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COVID-19 AND MARKET POWER IN LOCAL CREDIT MARKETS: THE ROLE OF DIGITALIZATION*

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Abstract

This paper investigates how COVID-19 and digitalization affected the market power in local Brazilian credit markets. We first propose a novel methodology to estimate bank market power at the local level. We design a data-intensive local version of the Lerner index by developing heuristics to allocate national-level banks' inputs, products, and costs across their branches using large-scale datasets from many sources. We then exploit the exogenous variation in COVID-19 intensity across Brazilian localities to analyze how the pandemic influenced local market power through the effective price and marginal cost channels. Despite reducing the economic activity, COVID-19 did not impact the effective price channel: bank branches offset the decrease in credit income by reducing credit concessions. However, bank branches more affected by COVID-19 experienced increased marginal costs as they could not rapidly adjust their cost factors in response to the decrease in credit concessions. Consequently, COVID-19 reduced banks' local market power via the marginal cost channel. More digitalized bank branches enjoy cost and lending flexibility: they experience less stickiness in their cost structure and complement the reduced credit concessions in localities more affected by COVID-19 by extending credit to borrowers in remote localities less affected. Consequently, more digitalized banks improve their market power compared to traditional banks. This paper provides new insights into how crises can affect local market power in non-trivial ways.

Keywords: COVID-19, market power, digitalization, information technology, Lerner index.

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1 Introduction

The COVID-19 pandemic affected the global economy, causing recessions, business failures, and increased unemployment. Governments have adopted several economic measures such as monetary policy stimuli, recomposition of family income via direct cash transfers, credit incentive programs for companies, and strengthening of financial markets to combat these effects.[1] The impact of the pandemic and the effect of economic policies on the economy are not straightforward. In this paper, we develop a methodology to assess how COVID-19 affected market power in credit markets for different banks and localities and apply it to the Brazilian banking sector by leveraging the use of many rich microdata databases. Additionally, we look at the role of digitalization in improving bank market power during the pandemic.

Pandemics can change or accelerate trends, significantly impacting the economy (Ceylan et al., 2020).[2] It may even be heterogeneous among regions[3] and economic agents, causing the bankruptcy of some and the strengthening of others, potentially increasing market power in some sectors.[4] The SARS-COV pandemic in 2003-2004 crippled the tourism and transport sectors in Hong Kong. Consumption and foreign trade also declined, resulting in job losses. In contrast, the industrial sector remained unaffected (Siu and Wong, 2004). The economic consequences of COVID-19 varied considerably between countries, depending on their pre-pandemic conditions, the extent to which governments implemented containment measures, the economy's sectoral composition and structure, and the quality of institutional settings (Muggenthaler et al., 2021). Regions with better conditions to control the effects of the pandemic suffered less economic damage.[5] Another factor that contributes to the disparity in economic effects of COVID-19 is the existence of platforms and digital technologies. On the one hand, they facilitate remote working, allowing businesses to continue operating while their employees and customers practice social distancing. On the other hand, retail giants have further expanded their market power. At the same time, numerous small offline firms experienced huge losses or went bankrupt (Bloom et al., 2021; Kenney and Zysman, 2020).[6] One should also expect these heterogeneous COVID-19 effects in the banking sector, as the health crisis, like a financial crisis, slowed economic growth, increased

[1]The IMF summarizes policies responses to the COVID-19 pandemic from 197 economies in Polices Responses to COVID-19. Cantú et al. (2021) provide information on central banks' responses to COVID-19 in 39 economies.

[2]The Black Death destroyed a large portion of the world's workforce and resources, contributing to the shift from labor-based to capital-based production and significantly increasing rural-urban migration (Clark, 2016; Pamuk, 2007). As of 2014, the Spanish flu was the fourth largest economic shock to income and consumption after WWII, WWI, and the Great Depression (Barro and Ursúa, 2008). Since the Spanish flu, the labor market has shifted, with female employment increasingly displacing male employment (Fornasin et al., 2018; Rao and Greve, 2018).

[3]Muggenthaler et al. (2021) describe how the COVID-19 pandemic has affected activity and demand in the Euro area. Portugal and Spain experienced the sharpest declines in real GDP (9.1% and 9.3% change in real GDP from the fourth quarter of 2019 to the first quarter of 2021 by demand components, respectively). In contrast, some countries' real GDP in the first quarter of 2021 exceeded the pre-crisis level: Estonia (3.4%), Ireland (13.2%), Lithuania (1.1%), and Luxembourg (3.2%).

[4]Rio-Chanona et al. (2020) made predictions about the pandemic's impact on the US economy at the beginning of the COVID-19 outbreak. They predicted a first-order impact of 22% on GDP, a 24% decline in employment, and a 17% reduction in income. A variety of factors are responsible for these effects: demand shocks (transport), supply shocks (manufacturing, mining, and services), or a combination of both (entertainment, restaurants, and tourism).

[5]Çolak and Özde Öztekin (2021) show that the contraction in credit supply was less pronounced in places with greater capacity to implement pandemic-containment measures and sufficient hospital capacity to meet the increased demand.

[6]For example, Amazon's revenues increased 47% year over year in the fourth quarter of 2020, while companies selling goods on Amazon were negatively impacted by rules that changed during the pandemic, restricting sales of non-essential products (see here and here for more information).

unemployment, and weakened many firms.

Empirical research shows that financial crises can affect the market power of banks (Cubillas and Suárez, 2018; Efthyvoulou and Yildirim, 2014). It is an empirical question to test whether the COVID-19 pandemic affected banks' market power through channels similar to those identified in previous research on financial crises. Cubillas and Suárez (2018) argue that borrowers from failed banks during the global financial crisis had to turn to banks they had no relationships with, which in turn charged higher interest rates. They also claim that banks with greater market power had access to funding more quickly. Consequently, they reduced credit less than financially constrained banks. In the COVID-19 crisis, something similar could happen.[7] Financially constrained banks may have their costs increased. Even if they do not go bankrupt, they can suffer significant losses from increased defaults and, consequently, reduce the credit supply or increase interest rates.[8] Increased uncertainty in times of crisis can also change banks' risk tolerance, leading them to lend to less risky sectors and, therefore, with lower returns (Detragiache et al., 2000). Furthermore, Berger and Bouwman (2013) find capital helps to increase market share. This effect varies according to the bank size and to the period being of crisis or normality. Therefore, considering the heterogeneity of banks and the potential impacts of the pandemic on banks' costs, prices, and profit margins, their market power may increase or decrease.

Innovation is another key factor that influences how the COVID-19 pandemic may have affected market power.[9] Before the COVID-19 outbreak, financial systems were undergoing a heavy process of digitalization.[10] With the introduction of public health measures discouraging person-to-person contacts, this process accelerated in both the financial and real sectors.[11] Aghion et al. (2005) show that competition encourages leaders to invest in innovation while discourages laggard firms from doing the same. These changes may have widened the gap between leading banks and followers, increasing the participation and market power of banks that are better prepared to face the adverse effects of the pandemic. Our paper adds to this literature by showing banks with more pre-pandemic IT spending improved their positioning in terms of market power.

Bank market power is an important topic for policymakers and academia because it directly impacts

[7]Health crises are more complex than financial crises. The contagiousness of COVID-19 required drastic measures to contain the outbreak and mitigate its economic consequences. Due to its severity, the pandemic triggered a medical crisis and an economic crisis whose challenges some researchers compare to those faced concurrently by the Spanish Flu pandemic and the Great Depression (Susskind and Vines, 2020). The economic impact of COVID-19 can affect banks like a financial crisis, including an increase in defaults, a decline in credit portfolio quality, and an increase in risk aversion.

[8]Çolak and Özde Öztekin (2021) use a sample of banks from 125 countries and show that, despite the measures to stimulate the economy and encourage bank credit supply, credit growth reduced, especially for smaller banks with lower returns on assets.

[9]Digital technologies were essential for sectors such as banking and commerce to face the economic consequences of lockdowns. However, the relevance of technology depends on the economic sector. For example, digital platforms linked to tourism and transport, such as Airbnb, Booking.com, and Uber, lost market value and had to lay off employees to survive (Kenney and Zysman, 2020).

[10]Philippon (2015) examines data up to the global financial crisis in 2008 and finds an interesting puzzle. Despite significant advances and investments in computer and communications technologies, the unit cost of financial intermediation remained close to 200 basis points for more than a century. Philippon (2020) reruns the model with data after the global financial crisis and finds that the unit cost of financial intermediation has declined during 2010–2020. He attributes this structural change to the rapid growth of fintechs, which benefit from the use of digital innovations that can disrupt industry structures, including blockchain technologies, new digital advisory and trading systems, machine learning, peer-to-peer lending, equity crowdfunding, and mobile payment systems.

[11]OECD (2020) identified the importance of assessing the consequences of the digital transformation accelerated by the COVID-19 pandemic in a wide range of economic sectors.

the real economy. A more competitive banking system offers lower loan interest rates and increase the returns on deposits, boosting savings and investment, thereby promoting economic development. However, it can exacerbate adverse selection and moral hazard problems and shrink the credit availability to more opaque borrowers. Besides, it reduces the diversification of business risk and the ability to extract benefits from economies of scale (Beck, 2015; Coccorese, 2017). Furthermore, banks with less market power have fewer alternative sources of funding (Segev and Schaffer, 2020). Banks' market power also has implications for financial stability (Beck et al., 2013; Berger et al., 2009; Schaeck et al., 2009).[12]

We estimate banks' market power using the Lerner index. This index evaluates the ability of banks to adjust prices above marginal costs in imperfectly competitive markets, serving a proxy for the bank's market power and competition.[13] Another property of a Lerner index is that it is proportional to the inverse of the demand's price-elasticity. This means that banks with greater market power can extract higher profits, as an increase in credit prices results in a comparatively lower decrease in the demand for loans.

Most studies assess bank market power using the Lerner index typically at the national level, partly because of the lack of microdata to estimate the banks' local cost function. This aggregate approach may overlook important aspects of local competition. [14] Local market power assessment poses two main challenges. The first is extending the methodological framework used at the national level to allow local level estimation. The second is obtaining local-level data. The usual methodology calculates the Lerner index by estimating banks' total cost at the national level using a translog cost function, hypothesizing that the estimation input data—total costs, input prices, and output volumes—result from a previous optimization process. That is, this approach takes as inputs the outcomes of banks' technology and decision-making process, without considering directly these factors, which can vary substantially across the sample. Our methodology for estimating local level Lerner has the same hypothesis. In fact, our method assumes that bank branches in a particular locality form an autonomous bank capable of making production decisions independently of other branches. While this may appear to be a strong assumption, it does not introduce a relevant distortion into our results because the modeling hypothesis assumes that banks have already optimized costs as a result of their size, geographical distribution, technology, governance *before the calculation*.[15]

[12]There are two views on competition and financial stability. The first is the "competition-fragility view," which states that increased competition reduces banks' market power, encouraging more risk-taking. The second is the "competition-stability view," which establishes that higher market power increases credit risk due to higher interest rates charged to borrowers. The two views do not necessarily have opposite effects on bank stability. For instance, banks can mitigate increased credit risk by raising capital.

[13]Central banks and academia have used Lerner indices (Lerner, 1934) to assess competition in banking systems and the market power of financial institutions. The World Bank uses Demirgüç-Kunt and Martínez Pería (2010)'s methodology as a benchmark to calculate the Lerner index of the banking systems of many countries at the national level. Lerner indices are also widely used by international organizations and central banks. Examples include the IMF (Tan et al., 2020), Bank of England (De-Ramon et al., 2018) and *Banco de España* (Cruz-García et al., 2018). Research on the Lerner index and its variants is also active in academia: Shaffer and Spierdijk (2020) provide a summary of recent banking studies that use the Lerner index.

[14]Loecker et al. (2020) highlight the importance of the level of granularity in the analysis. They document a rise of firms' market power for the U.S. economy since 1955 and discuss the macroeconomic implications of this increase. They show that the markup distribution suffers significant changes while the median is unchanged over time. Their results reinforce the importance of analyzing market power more granularly rather than relying on aggregate approaches or statistics.

[15]For instance, suppose a large bank with branches located throughout the country's regions. If there are multiple branches in the same locality, we compose a representative branch of that bank in the locality. Given local total costs, input prices and output volumes, we estimate a local Lerner index for each locality. If the bank's organizational structure changes, potentially

Regarding the lack of local data, we overcome this limitation by developing heuristics that reallocate national-level bank resources across local inputs, products, and costs for each of its branches using several proprietary and public data sources. Additionally, our methodology allows incorporating bank and geography-specific characteristics into the computation, yielding estimates of the marginal cost of each credit modality for each bank branch in the sample. By combining this information with local average credit prices, we construct local Lerner indices at the bank branch locality level, which provide insight into the banks' market power locally. Despite proposing the Lerner index at the local level, we also improve it in many aspects by leveraging available microdata.

