credit to these locations to meet this demand opportunity.

Table 5: *Baseline results (across-locality analysis): Do municipalities more exposed to COVID-19 reallocate credit away from capitals and improve financial conditions?*

Sample (borrower's location i):	State Capitals (Step 1)					Inland Municipalities (Step 2)				
Dependent variables:	$\log(Credit)$	$Int.Rate$	$Maturity$	$\%Provisions$	$\log(Clients)$	$\log(Credit)$	$Int.Rate$	$Maturity$	$\%Provisions$	$\log(Clients)$
(Jan 2019–Dec 2020, quarterly)	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables										
Post_t ·										
Municipality Exposure to COVID-19$_m$	-0.0685***	3.253***	-15.23*	-0.0126	-0.0013	0.0191***	0.9225***	0.8848	-0.0343	0.0093
	(0.0119)	(0.4167)	(8.833)	(0.0515)	(0.0065)	(0.0074)	(0.2341)	(4.898)	(0.0226)	(0.0059)
Population$_m$	-0.0080	-0.5835*	-0.2773	-0.0304	-0.0134***	-0.0005	-1.032***	-0.9329	0.0033	-0.0051*
	(0.0096)	(0.3360)	(9.632)	(0.0663)	(0.0029)	(0.0032)	(0.2252)	(3.424)	(0.0140)	(0.0028)
% Emergency Aid Recipients$_m$	0.0072	-0.4633	21.36	0.1414	-0.0005	0.0271	0.4768	-8.199	0.0871**	0.0192
	(0.0266)	(0.8868)	(20.06)	(0.1549)	(0.0114)	(0.0174)	(0.4484)	(7.822)	(0.0443)	(0.0135)
Per Capita GDP$_m$	-0.0329**	-0.9282*	-16.60	-0.1034	-0.0076	0.0012	-0.6050*	5.417	0.0528**	-0.0002
	(0.0142)	(0.5073)	(13.50)	(0.0959)	(0.0057)	(0.0075)	(0.3611)	(4.125)	(0.0223)	(0.0048)
Distance to the Capital$_m$	-0.0856**	-2.672*	-51.05	0.2473	-0.0144	0.0263	0.2242	-19.40	0.0547	0.0251
	(0.0382)	(1.599)	(31.25)	(0.2463)	(0.0171)	(0.0278)	(0.8372)	(12.83)	(0.0813)	(0.0198)
Credit HHI$_m$	-0.0257	0.2654	-17.24	-0.2752***	-0.0076	-0.0238***	2.602***	25.40***	-0.1958***	-0.0405***
	(0.0157)	(0.6848)	(12.79)	(0.1039)	(0.0070)	(0.0074)	(0.3215)	(4.258)	(0.0245)	(0.0063)
Preponderant activity is agriculture$_m$	-0.0244	0.9092	-67.24**	0.0031	0.0100	0.0380**	-0.0294	-14.62	-0.0800	0.0157
	(0.0364)	(1.606)	(30.24)	(0.2814)	(0.0161)	(0.0186)	(0.7203)	(10.50)	(0.0588)	(0.0145)
Preponderant activity is industry$_m$	-0.0057	-1.014	-16.31	0.8617***	0.0100	0.0339*	-1.354	-14.53	-0.1446*	0.0095
	(0.0472)	(1.581)	(47.81)	(0.2749)	(0.0194)	(0.0188)	(0.8509)	(13.80)	(0.0746)	(0.0157)
Fixed Effects										
Time · Bank Microregion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics										
Observations	37,165	37,165	37,165	37,165	37,165	43,611	43,611	43,611	43,611	43,611
R^2	0.9127	0.6396	0.5665	0.3959	0.9833	0.9824	0.8555	0.8489	0.6922	0.9917

Note: This table reports changes in municipalities' financial outcomes in Brazilian inland municipalities to borrowers in state capitals (Specs. I–V) and inland municipalities (Specs. VI–X) around the beginning of COVID-19 crisis in Brazil (March 2020) using Specification (7) at the municipality (m) $\times$ borrower's locality (i, binary: state or inland) $\times$ time (t) level. Data is aggregated quarterly from January 2019 to December 2020. We use the following dependent variables: log of the volume of credit issuances (Specs. I, VI), average interest rates in percentage terms (Specs. II, VII), average maturity in days (Specs. III, VIII), provisions as a percentage of the outstanding credit (Specs. IV, IX), and the log of the number of distinct clients (Specs. V, X). The variable Municipality Exposure to COVID-19$_m$ is our municipality-specific *continuous* treatment variable and follows Equation (6). The dummy Post_t represents the onset of the COVID-19 crisis in Brazil and equals 1 when $t \geq$ March 2020, and 0 otherwise. We add microregion-time and municipality-fixed effects. We also introduce the following set of control variables (Controls_m), all of which interacted with the Post_t binary variable (to avoid collinearity with the municipality fixed effects): population (in 2019), *per capita* GDP (in 2019), distance to the capital, average HHI evaluated from the outstanding credit across branches in the same municipality (in December 2019), dummy variables indicating whether the preponderant local activity is agriculture or industry (in 2019), and the percentage of the local population receiving emergency aid programs in 2020 to combat the economic effects of COVID-19. One-way (municipality) standard errors are in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