Regarding prices, due to data unavailability, the literature typically uses the *effective price* instead of the *contractual price* in the Lerner index, which corresponds to the ratio of credit income and outstanding credit.[16] We improve this definition in this paper. First, we do not use the bank's outstanding credit, which potentially contains previously granted credit operations that do not necessarily capture the current competitive market conditions. Instead, we explicitly separate new credit grants from older ones and focus on the former when evaluating the local competition. This approach enables us to measure the current competitive conditions more accurately. Second, we reduce the distortion between credit income and outstanding credit when we rely on end-of-month income statements. For very short-term operations, we would observe the credit income at the end-of-month financial statement but not the outstanding credit volume.[17] This limitation biases credit prices upwards materially if there is a substantial volume of very short-term credit. We mitigate this problem by resorting to (billions of records of) loan-level income data with balance position and cash flows before and after repayments and computing the monthly accrued income and the monthly average outstanding credit *for each loan*. Third, we estimate marginal costs for each bank branch and credit modality using a translog total cost functional form with bank branch and locality-time fixed effects, enabling us to control for many non-observable bank branch- and locality-specific factors that would not be possible in the usual estimation at the bank level.

In addition to the Lerner index, concentration indices, such as the Hirschman-Herfindahl Index (HHI), are widely used to assess the level of competition—hence the degree of market power—in the banking sector. While all of these measures may fail to identify market power accurately, concentration indices are more disputed (Shaffer and Spierdijk, 2020). The contestability theory suggests firms in concentrated markets can behave competitively if entry and exit barriers are low (Baumol et al., 1982). Concentration indices assume that only the internal characteristics of the market affect competition. However, Bernheim and Whinston (1990) argue that external characteristics, such as multimarket contact,[18] facilitate collusion, even with the presence of many firms in the local market. Another controversial point is the potential endogeneity between concentration and competition. More efficient firms can

resulting in changes in output volumes in each locality, we will observe changes in the estimated local Lerner indices. If these modifications do not alter production volumes or total costs, the Lerner indices will remain unchanged regardless of organizational transformations.

[16] *Effective prices* are net of losses due to default and other risk factors since they effectively measure the credit income that the bank receives in its credit operations. *Contractual prices* are not.

[17] As an example, consider a \$100 credit operation that matures in one week and begins on November 3, 2020. The weekly interest rate is 10%. If no default occurs, the bank will cash in ten dollars by the end of the current week. By the end of November 2020, the bank's income statements will include the credit income of \$10 generated from this credit operation. However, the outstanding balance for this operation at the end of the month will be zero.

[18] Multimarket contact occurs when companies compete with the same rivals in multiple markets. When companies compete in more than one market, their competitive behavior may differ from that of competitors in a single market.

increase their market shares, increasing concentration (Peltzman, 1977). It is also challenging to define a relevant local market or product empirically (Shaffer, 2004). The scarcity of microdata also encourages the use of concentration indicators, which are less data-intensive. Furthermore, Blair and Sokol (2014) claim the Lerner index is the standard measure of market power among economists. Therefore, in this paper, we adopt the Lerner index as a measure of market power and a proxy for competition.[19] The main advantage of the Lerner index is that it tells us about the channels through which market power changes: either through the *effective price channel* or the *marginal cost channel*. All else equal, increases in the first (second) lead to higher (lower) market power. This interpretability is important to rationalize our results and understand the mechanisms through which COVID-19 can affect market power.

We apply this methodology to the Brazilian banking system. This emerging market country has a considerable variety of economic development and diversity, climate, and demographics across localities, leading to very distinct settings of local market power. During the COVID-19, the federal government took most of the relevant economic measures to combat the pandemic, including financial support to families and small businesses, the possibility of deferring loan payments, changes to banking system requirements to increase credit capacity, and monetary policy loosening. The diversity of characteristics of the localities and the different ways in which the pandemic affected them led to a great diversity of local economic developments during the pandemic, even in the context of a similar set of government measures. This diversity provides the conditions for examining the COVID-19's impact on local credit market power. In addition, Brazil has rich datasets that make these analyses feasible.

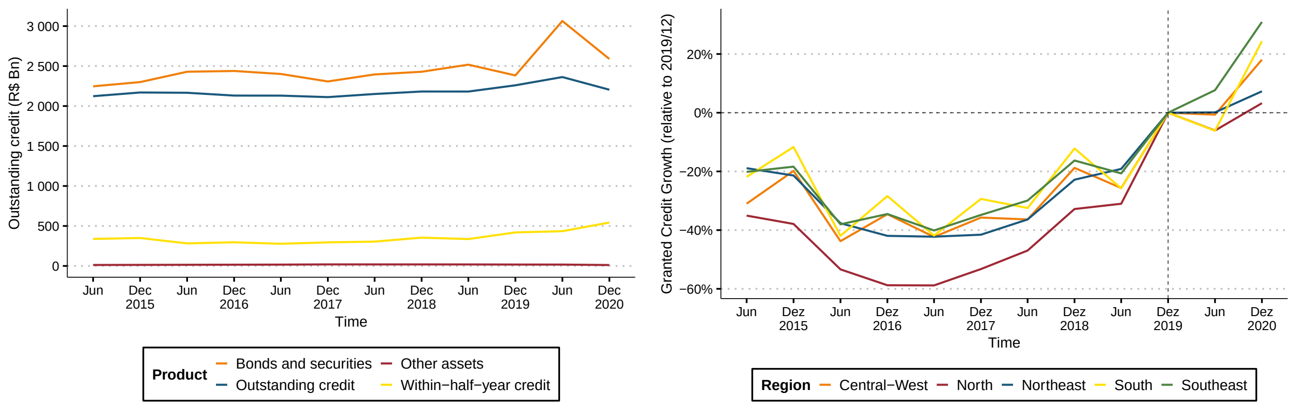
Brazil experienced a spreading pattern of COVID-19 similar to the United States.[20] First, the virus hit heavily state capitals, which are the most populated areas and host all core airports, before spreading significantly to inland municipalities. We measure the extent to which COVID-19 has affected localities using the number of COVID-19 cases as a share of the local population. In terms of identification, one potential concern is that the timing and intensity of local COVID-19 intensity are likely not exogenous to localities' economic and geographic conditions, such as population, economic development, distance to state capitals, and economic structure. The local economy's structure may affect COVID-19 transmission rates as activities related to agriculture are geographically sparser than services and industrial activities. We show that once we compare localities within the same macrolocality and with similar wealth levels, the local COVID-19 spreading becomes unrelated to many locality-specific correlates. This fairly exogenous variation of local COVID-19 intensity across localities within the same macrolocality and with similar wealth levels is essential to support the causal interpretation of the results.[21]

[19]We also provide robustness tests in which we employ alternative measures that are less data-intensive and require less assumptions, such as the HHI. This analysis aims at giving a sense of the marginal value of using the local Lerner index over other simpler approaches.

[20]The country's dimensions and the initial COVID-19 occurrence are critical factors in determining the COVID-19 spreading pattern. For instance, China was the initial COVID-19 epicenter, with the virus spreading primarily from the Hubei province to its closest neighbors. Therefore, the COVID-19 spreading correlated exclusively with the geographic distance from Hubei (Kang et al., 2020). In Italy, COVID-19 contagion was not uniform. Following the outbreak in the province of Lodi (northwestern region of the country), health authorities registered cases in three additional northern regions: Lombardy, Emilia-Romagna, and Veneto shortly after (Giuliani et al., 2020). In countries with continental dimensions, the virus typically targets larger urban areas first—which are more populated and closer to core airports—before moving on to inland municipalities (Paul et al., 2020; Wang et al., 2020).

[21]This empirical strategy also mitigates several non-observable and region-specific concerns. For instance, under-notification of COVID-19 cases was a serious concern at the beginning of the outbreak (Cintra and Fontinele, 2020). By comparing adjacent localities with similar wealth levels, local health institutions and authorities are likely to be more similar,

This paper concerns local market power in credit markets in Brazil, a strongly bank-oriented economy. Brazilian SME firms mostly rely on banking credit for external funding. Our study also includes credit for households, which is mainly from the banking system. Figure 1a displays the volume of each class of banking product offered in Brazil. Credit is an important product for Brazilian banks, accounting for nearly half of their assets. Figure 1b exhibits the relative growth rate of the volume of credit concessions in each half-year from 2015 to 2020 (reference: December 2019). Credit concessions increased substantially in Brazil during the pandemic. This effect was pervasive across all five Brazilian regions. This absolute increase is critical to keep in mind because our econometric exercises employ a difference-in-differences analysis, which produces conclusions that are in relative rather than absolute terms.



***(a)** Bank products*

***(b)** Credit concessions within half-year*

***Figure 1.** Overview of credit as a banking product in Brazil. (a) Comparison of outstanding credit volumes to the other main banking product classes over time. (b) Relative growth of half-yearly credit concessions across regions over time.*

We resort to a within-bank and across-locality empirical strategy to analyze how COVID-19 affected market power and its components in local Brazilian credit markets. This strategy enables us to isolate bank-specific temporal changes in credit supply while allowing variations in COVID-19 intensity across localities. Our variation comes from the *same* bank operating in *different* but *similar* localities experiencing *distinct* COVID-19 intensity levels. To further alleviate any issues with differences in the bank's credit composition portfolio in different localities, we also compare the same bank operating in the *same* credit modality market across similar localities. In this empirical setup, we can view the COVID-19 shock as a *local demand shifter*, as broad credit supply is controlled for in a within-bank analysis. Another empirical challenge is the existence of numerous concurrent confounding variables during the pandemic, such as the introduction of government programs designed to combat the economic effects of COVID-19. Most of these measures can influence the decision of credit-taking. We also account for these issues by introducing controls.

We find that COVID-19 did not impact effective prices in local credit markets. However, we find substantial changes in the effective price components: credit income and granted credit decline significantly in localities more affected by COVID-19. Therefore, the significant decrease of credit income

and we should not expect systematic differences in the under-notification levels across localities. In addition, authorities intervened in the economy with several programs to mitigate the effects of the pandemic, such as temporary direct cash transfers programs for individuals, repayment postponement, and subsidized loans. We can control for the intensity of these programs by comparing localities with similar wealth levels.

was offset by a corresponding reduction in credit concessions in the locality, resulting in unchanged effective prices. Using data on firm income from credit and debit card transactions, invoices, wire transfers, and exports, we show localities with higher COVID-19 intensity had lower local economic activity than similar localities with lower levels of COVID-19 prevalence. This decreased economic activity rationalizes the decrease in credit income and concessions in localities more affected by COVID-19.

In contrast, we find that COVID-19 significantly affects marginal costs. A one-standard-deviation increase in the local COVID-19 prevalence (4%) increases banks' marginal costs by 0.5 cents during the COVID-19 pandemic. This value is expressive as the marginal costs' sample mean is 4 cents. We show that the increase in marginal costs occurs because bank branches cannot adjust their total costs in the short term due to the stickiness of cost factors arising from economic rigidities and the existence of legal and financial frictions. Combining these findings, we find evidence that the COVID-19 pandemic reduced the local market power of Brazilian banks mainly through the marginal cost channel.

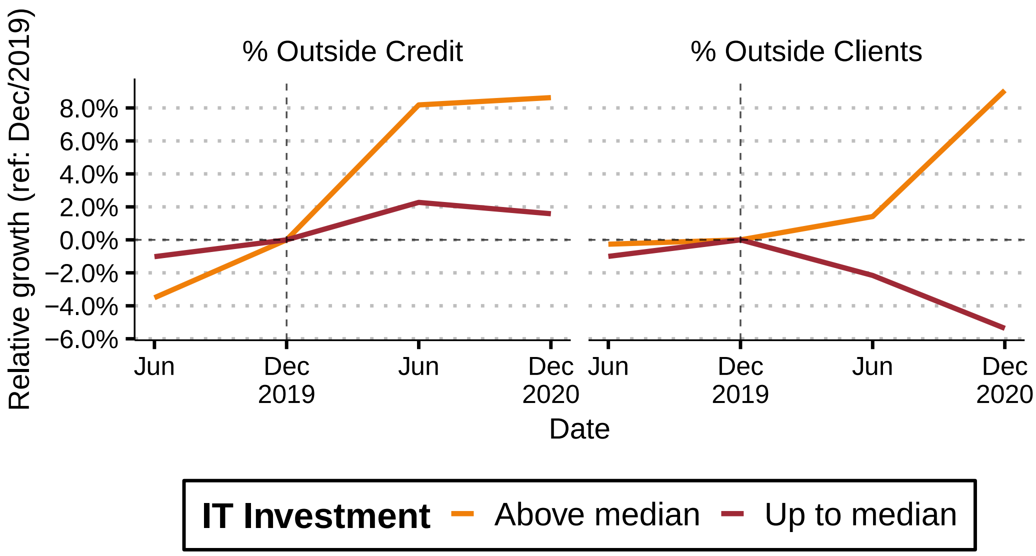


Figure 2. *Relative growth rate (reference: December 2019) of the volume of credit concessions (left) and clients (right) residing in areas outside the bank branch's locality in the aftermath of the COVID-19 outbreak (2019–2020) for banks with high IT spending (above the sample median) and low IT spending (up to the sample median) before the COVID-19 crisis.*

The COVID-19 pandemic highlighted the importance of IT development in the banking sector. In this paper, we proxy bank digitalization as the IT spending as a share of the bank's total costs in the pre-pandemic period. We find that digitalized banks enjoyed advantages over traditional banks during the pandemic. First, we show that bank digitalization provides cost flexibility. More digitalized banks experience fewer frictions in adjusting their cost structure in the short term, especially funding costs. Digitalization also warrants lending flexibility. Precisely banks that spent more on IT before the COVID-19 are likely to have more developed and trustworthy online banking systems, enabling these remote transactions to a more considerable extent. Figure 2 displays the raw growth rate (relative to December 2019) of the share of credit concessions and distinct clients external to the bank branch's locality for more (orange curve) and less (red curve) digitalized bank branches. After the COVID-19 outbreak, more digitalized banks expanded credit and engaged with new clients living outside the bank branches' physical locality. We corroborate this raw evidence with an econometric exercise. We find that more digitalized banks complement the decrease in credit concessions in localities more affected by COVID-

19 by extending credit to borrowers in remote localities.[22] Our results highlight the role of digitalization in allowing bank branches to be less sensitive to local borrowers' conditions. Consequently, more digitalized bank branches can mitigate the increase in marginal costs in localities more affected by COVID-19 than traditional banks, improving their market power in local credit markets comparatively to traditional banks.[23]

2 Related Literature

There is a large body of research on market power and competitiveness in the banking sector due to its relevance for assessing deregulation, mergers and acquisitions, technological innovations, entry of foreign banks, and, consequently, the impacts on the real economy and financial stability (Degryse et al., 2018). Regarding macroeconomic research on market power, Loecker et al. (2020) document a rise of firms' market power over the last six decades for the U.S. economy. They show that while the markup distribution changes significantly over time, the median remains unchanged. While firms with a high markup gain market power over time, the remaining firms maintain the same markup. As a result, the median markup remains stable over the period. At the same time, economic activity is reallocated toward high-markup and large firms. They also analyze firm profitability and conclude that its distribution has changed similarly with the changes in the markup distribution. They claim that the reduction in labor market dynamism is a macroeconomic implication of these changes.

Empirical studies use different ways to measure the market power and competitiveness of the banking sector. They mainly fall into two approaches. In the first—the "Structure-Conduct-Performance" (SCP) paradigm—the literature employs concentration measures, such as the HHI and the Concentration Ratio (CR), to proxy for market power. The underlying hypothesis is that collusion is easier in more concentrated markets, leading to anti-competitive behavior by banks. Empirical research shows mixed results, and there is no consensus about the validity of the SCP hypothesis. In the second—the "New Empirical Industrial Organization" (NEIO) paradigm—the literature directly estimates the banks' conduct using methodologies grounded on theory. These methodologies are more data-intensive, requiring detailed information on bank inputs and outputs. Measurements that use the NEIO paradigm include the mark-up test (Bresnaham, 1982; Lau, 1982), the H-statistic (Panzar and Rosse, 1987), the Boone indicator (Boone, 2008), and the Lerner index (Lerner, 1934).[24] We use the Lerner index to measure banks' market power at the local level in this work. Unlike the other measures, we can evaluate each

[22] We run additional tests to examine where more digitalized banks are expanding credit. We find that more digitalized banks increase credit concessions and the number of distinct borrowers in localities less affected by COVID-19 than the bank branch's physical location. Once controlled for the relative local COVID-19 intensity in the borrower's and bank branch's localities, more digitalized bank branches prefer expanding to remote localities with relatively higher market power and in remote localities that are less wealthy and more populated.

[23] While IT can warrant local market power during the COVID-19 pandemic, it may be a double-edged sword for financial stability. On the one hand, IT allows banks to rearrange their operations to accommodate their sticky cost factors. This feature increases efficiency from which clients can, in principle, benefit, yields higher market power, and leverages bank profitability. This feature is beneficial for financial stability. On the other hand, banks over-reliant on IT are likely to overemphasize hard information to the detriment of soft information because of the standardization of IT systems. This is especially important in lending to remote borrowers. Local competence becomes secondary in highly standardized banking processes, eliminating the soft information component from lending decisions. Since soft information becomes critically important in times of distress (D'Aurizio et al., 2015), this feature may undermine financial stability.

[24] Shaffer and Spierdijk (2017) provide a comprehensive comparison of measures of competition in banking markets.

bank's market power at each instant of time, leveraging the richness of our microdata. In this way, we can identify how COVID-19 affected local market power in different Brazilian localities using a cleaner identification strategy.

The literature on banks' market power is extensive and predominantly composed of studies comparing countries (Claessens and Laeven, 2004; Coccorese et al., 2021; Fungácová et al., 2017; Wang et al., 2020). There are also studies analyzing the market power of a country's financial system. For instance, Das and Kumbhakar (2016) examine the market power in the Indian banking system, Whited et al. (2021) investigate the relationship between market power, low interest rates, and risk-taking for US commercial banks, and Cruz-García et al. (2021) analyze the impact of multimarket contacts in the competition of Spanish banks. However, studies on market power at the local level investigate a broader range of research questions. Degryse and Ongena (2005) use a loan-level sample of corporate credit from a large Belgian bank and analyze the effect of the distance between firms and the creditor bank and the presence of other nearby banks. They find loan rates decrease for longer distances between the borrowing firm and the creditor bank and increase if the firm and competitor banks are further apart. Kick and Prieto (2014) investigate the competition-stability nexus for the United States using concentration measures and market power at the bank, county, and state level. They find evidence that reducing competition by regulation does not necessarily improve bank stability. Degl'Innocenti et al. (2018) study how changes in the structure of the bank branch network at the provincial level affect banks in Italy. Their results show geographical diversification can reduce lending activities but improve funding strategies, both measured by Lerner indices. Also for Italy, Coccorese (2008) uses the mark-up test to assess the level of local competition and identify factors that explain the differences in competition across localities. He concludes that the market power level of Italian banks is low and heterogeneous across localities, and the local banking market structure is more relevant than macroeconomic factors to explain local competition. Hakenes et al. (2014) study the role of small regional banks in the credit market. They show small German regional banks spur local economic growth, especially in localities with credit rationing. For Brazil, Joaquim et al. (2019) use bank-municipality data for the corporate sector and show that decreases in banking competition, measured by changes in local HHI arising from mergers and acquisition events, increase the cost and reduce the volume of credit.

Our work adds to local market power literature in two dimensions. First, we propose a new methodology to estimate market power locally using the Lerner index. Typically, the literature estimates Lerner at the national level, which may overlook many different local aspects of banks' market power. This problem becomes even more prominent for countries with continental dimensions, such as Brazil. Second, we leverage the proposed methodology and explore market power in Brazilian local credit markets at the locality *and* credit modality level for *different* samples of banks. Since municipalities *and* banks in Brazil have singular credit compositions, we believe it is crucial to measure market power not only locally, as the current research on local competition does, but also for each credit modality. For instance, one public bank is responsible for almost 70% of Brazil's real estate credit.

This paper also contributes to the literature on COVID-19. The research examining the impact of COVID-19 on banks has a wide range of goals. Regarding financial stability, Duan et al. (2021) analyze whether and how the COVID-19 crisis affects systemic risk in a cross-country setting. They also assess the banking sector's resilience and the role of bank features in alleviating the pandemic's effects. They find that systemic risk increases during the health crisis. However, deposit insurance and foreign and public banks help mitigate this risk. Igan et al. (2022) analyze the effectiveness of macroprudential policies implemented before the COVID-19 outbreak in mitigating bank risk during the pandemic crisis. They find that macroprudential policy strengthened bank resilience as assessed by stock market investors. Özlem Dursun-de Neef and Schandlbauer (2021) examine the lending responses of European banks to the COVID-19 outbreak. They find that higher exposure to COVID-19 leads to a relative increase in lending by poorly capitalized banks. Better-capitalized peers reduced their lending and experienced an increase in delinquent and restructured loans. Some researches focus on post-crisis recovery. For instance, Polyzos et al. (2021) forecast the banking sector's response to a pandemic based on various scenarios. Additionally, they recommend the optimal policy in light of these scenarios.

We believe this is the first study on how COVID-19 affected local market power using comprehensive data for an important emerging market country. Dadoukis et al. (2021) examine the effects of pre-pandemic IT investments on banks' performance during the COVID-19 crisis. They find that higher pre-pandemic IT spending is associated with better performance during the first quarter of 2020 in terms of stock price, credit supply, and credit renegotiation. Our results complement these findings by documenting that IT spending was crucial in securing higher market power in local credit markets.

3 Data

We first define the term *locality* used in this paper. Brazil had 5,570 municipalities in 2021, many of which sharing strong economic and financial relationships with neighboring municipalities. For instance, it is common to have a job and a bank account in a neighboring municipality. Therefore, we believe the effective circumscription of credit markets is broader than a municipality's boundaries in Brazil. In this way, we define locality as the Immediate Geographic Region, as defined and published by the Brazilian Institute of Geography and Statistics (IBGE).[25] These regions are strongly connected urban networks comprising a local and central urban center and nearby peripheral urban centers connected through relations of economic dependency and frequent displacement of the population in search of goods, work, health and education services, and the provision of public services, such as the judiciary and assistance and social security. For simplicity, we use *locality* to refer to an Immediate Geographic Region in this paper.[26] We use the location of bank branches instead of borrowers when estimating banks' total cost functions, which is more coherent from a production function viewpoint. In this setup, borrowers can be anywhere.[27]

We also need to define a time frame in which we evaluate the local competition. Ideally, it should not be too narrow because one would not have sufficient credit operations to observe competitive behavior

[25] IBGE groups the 5,570 municipalities into 510 Immediate Geographic Regions. However, there are no banks in the sample in two of them, restricting the analysis to 508 localities.

[26] We note that our methodology is flexible and can take any geographical area as the locality. For instance, localities can be entire states, municipalities, districts, or even streets. Limitation often comes from data availability and the economic sense of the best cut for a local credit market.

[27] Lending to remote borrowers has increased due to the bank digitalization provided by more developed IT systems. In December 2020, banks channeled 31.3% of the outstanding local credit to borrowers from other Immediate Geographic Regions (40.5% of the borrowers). In the wealthiest region in Brazil (Southeast Region), these amounts were maximal: 36.2% of the outstanding credit and 49.8% of the borrowers.

nor too broad because older credit operations could contaminate our analysis as they do not necessarily reflect the current market conditions. Therefore, we enclose credit operations within a semiannual period to evaluate the local competition over time.

We concentrate on the first year of the pandemic (2020) because we believe it to be the more interesting event empirically. During this initial phase, economic agents lacked a clear sense of the magnitude of the impending crisis and lacked sufficient time to adapt to the pandemic's unfolding. Such features make the identification of the first wave of the COVID-19 cleaner from an empirical perspective. We use the following datasets:[28]

- Banks' consolidated financial statements from the Accounting Plan of the Institutions of the National Financial System (Cosif) maintained by the Central Bank of Brazil (BCB). The BCB frequently uses this dataset for monitoring purposes, thereby increasing the data quality. Cosif is only available at the national bank level (proprietary data);

- Individual and firm registration data from the Brazilian Federal Revenue Service (RFB), to identify the borrower's and bank's locations (proprietary data);

- Identified bank credit operations of individuals and companies in Brazil from the Credit Information System (SCR) maintained by the BCB. Together with the RFB data, these datasets allow obtaining the credit volume for each modality granted by each bank within a period in a specific location. We can also evaluate the average effective price of these operations locally for each bank and credit modality (proprietary data);

- Identified historical registry of financial institutions from the Information on Entities of Interest to the Central Bank (Unicad) by the BCB. This dataset contains bank-level meta-information, such as bank type of control, size, prudential segment, among others (proprietary data);

- Monthly Banking Statistics by Municipality (ESTBAN) maintained by the BCB. This dataset is a declaratory database that contains *limited* balance-sheet information for each bank branch in Brazilian municipalities over time (public data);

- IBGE geographic data to associate municipalities with corresponding localities (public data);

- Identified formal employment relationships from the Annual List of Social Information (RAIS) and the General Register of Employed and Unemployed (Caged), both maintained by the Ministry of Economy. The data contains information on the payroll and the number of employees in each bank branch in Brazil (proprietary data).

- COVID-19 epidemiological bulletins from the Ministry of Health. The data contains the number of COVID-19 cases per municipality (public data).

- Emergency Aid Beneficiaries from the Ministry of Economy. The data contains the value received for each beneficiary and their location (public data).

[28] Appendix A provides details regarding data treatment procedures employed before the computations and analyses. Then, using these data, we bring an overview of local bank credit markets that contextualize our results of bank competition in Brazilian localities.

4 Measuring local competition

Since we deal with market power locally, we first formalize the definition of a local credit market. We define a *local credit market* as a set of "local banks" in a delimited locality—an Immediate Geographic Region—granting credit of a specific modality. The term "locality" refers to the physical location of the bank branch that extends the credit. Borrowers can be anywhere. This approach is coherent with production and cost functions because costs are allocated at the locality of the branch and not of the borrower. "Local banks" refer to the sum of all branches of a specific bank operating in the locality (the representative bank branch in the locality).[29] Our definition of local credit markets is sensitive to the credit modality because these have very peculiar prices and marginal costs, leading to distinct market power levels.