6. Conclusions

This paper investigates how an exogenous negative shock in the real economy hits and propagates to the financial side. We analyze whether and how banks reallocate credit to different Brazilian municipalities due to the COVID-19 pandemic, based on a particular pattern in Brazil: first, the pandemic hit more severely state capital cities and only afterward arrived at inland cities, generating an incentive for banks to update their expectations regarding the riskiness of their credit lending operations.

To perform our study, we explore a set of publicly available databases provided by many governmental entities, merged with proprietary data from the Central Bank of Brazil. We find that during the COVID-19 pandemic, the growth in total credit operations done by banks has

Table 6: *Baseline results (across-locality analysis): do municipalities more exposed to COVID-19 reallocate credit away from capitals and improve financial conditions?*

Dependent variable:	log$(Credit)$									
Sample (borrower's location i):	State Capitals (Step 1)					Inland Municipalities (Step 2)				
(Jan 2019–Dec 2020, quarterly)	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables of interest										
Post$_t$ ·										
· Municipality Exposure to COVID-19$_m$	-0.0677***	-0.0689***	-0.1149***	-0.0612***	-0.1155***	0.0178**	0.0141*	0.0265***	0.0177**	0.0254**
	(0.0118)	(0.0127)	(0.0176)	(0.0130)	(0.0192)	(0.0072)	(0.0076)	(0.0099)	(0.0083)	(0.0109)
· Municipality Exposure to COVID-19$_m$ ·										
· Population$_m$	0.0042				0.0178**	-0.0059**				-0.0066**
	(0.0054)				(0.0090)	(0.0026)				(0.0033)
· *Per Capita* GDP$_m$		-0.0012			0.0029		-0.0154**			-0.0145*
		(0.0129)			(0.0150)		(0.0071)			(0.0084)
· Credit HHI$_m$			0.0469***		0.0604***			-0.0073		-0.0153*
			(0.0135)		(0.0154)			(0.0074)		(0.0081)
· Preponderant activity is agriculture$_m$				-0.0397	-0.0473*				0.0155	0.0202
				(0.0253)	(0.0250)				(0.0162)	(0.0160)
· Preponderant activity is industry$_m$				0.0231	0.0371				-0.0367**	-0.0250
				(0.0467)	(0.0521)				(0.0183)	(0.0206)
Controls										
Post$_t$ ·										
· Population$_m$	-0.0107	-0.0079	-0.0006	-0.0087	-0.0111	0.0032	0.0009	-0.0018	-0.0002	0.0029
	(0.0103)	(0.0097)	(0.0097)	(0.0096)	(0.0104)	(0.0039)	(0.0033)	(0.0035)	(0.0032)	(0.0039)
· *Per Capita* GDP$_m$	-0.0330**	-0.0329**	-0.0321**	-0.0325**	-0.0319**	0.0013	0.0008	0.0010	0.0011	0.0006
	(0.0142)	(0.0142)	(0.0141)	(0.0142)	(0.0142)	(0.0075)	(0.0074)	(0.0075)	(0.0075)	(0.0074)
· Credit HHI$_m$	-0.0264*	-0.0257	-0.0211	-0.0268*	-0.0241	-0.0228***	-0.0236***	-0.0249***	-0.0236***	-0.0245***
	(0.0158)	(0.0157)	(0.0155)	(0.0157)	(0.0156)	(0.0075)	(0.0074)	(0.0075)	(0.0074)	(0.0075)
· Preponderant activity is agriculture$_m$	-0.0246	-0.0243	-0.0207	-0.0243	-0.0210	0.0384**	0.0387**	0.0375**	0.0402**	0.0405**
	(0.0364)	(0.0365)	(0.0364)	(0.0365)	(0.0364)	(0.0186)	(0.0185)	(0.0185)	(0.0186)	(0.0185)
· Preponderant activity is industry$_m$	-0.0057	-0.0057	-0.0036	-0.0056	-0.0032	0.0340*	0.0332*	0.0336*	0.0314*	0.0309*
	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0188)	(0.0188)	(0.0188)	(0.0187)	(0.0187)
· % Emergency Aid Recipients$_m$	0.0069	0.0072	0.0109	0.0066	0.0099	0.0275	0.0277	0.0266	0.0271	0.0272
	(0.0266)	(0.0266)	(0.0266)	(0.0266)	(0.0266)	(0.0174)	(0.0174)	(0.0174)	(0.0174)	(0.0174)
· Distance to the Capital$_m$	-0.0855**	-0.0856**	-0.0948**	-0.0867**	-0.0987**	0.0262	0.0261	0.0276	0.0268	0.0294
	(0.0382)	(0.0382)	(0.0384)	(0.0382)	(0.0384)	(0.0278)	(0.0278)	(0.0279)	(0.0278)	(0.0278)
Fixed Effects										
Time · Bank Microregion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics										
Observations	37,165	37,165	37,165	37,165	37,165	43,611	43,611	43,611	43,611	43,611
R^2	0.9127	0.9127	0.9127	0.9127	0.9128	0.9824	0.9824	0.9824	0.9824	0.9824