In contrast to the typical Lerner index at the national bank level already explored in the literature, we design a local and data-intensive version of the Lerner index that assesses each bank branch's degree of market power in each local credit market. This is one of the methodological contributions of this paper. We should note that it is important to have locality-specific measures of competition to identify COVID-19 shocks across local markets in the following sections. Unlike structural measures, we are particularly interested in the Lerner index because it enables us to understand the channels through which market power is changing: either through price or marginal costs. We thoroughly explore the theoretical and computational details of the local Lerner index in Appendix B. Here, we streamline the main rationale of the method and the outputs from this methodology that will be critical for our empirical strategy in the following sections. Mathematically, we evaluate the local Lerner index $L_{blt}^{(m)}$ for bank b in locality l at time t for the credit modality m as follows:

$$L_{blt}^{(m)} = \frac{p_{blt}^{(m)} - MC_{blt}^{(m)}}{p_{blt}^{(m)}}, \qquad p_{blt}^{(m)} = \frac{\text{Credit Income}_{blt}^{(m)}}{\text{Credit Concessions}_{blt}^{(m)}} \tag{1}$$

in which $p_{blt}^{(m)}$ and $MC_{blt}^{(m)}$ are the bank b's effective price and marginal cost at location l during time t (semiannually) for product m. Effective prices include the contractual rate, taxes, and other fees and are net of losses. We evaluate effective prices by dividing the credit income in time t by the average outstanding credit among the concessions in t, for a specific credit modality and a bank in a specific locality. We estimate the marginal costs using a translog function that models local total costs at the bank branch level rather than the usual bank level, enabling us to estimate marginal costs locally for each bank.

One of the main empirical challenges of estimating total costs at the local level is the lack of data on cost components at the bank branch level. The Central Bank of Brazil has detailed consolidated financial statements of banks at the national level but not at the bank branch level. We resort to a strategy to distribute these aggregate cost factors to each branch. Figure 3 brings a schematic of this allocation of cost factors within branches of the same bank. In the translog function, banks have four

[29] The term "local bank" refers to a bank's physical presence in a specific locality. It does not relate to the scope of its business. For example, universal banks that operate throughout the country and internationally are considered local banks in each locality with at least one branch.

types of costs: funding, tax, labor, and other administrative costs. Our strategy is to distribute these bank-level aggregates across branches by combining Cosif (national bank-level data) with other datasets that include geographic information, such as the SCR, ESTBAN, and RAIS. Our allocation strategies are cost-specific. For example, we use RAIS, which contains detailed payroll and the number of employees of each branch, to distribute national bank-level labor costs to each bank branch proportionally to each branch's local workforce size and salary.

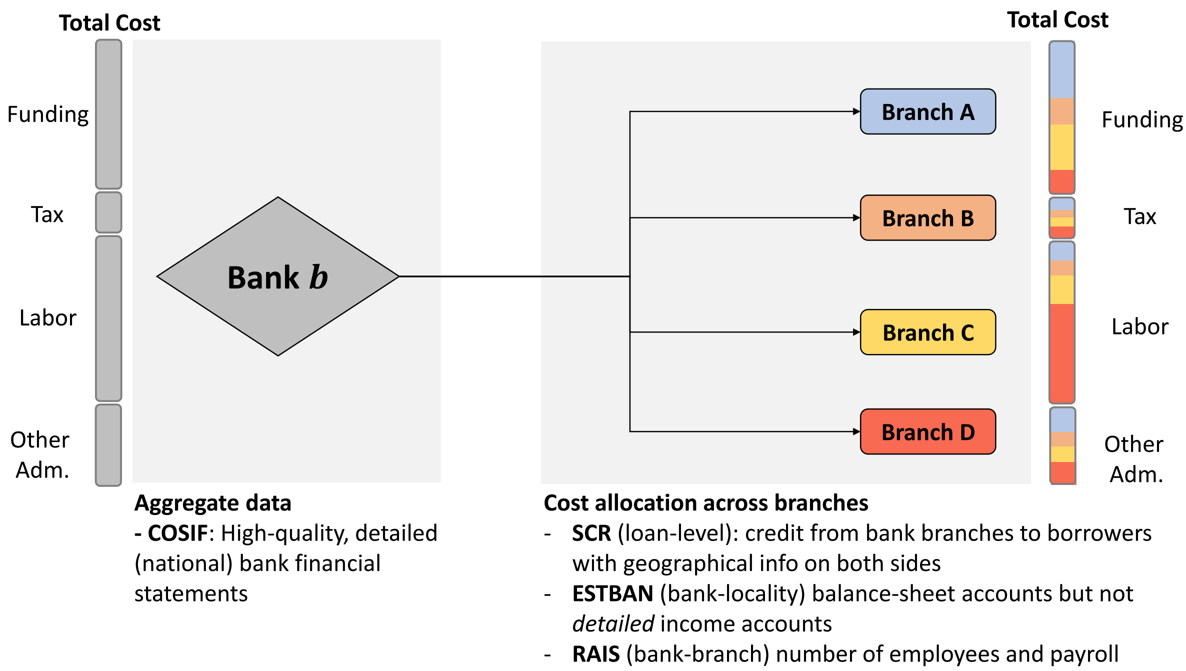


Figure 3. *Schematic of the allocation of costs factors of the same bank across its branches in different localities. We have aggregate national-level information on funding, tax, labor, and other administrative costs. We allocate these costs across bank branches in different localities of the same bank, such that the sum of all bank branch's costs match the national bank-level data. For that, we combine Cosif, which has detailed bank-level cost components, with other datasets that include geographic information, such as the SCR, ESTBAN, and RAIS.*

The literature typically uses credit, bonds and securities, and other assets as outputs of the translog function. One significant distinction of our approach is with the credit product (among others discussed in Appendix B). We consider credit modalities as individual products instead of the entire credit portfolio as a single product. We believe this segregation is important because credit modalities are distinct from each other.[30] Additionally, we separate credit granted within from those granted before the current half-year for each credit modality. The idea here is to segregate older from newer credit in the local total cost function, allowing us to estimate their marginal costs separately. We then focus on credit operations within the current half-year when evaluating effective prices and marginal costs of a particular credit modality for each bank in each locality. This approach allows us to measure the current local market's competitive conditions more accurately. To the best of our knowledge, this is the first work that considers this feature when estimating market competition. We believe this approach has not been taken before because of the lack of sufficient data at the bank-branch level. Our cost reallocation strategies together with the many micro-level datasets enables us to accomplish this task.

[30]Credit modalities have different characteristics that impact price and cost, such as collateralization (vehicle financing), non-collateralization (non-payroll-deducted personal credit), long-term maturity (real estate financing), short-term maturity (revolving working capital credit), and earmarked credit (infrastructure financing).

Following this approach, each bank branch produces 30 banking products in total: (i) 14 credit products (modalities) granted within the half-year of analysis; (ii) 14 credit products corresponding to the first 14 ones, but granted before the half-year; (iii) 1 for operations with bonds and securities; and (iv) 1 for operations with other assets. Credit modalities for individuals (6 modalities) include payroll-deducted personal credit, non-payroll-deducted personal credit, real estate financing, rural credit, vehicle financing, and other credit. Credit modalities for non-financial firms (8 modalities) encompass working capital, revolving working capital, infrastructure financing, real estate financing, investment credit, account receivables, agribusiness, and other credit.

To get a sense of the level of variation of our local estimates, Figure 4 shows the spatial distribution of the average effective prices, marginal costs, and Lerner indices across each of the Brazilian localities in the pre-pandemic (2019) and the first year of the pandemic (2020). These three measures exhibit considerable heterogeneity, even within adjacent localities. Additionally, the three measures substantially changed during the COVID-19 outbreak compared to their previous values. For instance, prices mostly decreased in all regions. However, the changes in marginal costs were specific to each locality. Consequently, the Lerner index changed in nontrivial ways. Overall, these results suggest that competition at a national level may overlook many important local aspects of local credit markets. Our method enables us to capture regional differences in competition.

5 Measuring local COVID-19 intensity across localities

This section defines our measure of *local COVID-19 intensity*. We measure the local COVID-19 intensity with the locality's number of COVID-19 confirmed cases as a share of its population. We collect daily data on the number of COVID-19 cases per municipality in Brazil using COVID-19 epidemiological bulletins of all 27 State Health Departments from the first reported COVID-19 case in Brazil on February 25, 2020, São Paulo (SP), to June 16, 2021.[31] Each Brazilian State Health Department compiles local reports from municipalities inside their geographical circumscription and submits them to the Federal Ministry of Health for consolidation daily. We end up with 2,238,003 municipality-time epidemiological bulletins.

Figure 5a shows the total number of new COVID-19 cases (incidence) as a share of the local population in capital (27) and inland (5,543) municipalities. There are two waves, with the first escalating from April 2020 to August 2020 and the second soaring from December 2020 to April 2021. In the first wave, there is an offset in the dynamics of capital and inland municipalities, mainly driven by the timing that COVID-19 hit these localities. In the second wave, both areas evolved similarly. This fact occurred because, by October 2020, every municipality in Brazil had registered at least one COVID-19 case, as Figure 5b reveals. Before that, inter-municipality contagion was a significant catalyst of COVID-19 cases in inland municipalities, with epidemic dynamics in neighboring or economically connected capitals serving as the primary driver. Following that, the primary factor was intra-municipality contagion.

Figure 6 displays the spatial COVID-19 prevalence (accumulated cases) in Brazilian municipalities as a share of the local population three, six, and ten months after the first case was reported in São

[31] This data is scattered around a large quantity of state government sites. In general, the bulletins are not standardized across different states and not even adjacent municipalities. We use the compiled dataset from Brasil.io for this task.

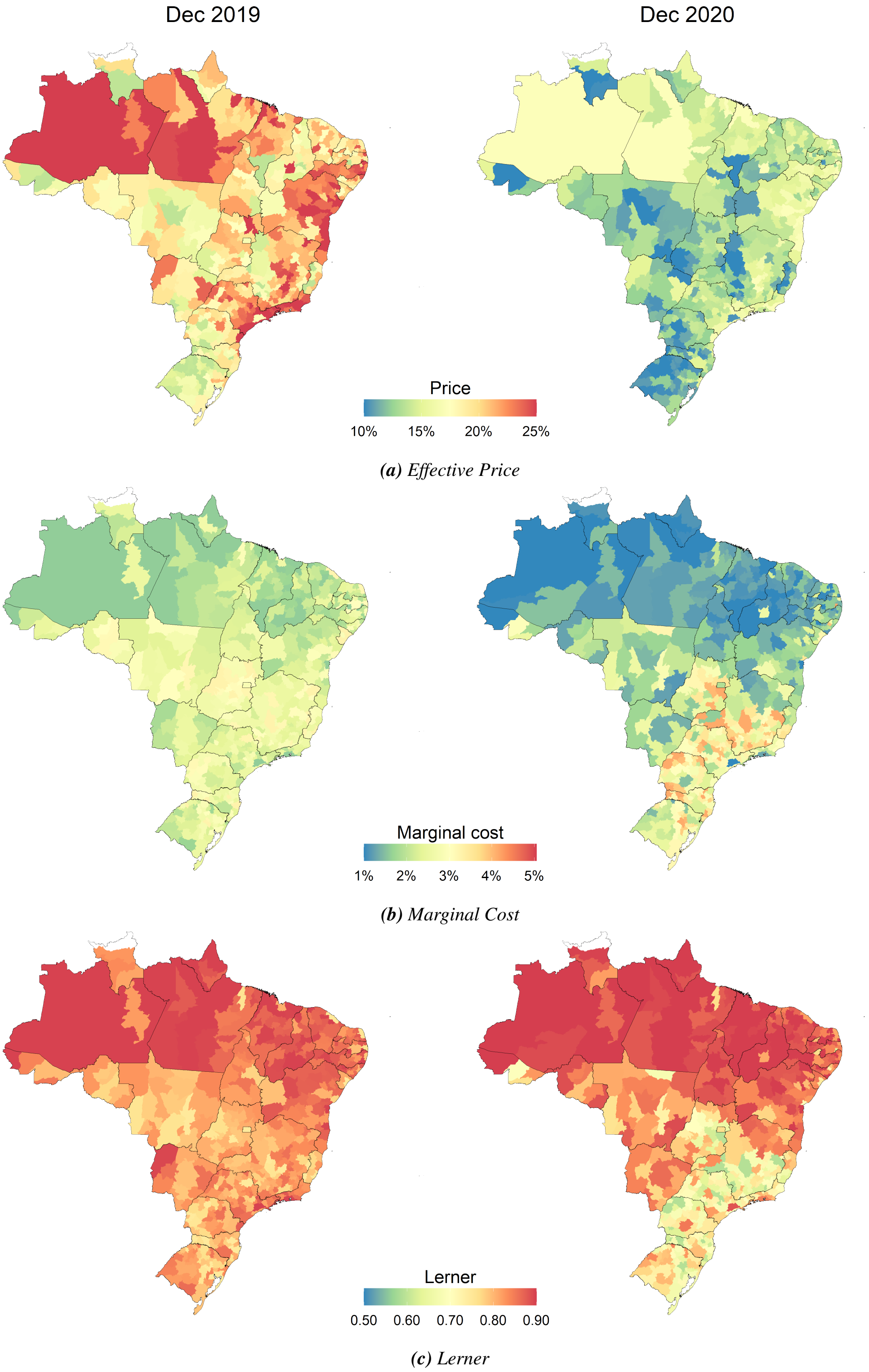
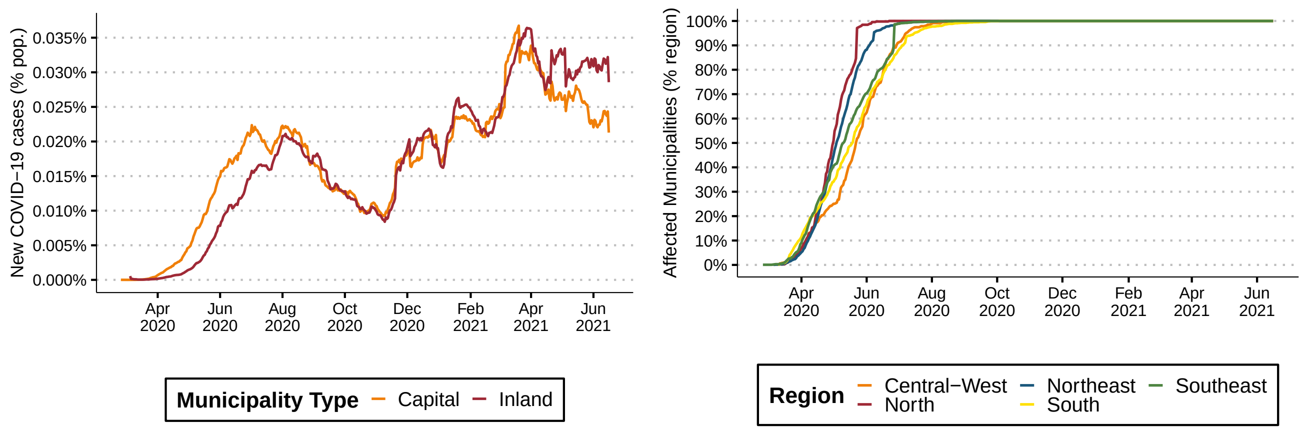


Figure 4. *Spatial distribution of the average effective prices, marginal costs, and Lerner indices across each of the Brazilian localities. We aggregate bank-modality observations within the same locality, including modalities for individuals and non-financial firms. We compare the pre-pandemic (left panel) and pandemic (right panel) periods.*

Paulo in February 2020. After three months, 4,255 (76.4%) municipalities had already registered at least one case of COVID-19, showing the spreading was very quick. After six months, 5,558 (99.8%) municipalities had reported at least one COVID-19 case. There is a large variation of the share of local affected population even across adjacent municipalities.



(a) *Incidence of COVID-19 cases (% local population)*

(b) *Share of municipalities with at least one COVID-19 case*

Figure 5. *Evolution of COVID-19 across Brazilian municipalities from the first case (February 25, 2020) to June 16, 2021. (a) Number of new COVID-19 cases (incidence) as a share of the local population in capital and inland municipalities with at least one COVID-19 case. (b) Number of municipalities with local bulletins registering at least one COVID-19 case as a share of the total number of municipalities within the region.*

To run our econometric exercises, we first aggregate the municipality-level number of COVID-19 cases to the locality level by summing all cases within the same locality. We then divide by the corresponding locality's population at the end of 2020 to obtain the share of the population affected by COVID-19 for each month-year.[32] Finally, we take the average of this share over January to December 2020, obtaining our local COVID-19 Intensity$_l$, as in (2),

$$\text{COVID-19 Intensity}_l = \frac{1}{12}\sum_t \frac{\text{COVID-19 Cases}_{lt}}{\text{Population}_l}, \tag{2}$$

in which t are months from January to December 2020 and l are localities. In terms of identification, one potential concern is that the timing and intensity of local COVID-19 intensity is likely not exogenous to localities' economic and geographic conditions, such as population, economic development, distance to state capitals, and economic structure. The local economy's structure may affect COVID-19 transmission rates as activities related to agriculture are geographically sparser than services and industrial activities. We run a cross-section regression to correlate the share of the population affected by COVID-19 with the following *ex-ante* locality-level determinants (fixed with values in December 2019): distance to the locality's state capital, *per capita* GDP, population, and the preponderant activities (agriculture and industry). This empirical exercise is important to understand if observable locality-specific characteristics correlate with our local COVID-19 intensity. These systematic differences, if present, could drive our results and invalidate our causal interpretations.

Table I shows the results of the cross-section estimation. We compare across localities with increasing saturated specifications: localities all over the country (Spec. I), within the same region (Spec. II), state (Spec. III), macrolocality or Intermediate Geographical Region[33] (Spec. IV), and within the same

[32]We aggregate from municipality to locality to make compatible the geographical units of the COVID-19 dataset and the locality-level variables on effective prices, marginal costs, and Lerner indices for each bank-modality reported in the previous sections.

[33]The Intermediate Geographical Region encompasses contiguous and economically dependent Immediate Geographical Regions (our unity of locality in this paper). All municipalities within the same Intermediate Geographical Region belong

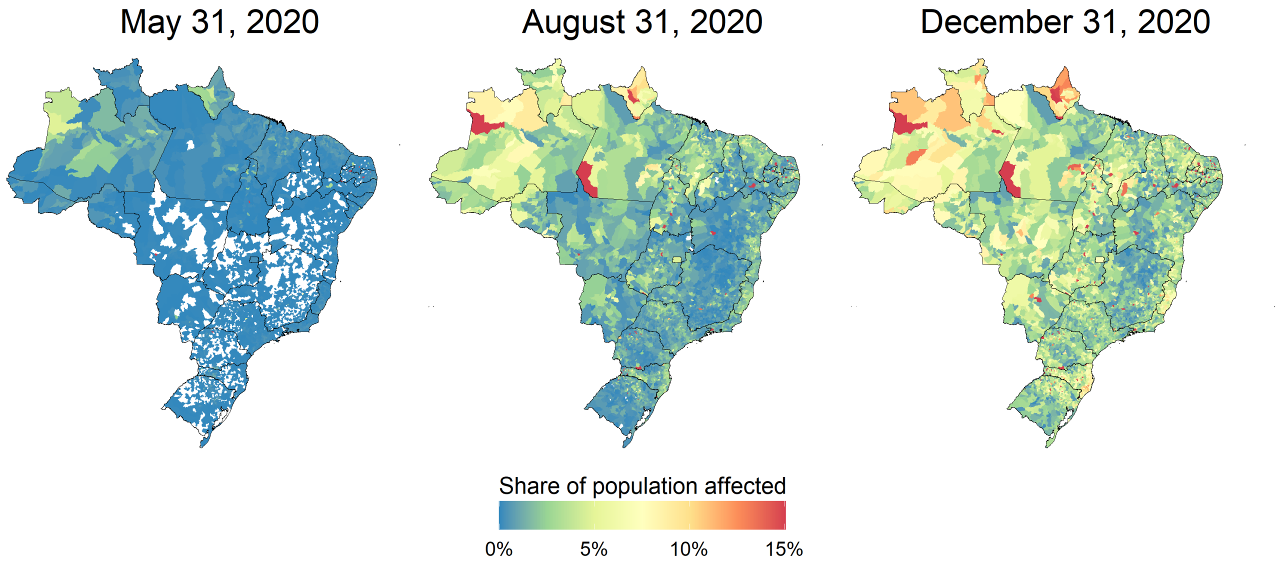


Figure 6. *Spatial COVID-19 prevalence in Brazilian municipalities. Total number of local COVID-19 cases as a share of the local population on May 31, 2020 (left); August 31, 2020 (center); December 31, 2020 (right). Colors from cold to warm represent increasing local COVID-19 prevalence. Blank localities represent places without occurrences of COVID-19 at that time. Shares were winsorized for better visualization.*

macrolocality *and* localities of similar *per capita* GDP.

We use within-macrolocality comparisons of localities with similar *per capita* GDP in the following sections because our local COVID-19 intensity measure becomes unrelated to the observable locality-level characteristics (see Spec. IV in Table I). This empirical strategy also mitigates several non-observable macrolocality-level concerns. For instance, under-notification of COVID-19 cases was a serious concern in the beginning of the outbreak (Cintra and Fontinele, 2020). By comparing adjacent localities with similar wealth levels, local health institutions and authorities are likely to be more similar and we should not expect systematic differences in the under-notification levels across localities. In addition, authorities intervened in the economy with several programs to mitigate the effects of the pandemic, such as temporary direct cash transfers programs for individuals, repayment postponement, and subsidized loans. It is more likely that nearby localities with similar *per capita* GDP will be exposed to these government programs more evenly.

6 Empirical results

This section explores how the COVID-19 pandemic affected local credit markets and the role of digitalization. We first examine how COVID-19 affected market power of local credit markets via changes in the effective price and marginal cost channels. We then analyze the role of digitalization in market power during COVID-19. Table II reports the summary statistics of the dependent and independent

to the same state. Therefore, we have the following geographical hierarchy in Brazil: municipalities (5,570 municipalities in 2021) $<$ Immediate Geographical Region (510 units) $<$ Intermediate Geographical Region (133 units) $<$ state (27 states) $<$ region (5 regions) $<$ country (Brazil).

TABLE I. *Correlates of the measure "COVID-19 Intensity$_l$," our proxy for local COVID-19 intensity*

Dependent Variable:	COVID-19 Intensity$_l$				
Model:	(I)	(II)	(III)	(IV)	(V)
Variables					
Distance to Capital$_l$	0.0399	-0.0315	-0.0722	0.1608	0.2112
	(0.0429)	(0.0469)	(0.0680)	(0.1559)	(0.2215)
Per Capita GDP$_l$	0.2296***	0.2599***	0.2498***	0.2377***	0.1338
	(0.0540)	(0.0587)	(0.0771)	(0.0812)	(0.0870)
Population$_l$	-0.1587***	-0.1239**	-0.0745**	-0.0365	-0.0476
	(0.0583)	(0.0492)	(0.0306)	(0.0445)	(0.0374)
Has Capital$_l$ (dummy)	0.8025***	0.5607***	0.3779*	0.0720	0.2681
	(0.2274)	(0.2077)	(0.2055)	(0.3800)	(0.2994)
Agriculture as Preponderant Activity$_l$ (dummy)	-0.3963***	-0.5405***	-0.5461***	-0.4735	-0.7117
	(0.1050)	(0.1191)	(0.1669)	(0.2942)	(0.4938)
Industry as Preponderant Activity$_l$ (dummy)	-0.0357	-0.1071	-0.1648	-0.2432	-0.3220
	(0.1698)	(0.1696)	(0.1916)	(0.2335)	(0.3011)
(Intercept)	-0.0289				
	(0.0517)				
Fixed effects					
Region	—	Yes	—	—	—
State	—	—	Yes	—	—
Macrolocality	—	—	—	Yes	—
Macrolocality · *Per capita* GDP(3)	—	—	—	—	Yes
Fit statistics					
Observations	508	508	508	506	425
R^2	0.0643	0.0983	0.2506	0.3789	0.4613

Note: This table reports coefficient estimates of the cross-section regression COVID-19 Intensity$_l = \alpha_{g(l)} + \beta$Local Covariates$_l + \varepsilon_l$, in which l is the locality. The dependent variable is the monthly average share of affected population by COVID-19 during 2020. We use the following local covariates (fixed with the last available information *ex-ante* to the pandemic values): distance to capital, *per capita* GDP, population, dummy variable that equals one if the locality contains the state capital, dummy variables that equal one if agriculture or industry activity is the local preponderant activity. We follow Silva et al. (2021) and define the local preponderant activity as the one that contributes the most to local GDP. The term $\alpha_{g(l)}$ represents geographical fixed effects that permits us to perform comparisons across localities within the same geographical circumscription g: all over the country (Spec. I), within the same region (Spec. II), state (Spec. III), within the same macrolocality or Intermediate Geographical Region (Spec. IV), and within the same macrolocality *and* localities of similar *per capita GDP* (discretized in terciles). We standardize numerical variables. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

variables used in the empirical specifications in this paper.

6.1 COVID-19 and local market power

This section investigates how the COVID-19 prevalence affected the market power of local credit markets during the first year of the pandemic. There are two channels through which the local market power can be affected: (i) the effective price and (ii) marginal cost channels. Figure 7 illustrates the empirical setup designed to estimate the effect of COVID-19 on the local market power. Below we discuss the challenges and concerns that our empirical strategy addresses.