Note: This table reports changes in municipalities' financial outcomes in Brazilian inland municipalities to borrowers in state capitals (Specs. I–V) and inland municipalities (Specs. VI–X) around the beginning of COVID-19 crisis in Brazil (March 2020) using Specification (7) at the municipality (m) $\times$ borrower's locality (i, binary: state or inland) $\times$ time (t) level. Data is aggregated quarterly from January 2019 to December 2020. We use the following dependent variables: log of the volume of credit issuances (Specs. I, VI), average interest rates in percentage terms (Specs. II, VII), average maturity in days (Specs. III, VIII), provisions as a percentage of the outstanding credit (Specs. IV, IX), and the log of the number of distinct clients (Specs. V, X). The variable Municipality Exposure to COVID-19$_m$ is our municipality-specific *continuous* treatment variable and follows Equation (6). The dummy Post$_t$ represents the onset of the COVID-19 crisis in Brazil and equals 1 when $t \geq$ March 2020, and 0 otherwise. We add microregion-time and municipality-fixed effects. We also introduce the following set of control variables (Controls$_m$), all of which interacted with the Post$_t$ binary variable (to avoid collinearity with the municipality fixed effects): population (in 2019), *per capita* GDP (in 2019), distance to the capital, average HHI evaluated from the outstanding credit across branches in the same municipality (in December 2019), dummy variables indicating whether the preponderant local activity is agriculture or industry (in 2019), and the percentage of the local population receiving emergency aid programs in 2020 to combat the economic effects of COVID-19. One-way (municipality) standard errors are in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

been heterogeneous across municipalities, and we relate this fact to the Pandemic as a result of portfolio reallocation in the intensive margin toward less risky borrowers (located in inland cities).

Using the Difference-in-difference approach, we analyzed both bank and municipality levels in our empirical investigation. We found causal evidence to support our idea that banks more exposed to capital cities - and, consequently, to COVID-19 - increased credit to inland municipalities.

We found that the more a bank is exposed to COVID-19, the more it will reallocate the credit lent to inland clients, probably perceiving an increase in the risk of their portfolio in state capitals. Also, large banks are the more exposed ones and, consequently, the bigger it is, the more significant if the reallocating toward inland clients. It means that big banks tend to hold, proportionately, more part of their portfolio covering state capital clients, and that smaller banks with a more geographically balanced portfolio did not reallocate the additional credit as intensively. On the other hand, credit unions had a less significant shift compared to commercial banks, reflecting its characteristics of associative clients.

Regarding ownership, private banks reallocated more to inland clients. Since state-owned banks do not depend only on market forces to keep their activities going (the Brazilian central government can provide them with funding and also use them to implement public policy). Following that train of thought, less liquid banks have more proclivities to credit reallocation, considering that drawbacks in their exposition to locations heavily hit by COVID-19 could impact their bankruptcy odds.

At the level of municipalities, we also found evidence that the more exposed a city is to COVID-19, the more significant the growth of credit allocated inland. This result is consistent with the same region, state, and micro-regions. As in our bank-level analysis, we also found that a bigger share of larger banks means more additional credit directed to inland clients.

Our findings shed light on the mechanisms behind crisis propagation, particularly studies examining shock transmission through production networks. During the pandemic, Brazilian banks shifted credit operations from clients in capital cities to those in inland regions. Simultaneously, companies in capital cities bore the brunt of the pandemic's impact. This combination suggests that crucial channels for firm performance, namely bank financing and trade credit, were disrupted. Our empirical evidence thus indicates that the banking financing channel failed to mitigate the COVID-19 impact on the Brazilian real economy.

For future research, we propose expanding this study on credit operations by economic activities. This will enable us to connect financial inputs to studies assessing the pandemic's impact on the supply chain, uncovering the channels that propagated the crisis across economic activities. This will also allow us to investigate shock transmission in business-to-business relationships between firms and banks. Such insights would be valuable for policymakers in evaluating the effectiveness of credit policies for companies, particularly those designed by the Brazilian government to mitigate the effects of COVID-19.

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