A first empirical challenge is in isolating bank-specific supply variations across time. Since our goal is to quantify the effect of COVID-19 on banks' local market power, we need to control for changes in the bank's credit supply while allowing variations in locality-specific conditions. This locality-specific variation should be only due to differences in COVID-19 intensity if we desire to attribute our findings to the pandemic. To this end, we identify COVID-19 shocks across localities by differences in the local COVID-19 measure discussed in the previous section. Empirically, we compare the *same* bank operating in *different* but *similar* localities experiencing *distinct* COVID-19 intensity levels (within-

__TABLE II.__ Summary statistics of the dependent and independent variables employed in this paper.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
A. Dependent Variables (Variation: Bank-Modality-Locality-Time)								
Effective Price (%, semiannual rate)	79,256	13.319	12.043	0.363	5.293	9.007	17.049	68.241
Marginal Cost (R$ / +1 R$ credit)	79,256	0.043	0.272	−0.657	0.003	0.015	0.044	1.073
Lerner	79,256	0.466	1.489	−6.778	0.502	0.846	0.971	3.299
Credit Income (in mill. R$)	78,847	5.591	111.339	0.000	0.145	0.598	2.294	23,616.480
Granted Credit (in mill. R$)	79,256	15.896	9.665	0.000	0.224	1.239	5.533	17,231.310
Provision/Credit (%)	79,256	7.921	15.215	0.000	0.932	2.385	6.937	100.000
Contractual Price (%, annual rate)	78,783	51.023	70.063	0.000	13.567	24.155	54.533	1,060.101
Credit Market Share	79,195	16.789	20.003	0.000	2.652	10.108	22.536	100.000
B. Dependent Variables (Variation: Bank-Locality-Time)								
Local Cost (in bill. R$)								
Total	7,788	0.030	0.050	0.002	0.005	0.011	0.027	0.231
Funding	7,788	0.015	0.029	−0.0002	0.002	0.005	0.014	0.142
Tax	7,788	0.001	0.002	0.00003	0.0002	0.0004	0.001	0.010
Labor	7,788	0.009	0.016	0.001	0.002	0.003	0.007	0.080
Other Administrative	7,788	0.005	0.009	0.0001	0.001	0.002	0.004	0.044
% Credit Outside Locality	7,788	18.716	11.790	0.000	11.264	15.291	21.863	98.031
% Clients Outside Locality	7,788	16.908	8.293	7.633	11.444	14.435	19.539	47.043
C. Dependent Variables (Variation: Modality-Locality-Time)								
Credit HHI	43,164	0.261	0.221	0.017	0.087	0.185	0.377	0.811
D. Dependent Variables (Variation: Bank-Bank Locality-Borrower Locality-Time)								
Outside Granted credit (in mill.)	1,185,267	0.209	0.683	0.00002	0.002	0.013	0.079	4.567
Outside #Clients	1,185,267	78.570	3,251.422	1	1	2	6	1,488,752
E. Dependent Variables (Variation: Locality-Time)								
Firm Income (in mill. R$)								
Total	13,514	1,445.088	10,918.330	2.812	64.333	202.191	586.779	275,666.300
Credit and Debit Cards	13,514	254.653	2,151.801	0.405	15.487	38.962	108.770	60,210.090
Invoice	13,514	582.612	4,507.953	0.018	13.927	63.814	207.533	110,986.700
Exports	9,360	45.931	364.829	0.0003	0.519	3.064	14.032	12,770.330
Wire Transfers	13,514	575.757	4,097.172	1.086	25.475	83.001	249.648	102,043.900
Firms w/o Branches Income (in mill. R$)								
Total	13,514	412.327	2,522.329	0.930	32.535	84.329	236.356	65,044.750
Credit and Debit Cards	13,514	94.325	528.756	0.203	8.454	21.275	57.698	13,579.820
Invoice	13,514	138.314	907.829	0.003	6.315	24.303	70.798	24,080.300
Exports	6,193	2.317	9.956	0.00002	0.099	0.475	1.935	209.104
Wire Transfers	13,514	178.566	1,087.497	0.633	14.782	36.370	102.539	28,034.600
F. COVID-19 intensity measurement (Variation: Locality)								
COVID-19 intensity	509	4.887	3.963	0.514	2.732	4.034	5.932	40.898
G. Time-invariant, pre-pandemic covariate (Variation: Bank-Modality-Locality)								
Market Share (%)	25,095	15.374	20.070	0.000	2.255	8.808	19.491	100.000
Provisions / Total Credit (%)	26,689	5.863	13.687	0.000	0.000	1.185	4.643	100.000
Avg. Maturity (in months)	22,995	71.275	80.784	0.000	31.796	47.553	73.871	426.133
Avg. Local Ticket (in thous. R$)	22,995	2.138	2.424	0.000	0.954	1.427	2.216	12.784
H. Time-invariant, pre-pandemic covariate (Variation: Bank-Locality)								
Local Cost Factor (% Local Total Cost)								
Funding	1,983	48.007	11.496	0.561	41.162	47.812	55.813	88.867
Tax	1,983	3.691	1.399	0.006	2.723	3.756	4.520	10.132
Labor	1,983	32.901	12.873	1.779	24.600	32.067	39.170	99.411
Other Administrative	1,983	15.400	6.560	0.021	11.113	14.053	19.327	49.591
I. Time-invariant, pre-pandemic covariate (Variation: Bank)								
IT Cost (% total cost)	74	5.502	8.738	0.063	2.047	3.203	4.468	61.691
Bank Capitalization (capital / total assets, %)	74	17.620	16.012	2.568	9.946	13.675	18.052	93.925
Bank Liquidity (LCR)	74	4.288	8.403	0.308	1.469	2.314	3.309	67.308
J. Time-invariant, pre-pandemic covariate (Variation: Bank-Bank Locality-Borrower Locality)								
ΔCOVID-19 Intensity	1,185,267	0.005	0.876	−5.921	−0.227	−0.002	0.223	5.921
ΔLerner	1,185,267	−0.073	0.132	−0.933	−0.161	−0.075	0.013	0.723
ΔCredit Market Share (%)	1,185,267	−0.676	15.247	−93.537	−9.293	−0.631	7.979	93.537
Δ*Per capita* GDP (in thous.)	1,185,267	−1.591	23.076	−85.415	−15.572	−1.497	12.063	85.600
ΔPopulation (in mill.)	1,185,267	−0.010	3.108	−21.538	−0.339	−0.003	0.313	21.538
ΔLocality's IT Readiness	1,185,267	−0.988	1.951	−9.169	−2.314	−1.002	0.337	7.122
K. Time-invariant controls (Variation: Locality)								
Emergency Aid Volume / GDP (%)	509	14.947	10.628	2.159	6.345	10.944	22.569	49.586
SMEs (% total firms in locality)	509	64.523	4.980	46.271	61.212	64.732	67.698	80.403
Distance to Capital (in km)	508	402.950	207.590	49.936	251.691	364.315	509.751	1,485.773
Per Capita GDP (in thous. R$)	509	25.730	15.098	6.525	13.186	23.291	34.522	92.171
Population (in mill.)	509	0.410	1.219	0.033	0.120	0.192	0.327	21.571
Agriculture as Preponderant Activity	509	0.057	–	–	–	–	–	–
Industry as Preponderant Activity	509	0.067	–	–	–	–	–	–
Locality's IT Readiness	509	9.425	3.379	1.194	8.875	9.556	13.422	16.792

Note: Panels A–D: data ranges from January 2019 to December 2020, semiannually. Panel D: variables refer to the volume of credit and number of clients of a bank in another locality different from the bank branch's physical locality. Panel E: data range from January 2019 to June 2021, monthly. Panel F: "COVID-19 Intensity" is the average number of local infectious persons per month of 2020 divided by the local population at the end of 2020. Panels G and H: data is from December 2019. Panel I: Bank's IT spending as a share of its total cost from 2015 to 2019. Panel J: difference is taken from the borrower's minus bank branch's physical locality. "Credit Market Share" is the bank's credit share with respect to each locality-level credit."Locality's IT Readiness" is the average IT spending share with respect to the total cost across banks in the locality weighted by their credit volume. Panel K: The variable "Emergency Aid Volume / GDP" is the total volume of emergency aid received by residents during 2020 in a locality as a share of that locality's GDP. The variable "% SMEs" refers to the share of firms in a locality with up to three formal employees by the end of 2019. The terms *Per capita* GDP, the dummy variables "Agriculture as Preponderant Activity" and "Industry as Preponderant Activity" refer to 2018 (end-of-year, latest information available at the time of writing this paper). The remaining variables are from 2019.

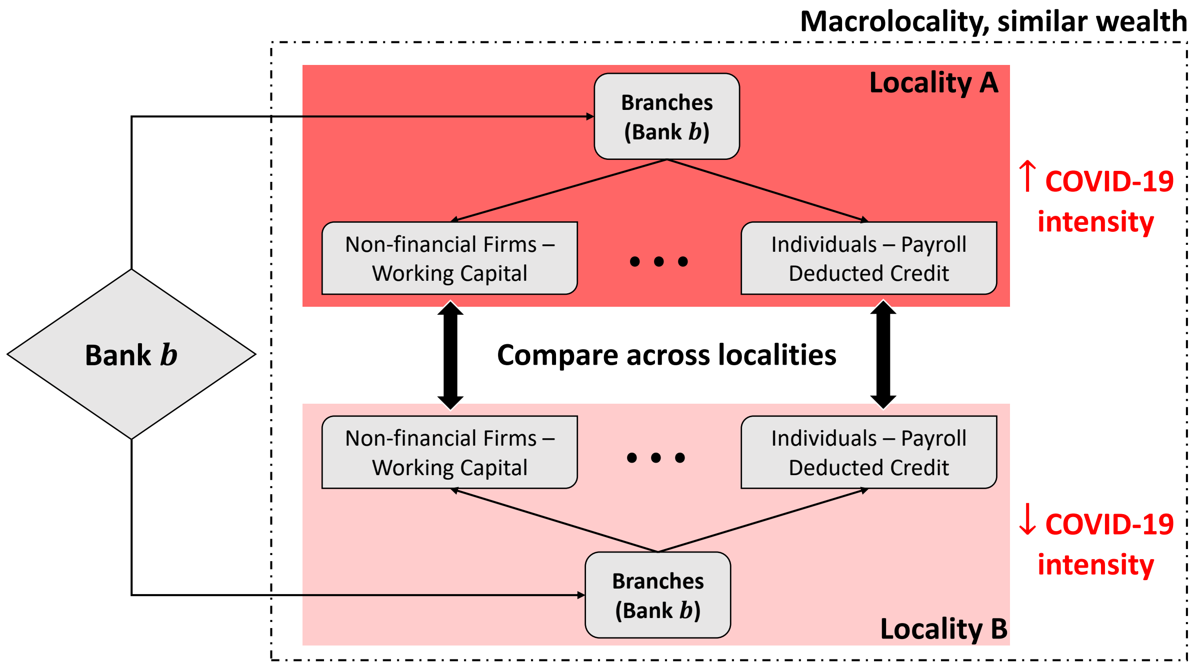


Figure 7. *Empirical setup: viewing COVID-19 as a local demand shock. Data is at the bank-locality-modality-time level.*

bank and across-locality approach). We compare across localities within the same macrolocality and with similar *per capita* GDP levels. With this approach, differences in COVID-19 intensity across localities are likely to be exogenous, as discussed in the previous section, which is important to interpret our estimates causally. Additionally, localities that are part of the same macrolocality tend to be similar, mitigating concerns about potential omitted variables. Since credit modalities tend to have specific effective prices and marginal costs, we also compare within the *same* credit modality. This strategy also alleviates concerns about differences in a bank's credit composition portfolio across localities.[34] In this empirical setup, we can view the COVID-19 shock as a *local demand shock*, as broad credit supply is controlled for in a within-bank analysis.

Another empirical challenge in identifying the effect of COVID-19 on local credit markets is the existence of numerous concurrent confounding variables during the pandemic, such as the introduction of government programs designed to combat the economic effects of COVID-19. Most of these measures can influence the decision of credit-taking. We carry out the following treatments for recipients of government policies during the COVID-19 outbreak:

1. **Households:** received financial support in the form of direct cash transfers and incentives for credit renegotiation and restructuring.

   Treatment: introduce the control "emergency aid volume received by residents in a locality over the local GDP."

2. **Firms:** received financial assistance via incentives for banks to renegotiate and extend credit to the corporate sector, as well as special credit line programs for SMEs.

   Treatment: introduce the control "number of SMEs in each location."

[34] To illustrate the rationale used in our empirical setup, we compare the same bank (e.g., Banco do Brasil) operating in two different but similar localities within the same macrolocality and with similar *per capita* GDP (e.g., localities Limeira – SP and Rio Claro – SP, both in the Campinas – SP macrolocality) in a specific credit market (e.g., working capital for firms).

3. **Banks:** experienced changes in the regulatory framework aimed at fostering credit concessions, such as reductions in reserve requirements and the Countercyclical Capital Buffer.

   Treatment: since we compare branches of the same bank across different localities, changes are netted out (within-bank analysis).

4. **Macroeconomics:** changes in monetary and exchange policies

   Treatment: changes are also netted out due to the difference-in-differences analysis.

The following DiD specification operationalizes the empirical strategy outlined in Figure 7:[35]

$$
\begin{aligned}
y_{b,m,l,t} = \alpha_{b,m,g(l),t} + \alpha_l + \beta \cdot \text{COVID-19}_t \cdot \text{COVID-19 Intensity}_l + \\
+ \gamma^T \cdot \text{COVID-19}_t \cdot \text{Controls}_{b,m,l} + \varepsilon_{b,m,l,t},
\end{aligned}
\tag{3}
$$

in which b, m, l, t index the bank, credit modality (as defined in Appendix B–Table B3), localities (508 Immediate Geographical Regions), and time (semiannually from 2019 to 2020). We examine the following dependent variables $y_{b,m,l,t}$: average effective price (credit income / granted credit), marginal cost, Lerner index, credit income, granted credit, provisions as a share of the outstanding credit, and contractual prices (interest rate), all of which specific for each bank b and credit modality m at locality l during the semiannual period t. The vector $\text{Controls}_{b,m,l}$ comprises two dimensions of variables. The first dimension controls for government policies introduced to combat the economic effects of COVID-19: the total emergency aid volume received by residents in the locality during 2020 as a share of the local GDP and the share of SMEs at the locality before COVID-19. The second dimension includes *ex-ante* bank-modality-locality controls (fixed with December 2019 values): local market share, credit provisions as a share of the total credit, average maturity, and average ticket.[36] We standardize all numeric variables. Following Abadie et al. (2020), we cluster errors at the locality level, which coincides with the level of variation of our COVID-19 intensity measure.

The introduction of the time-varying fixed effects $\alpha_{b,m,g(l),t}$ enables us to interpret our estimates in terms of the *same* bank b operating in a set of similar localities $g(l)$—i.e., localities with similar wealth levels and in the same macrolocality—for the *same* credit modality m. We further introduce locality fixed effects α_l to absorb time-invariant locality-specific non-observable factors.

Our coefficient of interest is β in (3). It captures the *relative effect* of a one-standard-deviation increase in a locality's COVID-19 intensity on the outcome variable compared to similar localities with a COVID-19 intensity corresponding to the sample's mean. Table III shows our coefficient estimates

[35] As a general note, we include lower-order terms for all interactions introduced in empirical specifications. For example, if a covariate represents the interaction of three terms, then all pairs of these terms and the marginal terms will also be covariates in the regression (provided they are not collinear with fixed effects). To maintain clarity, we do not explicitly display all of these lower-order interactions in the written specifications nor show them in the regression tables. The only exception is when a particular lower-order term is a coefficient of interest. In any case, the notes in the regression tables are complete and will explicitly state each regression's specificities.

[36] Joaquim et al. (2019) show how changes in credit concentration affect banks' local behavior in credit markets. Therefore, we introduce the covariate "local market share" to control for differences in the local credit concentration in a specific local credit market. Following Schnabl (2012), we also include the controls "credit provisions as a share of the total credit," "average maturity," and "average ticket" to account for differences in the riskiness profiles and locality-specific idiosyncrasies that may exist across localities within the same bank-modality.

for (3). We also rerun the specification in (3) but (i) substituting semiannual pulse dummies for the step variable COVID-19$_t$ and (ii) expanding the temporal window from the beginning of 2017 to the end of 2020 to examine the parallel trends assumption. Figure 8 displays the estimated β coefficients for our three main variables: effective prices, marginal costs, and Lerner indices. The dynamics of these three variables are statistically equivalent in localities with different levels of COVID-19 intensity in the pre-pandemic period. Only after the pandemic outbreak did the dynamics diverge.

TABLE III. *How does COVID-19 affect market power components and lending behavior in localities?*

Dependent Variables:	Effective Price$_{bmlt}$	Marginal Cost$_{bmlt}$	Lerner$_{bmlt}$	Credit Income$_{bmlt}$	Granted Credit$_{bmlt}$	$\frac{\text{Provision}_{bmlt}}{\text{Credit}_{bmlt}}$	Contractual Price$_{bmlt}$
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Variable of interest							
COVID-19$_t$ · COVID-19 Intensity$_l$	-0.0032	0.0187***	-0.0221***	-0.0058**	-0.0231***	0.0126*	0.0057**
	(0.0037)	(0.0062)	(0.0076)	(0.0028)	(0.0062)	(0.0072)	(0.0024)
Controls							
COVID-19$_t$ · Emergency Aid Volume/GDP$_l$	-0.0106	-0.0302*	0.0131	0.0032	0.0121	-0.0214	-0.0088
	(0.0110)	(0.0169)	(0.0196)	(0.0069)	(0.0096)	(0.0164)	(0.0055)
COVID-19$_t$ · % SMEs$_l$	0.0033	0.0260***	-0.0239***	-0.0023	-0.0356***	-0.0001	0.0009
	(0.0041)	(0.0077)	(0.0090)	(0.0032)	(0.0062)	(0.0069)	(0.0022)
COVID-19$_t$ · Distance to Capital$_l$	0.0011	-0.0050	0.0056	-0.0018	-0.0027	0.0058	0.0006
	(0.0063)	(0.0104)	(0.0107)	(0.0050)	(0.0086)	(0.0098)	(0.0032)
COVID-19$_t$ · Population$_l$	0.0017	0.0135**	-0.0022	-0.0055	0.0083	0.0001	0.0030***
	(0.0021)	(0.0063)	(0.0068)	(0.0051)	(0.0156)	(0.0038)	(0.0010)
COVID-19$_t$ · Market Share$_{bl}$	0.0222***	0.0407***	-0.0463***	-0.0180***	-0.0112	0.0085	0.0051
	(0.0069)	(0.0074)	(0.0097)	(0.0065)	(0.0069)	(0.0136)	(0.0046)
COVID-19$_t$ · Provision/Credit$_{bl}$	-0.0035	-0.0234**	0.0102	-0.0055	-0.0094**	-0.3297***	0.0103**
	(0.0104)	(0.0099)	(0.0100)	(0.0035)	(0.0044)	(0.0229)	(0.0049)
COVID-19$_t$ · Credit Maturity$_{bl}$	-0.0256	0.0428*	-0.0204	-0.0222	0.0377*	0.0157	0.0709***
	(0.0200)	(0.0257)	(0.0415)	(0.0146)	(0.0192)	(0.0329)	(0.0087)
COVID-19$_t$ · Credit Ticket$_{bl}$	-0.0016	0.0038	-0.0201	-0.0197*	-0.0404	-0.0014	-0.0014
	(0.0024)	(0.0061)	(0.0181)	(0.0111)	(0.0479)	(0.0025)	(0.0011)
Fixed effects and controls							
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Modality · · Macrolocality · *Per capita* GDP(3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	78,535	78,535	78,535	78,535	78,535	78,535	78,362
R^2	0.9242	0.7674	0.7691	0.7367	0.7494	0.9094	0.9731

Note: This table reports coefficient estimates for the specification in Equation (3) using semiannual data from 2019 to 2020 at the bank-modality-locality-time level. We use the following dependent variables: effective price (Spec. I), marginal cost (Spec. II), Lerner (Spec. III), credit income of within-half-year granted credit (Spec. IV), within-half-year granted credit (Spec. V), provisions as a share of the outstanding credit (Spec. VI), and contractual price or interest rate (Spec. VII). All specifications have two sets of control variables. The first set comprises controls for government policies introduced to combat the economic effects of COVID-19: the total emergency aid volume received by residents in the locality during 2020 as a share of the local GDP and the share of SMEs in the locality (firms with up to three employees) by the end of 2019. The second set encompasses *ex-ante* bank-modality-locality controls (fixed with December 2019 values) encompassing: local market share (bank outstanding credit as a share of the locality-level outstanding credit), provisions as a share of the outstanding credit, average maturity and average ticket. We add all low-order interactions and marginal terms for covariates appearing in a higher-order interaction that are not collinear with the fixed effects. We also introduce locality and time-bank-modality-macrolocality-*per capita* GDP (discretized in terciles) fixed effects. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Effective price channel: we find that the local COVID-19 intensity does not alter effective prices (Spec. I). However, there are substantial changes in the effective price's components: the credit income (Spec.

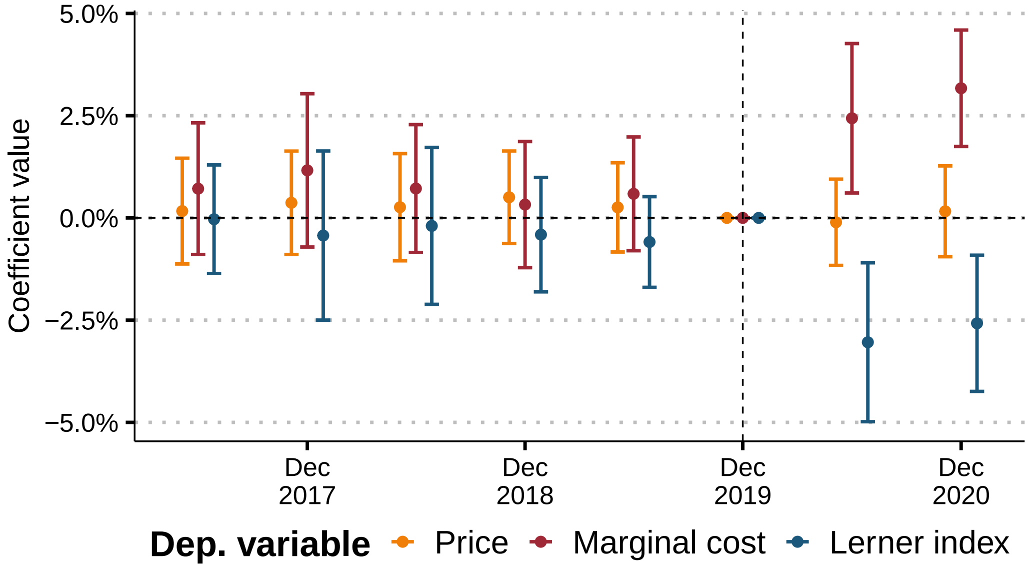


Figure 8. *Parallel trends check. We run specification in (3) but (i) changing the step variable COVID-19$_t$ with semiannual pulse dummies and (ii) widening the temporal window from the beginning of 2017 to the end of 2020. The figure displays the estimated β coefficients for each half-year. Vertical bars denote the 95% confidence interval.*

IV) and granted credit (Spec. V). A one-standard-deviation increase in the local COVID-19 prevalence (4%) reduces credit income by 0.0058 standard deviation, corresponding to $0.0058 \cdot$ R\$ 111.339 million = R\$ 0.65 million or 12% of the sample average. Simultaneously, granted credit decreases by 0.231 standard deviation, equivalent to $0.0231 \cdot$ R\$ 9.66 million = R\$ 2.23 million or 14% of the sample average.[37] The decline in credit income and granted credit is economically relevant. Section 7.1 provides a rationalization of this result, showing that localities more affected by COVID-19 experienced decreased economic activity, leading to a deterioration of financial conditions.[38] Therefore, the substantial decrease in credit income was offset by a corresponding decrease in credit concessions in the locality, resulting in an unchanged effective price. We conclude that the effective price channel is not a substantial component that affected banks' local market power during the pandemic.

Marginal cost channel: A one-standard-deviation increase in the local COVID-19 prevalence (4%) causes a 0.0187-standard-deviation increase in banks' marginal costs, corresponding to a $0.0187 \cdot 0.272 \approx 0.5$ cents more expensive marginal cost for a sample mean of 4 cents (12% of the sample mean). We have seen that granted credit decreases in localities with more COVID-19 prevalence (Spec. V, Table III). The increase in marginal costs suggests banks are unable to reduce their total costs mostly because cost factors are sticky in the short term as a result of economic rigidities and the existence of legal and financial frictions.

We test this hypothesis empirically by examining whether bank branches' total cost $TC_{b,l,t}$—which is the sum of local funding, tax, labor, and other administrative costs (see Appendix B–Table B2)—reduces in localities more affected by COVID-19. We run the following econometric specification:

[37] While the bank-time fixed effects in (3) capture the bank balance-sheet channel, we cannot cleanly identify the borrower balance-sheet channel (credit demand) because our data are not at the loan level.

[38] Additionally, a higher COVID-19 prevalence increased (i) borrowers' aggregate riskiness measured in terms of credit provisions as a share of the total credit (Spec. VI of Table III) and (ii) contractual prices or interest rates (Spec. VII of Table III), indicating that banks perceived borrowers as more financially constrained in areas more severely affected by COVID-19.

$$TC_{b,l,t} = \alpha_{b,g(l),t} + \alpha_l + \beta \cdot \text{COVID-19}_t \cdot \text{COVID-19 Intensity}_l + \\ + \gamma^T \cdot \text{COVID-19}_t \cdot \text{Controls}_{b,l} + \varepsilon_{b,l,t}, \tag{4}$$

in which b, l, and t index bank, locality, and time, respectively. The fixed effects $\alpha_{b,g(l),t}$ allow us to interpret the results in terms of the *same* bank operating in *different* but *similar* localities $g(l)$ (within the same macrolocality and comparable *per capita* GDP levels) over time. Our coefficient of interest is β in (4). It quantifies the effect of a one-standard-deviation increase in a locality's COVID-19 intensity (2) on the bank branch's total cost *vis-à-vis* another branch of the same bank in similar localities with average levels of COVID-19 intensity. All the remainder setup is identical to specification (3) but at the bank-locality-time instead of bank-modality-locality-time level. Specification I of Table IV shows the estimated coefficients of (4). We confirm our hypothesis that bank branches in localities more affected by COVID-19 are unable to adjust their local total costs in response to the reduction in credit concessions. This finding reflects the stickiness of bank branch's cost factors, which cannot be easily adjusted in the short term.

Local market power: COVID-19 does not change effective prices in more affected localities. However, bank branches' marginal costs increase substantially in more affected localities by COVID-19 due to a combination of (i) reduced credit concessions and (ii) the stickiness of bank branches' cost factors in the short term. In net terms, the COVID-19 pandemic reduced the local market power of Brazilian banks through the marginal cost channel during 2020. One advantage of performance measures—such as our local Lerner index—is the possibility of understanding the sources leading to changes in competition. Structural measures, such as the HHI, do not provide us with this information despite being less data-intensive. We revisit our baseline regressions but substituting the HHI for the local Lerner index in Section 7.2. We also check the robustness of our results with alternative specifications that do not employ controls or use a less comprehensive set of fixed effects in Section 7.3.

6.2 The role of IT development for the banking sector during the pandemic

This section examines how *bank digitalization*—measured as the (national) bank's IT spending as a share of its total costs in the pre-pandemic period—influenced market power in local credit markets. We first examine the flexibility that digitalization brings to banks regarding costs and lending. We then discuss the role of digitalization in local market power during the COVID-19.

Table V reports correlates of pre-pandemic bank digitalization for our full sample (Spec. I), sub-sample of banks with IT spending lower than the median (Spec. II), and sub-sample of banks with IT spending higher than the median (Spec. III). We use bank-specific variables and variables averaged across bank branches' localities. Pre-pandemic digitalization does not correlate with bank control or size. Additionally, more digitalized banks do not have significant differences in terms of capitalization and liquidity when compared to less digitalized banks before COVID-19. However, more digitalized banks have lower funding costs. Bank digitalization is more present in nearer capitals and less populated areas.

IT and cost flexibility: the previous section showed that bank branches are unable to adjust their local

TABLE IV. *How does COVID-19 affect bank branches' total costs? Does IT development provide cost flexibility?*

Dependent Variable:	Local Total Cost$_{blt}$					
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)
Variables of interest						
COVID-19$_t$ · COVID-19 Intensity$_l$	0.0029	0.0031	-0.0011	0.0034	-0.0012	0.0087
	(0.0053)	(0.0057)	(0.0069)	(0.0055)	(0.0060)	(0.0062)
COVID-19$_t$ · COVID-19 Intensity$_l$ · % Cost Factor$_{bl}$		0.0072	0.0025	-0.0006	-0.0144	-0.0116**
		(0.0323)	(0.0274)	(0.0095)	(0.0090)	(0.0053)
Controls						
COVID-19$_t$ · % Cost Factor$_{bl}$		0.0396	0.0416	0.0201*	0.0493**	-0.0357***
		(0.0347)	(0.0273)	(0.0107)	(0.0214)	(0.0125)
COVID-19$_t$ · Emergency Aid Volume/GDP$_l$	-0.0285	-0.0245	-0.0242	-0.0280	-0.0281	-0.0263
	(0.0221)	(0.0217)	(0.0214)	(0.0217)	(0.0220)	(0.0219)
COVID-19$_t$ · % SMEs$_l$	0.0507***	0.0466***	0.0451***	0.0479***	0.0505***	0.0503***
	(0.0140)	(0.0139)	(0.0139)	(0.0141)	(0.0141)	(0.0139)
COVID-19$_t$ · Distance to Capital$_l$	-0.0080	-0.0081	-0.0085	-0.0086	-0.0063	-0.0078
	(0.0116)	(0.0112)	(0.0112)	(0.0114)	(0.0115)	(0.0114)
COVID-19$_t$ · Population$_l$	0.0101	-0.0133	-0.0182	-0.0025	0.0008	0.0116
	(0.0144)	(0.0166)	(0.0153)	(0.0155)	(0.0161)	(0.0139)
COVID-19$_t$ · Average Market Share$_{bl}$	0.0075	0.0015	0.0045	0.0109	-0.0031	0.0083
	(0.0104)	(0.0111)	(0.0104)	(0.0111)	(0.0117)	(0.0103)
COVID-19$_t$ · Average Provision/Credit$_{bl}$	0.0022	0.0034	0.0029	0.0022	0.0024	0.0029
	(0.0057)	(0.0058)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
COVID-19$_t$ · Average Credit Maturity$_{bl}$	-0.0990***	-0.0950***	-0.0953***	-0.0992***	-0.0954***	-0.0998***
	(0.0287)	(0.0285)	(0.0284)	(0.0286)	(0.0286)	(0.0287)
COVID-19$_t$ · Average Credit Ticket$_{bl}$	0.0133***	0.0133***	0.0133***	0.0139***	0.0118***	0.0134***
	(0.0044)	(0.0043)	(0.0043)	(0.0044)	(0.0044)	(0.0044)
Cost Factor	—	Funding	Tax	Labor	Other Adm.	IT
Variation of the Cost Factor	—	Local	Local	Local	Local	National
Fixed effects and controls						
Locality	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Macrolocality · *Per capita* GDP(3)	Yes	Yes	Yes	Yes	Yes	Yes
Other controls and interactions?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,788	7,788	7,788	7,788	7,788	7,788
R^2	0.9196	0.9209	0.9199	0.9202	0.9201	0.9201

Note: This table reports coefficient estimates for the specifications in Equations (4) (Spec. I) and (5) (Specs. II-VI) using semiannual data from 2019 to 2020 at the bank-locality-time level. The dependent variable is the bank branch's total cost, which is the sum of the local funding, tax, labor, and other administrative costs (see Appendix B–Table B2). We make triple interactions of our local COVID-19 intensity measure, the step variable COVID-19, and the following cost factors (fixed with December 2019): funding (Spec. II), tax (Spec. III), labor (Spec. IV), other administrative costs (Spec. V), and IT (Spec. VI). The first four cost factors vary at the local level (bank-branch-specific) while the last one varies at the national level (bank-specific). Cost factors are normalized by the bank branch's local total cost in Specs. II–V and by the bank's total cost in Spec. VI. We add municipality-level controls for the local intensity of government programs to combat the economic effects of COVID-19 (Emergency Aid Volume / GDP$_l$ and Share of SMEs$_l$) and the locality's distance and population. We also introduce ex-ante controls for the bank-branch-specific market share, provision/credit, credit maturity, and credit ticket by taking their averages across credit modalities weighted by the credit volume in the pre-pandemic period. We add all low-order interactions and marginal terms for covariates appearing in a higher-order interaction that are not collinear with the fixed effects. We add locality and time-bank-macrolocality-*per capita* GDP (discretized in terciles) fixed effects. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

total costs in the short term. We refine this analysis by examining whether bank branches more reliant on a specific cost factor gain more flexibility in their cost structure, i.e., whether there exist cost factors that are less (or even more) sticky. We use two different cost factors: local factors (funding, tax, labor, and other administrative) as a share of the branch's local total costs and a national factor (IT) as a share of the bank's total costs. For each specification, we triple interact our measure of local COVID-19 intensity,

TABLE V. Correlates of pre-pandemic bank digitalization (IT spending in terms of total costs during 2015–2019).

Dependent Variables:	% IT Share$_b$		
Model:	(I)	(II)	(III)
Bank-specific variables			
Public Bank$_b$ (dummy)	-0.2649	0.0921	-0.4313
	(0.4136)	(0.1176)	(1.119)
Medium-Sized Bank$_b$ (dummy)	-0.2410	0.1209	-0.2026
	(0.2207)	(0.0929)	(0.6092)
Small-Sized Bank$_b$ (dummy)	-0.2875	0.0747	-0.5839
	(0.1929)	(0.1105)	(0.5183)
Micro-Sized Bank$_b$ (dummy)	-0.0784	0.1359	-0.1024
	(0.2002)	(0.1159)	(0.5976)
Bank Capitalization$_b$	-0.2044	-0.0326	-0.3436*
	(0.1244)	(0.0603)	(0.2024)
Bank Liquidity$_b$	0.1342	0.0080	0.1344
	(0.1416)	(0.1619)	(0.2115)
% Funding Cost$_b$	-0.3527*	-0.0881*	-0.6956**
	(0.1972)	(0.0475)	(0.3056)
% Tax Cost$_b$	-0.3460**	-0.0445	-0.4229
	(0.1565)	(0.0315)	(0.2683)
% Labor Cost$_b$	0.2808	-0.0030	0.0783
	(0.2303)	(0.0492)	(0.4163)
Variables averaged across bank branch's localities			
Average *Per Capita* GDP$_b$	-0.1788	0.0449	-0.2843
	(0.1845)	(0.0437)	(0.5350)
Average Population$_b$	-0.2983*	-0.0059	-0.2904
	(0.1752)	(0.0307)	(0.4208)
Average Distance to Capital$_b$	-0.2438*	0.0436	-0.2634
	(0.1344)	(0.0511)	(0.2061)
Average Exposure to Emergency Aid Volume/GDP$_b$	0.0107	0.0708	0.1087
	(0.0790)	(0.0551)	(0.3823)
Average Exposure to SMEs$_b$	-0.3565*	-0.0197	-0.5812
	(0.2064)	(0.0275)	(0.3707)
Average % Credit Outside Bank Branch's Locality$_b$	-0.0466	0.0052	0.1052
	(0.3302)	(0.0572)	(0.5179)
Average % Clients Outside Bank Branch's Locality$_b$	0.2627	0.0185	0.0990
	(0.2344)	(0.0575)	(0.5220)
(Intercept)	0.1983	-0.4773***	0.2492
	(0.1913)	(0.1004)	(0.4486)
Sample	Full	Less Digitalized	More Digitalized
Observations	74	37	37
R^2	0.6290	0.4391	0.6983

Note: This table reports coefficient estimates of the cross-section regression % IT Share$_b = \beta$Bank Covariates$_b + \varepsilon_b$, in which b is the (national) bank. The dependent variable is the total spending on IT as a share of bank's total costs from 2015 to 2019. Results are reported for the full sample of banks (Spec. I), banks less digitalized or with % IT Share lower than the median (Spec. II), and banks more digitalized or with %IT Share higher than the median (Spec. III). We employ two types of bank covariates: bank-specific variables and variables averaged across bank branch's localities (weighted by the volume of credit concessions in each bank branch's locality). The dummy "Public bank" is relative to the observed values for private banks. The dummies "Medium-Sized Bank,", "Small-Sized Bank," "Micro-Sized Bank" are relative to values observed for large banks. "Bank capitalization" is the bank capital as a share of its total assets. "Bank Liquidity" is the Liquidity Coverage Ratio (LCR). "% Funding Cost," "% Tax Cost," and "% Labor Cost" are in terms of the bank's total costs, which is the sum of funding, tax, labor, and other administrative costs. Data on bank control and size comes from the Registry of Financial Institutions (Unicad). Bank capitalization and liquidity comes from Cosif. "Average Exposure to Emergency Aid Volume/GDP" is locality-specific Emergency Aid Volume/GDP$_l$ averaged across localities in which the bank has at least one branch. The other variables that are averaged across bank branch's localities follow the same rationale. We standardize numerical variables, including the dependent variable. One-way (bank) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

the step variable COVID-19, and the cost factor (fixed with December 2019 values) as follows:

$$TC_{b,l,t} = \alpha_{b,g(l),t} + \alpha_l + \beta \cdot \text{COVID-19}_t \cdot \text{Intensity}_l + \lambda \cdot \text{COVID-19}_t \cdot \text{Intensity}_l \cdot \text{Cost Factor}_{bl} + \\ + \gamma^T \cdot \text{COVID-19}_t \cdot \text{Controls}_{b,l} + \varepsilon_{b,l,t}, \tag{5}$$

in which $TC_{b,l,t}$ is the bank branch's local total costs and Cost Factor_{bl} is one of the five cost factors discussed above. For convenience, the variable Intensity_l is a shorthand for COVID-19 Intensity_l. Our coefficient of interest is λ in (5). If banks can adjust a specific cost factor more quickly than the average following the COVID-19 outbreak, this should be loaded in this coefficient. Specifications II–VI of Table IV show the coefficient estimates of (5) for each cost factor, one at a time. Local spending patterns during the pre-pandemic period on funding, tax, labor, and other administrative costs are unrelated to the bank branch's ability to adjust more easily its local total costs during the pandemic, suggesting a strong stickiness of these factors.

In contrast, banks with more IT spending relative to their total costs can reduce local costs. For each one-standard-deviation increase in the bank's IT cost share (5.5%) *ex-ante* the COVID-19 outbreak, local total costs reduce by 0.0116 standard deviation, or $0.0116 \cdot$ R\$ 0.05 billion $\approx$ R\$ 0.58 million (1.9% of the sample average). This finding highlights the critical nature of IT development and the cost flexibility it provides during times of distress.

We now analyze through which channels digitalization enables reduced costs. We examine how each of the four local cost factors—funding, tax, labor, and other administrative costs—behaves during the pandemic for banks with different levels of digitalization. We employ a similar empirical setup as in (5), except that we (i) change the dependent variable for each of the four specific local cost factors above ($C_{b,l,t}$) and (ii) triple interact the IT cost share with the local COVID-19 intensity, and the step variable COVID-19, yielding:

$$C_{b,l,t} = \alpha_{b,g(l),t} + \alpha_l + \beta \cdot \text{COVID-19}_t \cdot \text{Intensity}_l + \lambda \cdot \text{COVID-19}_t \cdot \text{Intensity}_l \cdot \%\ \text{IT Cost}_b + \\ + \gamma^T \cdot \text{COVID-19}_t \cdot \text{Controls}_{b,l} + \varepsilon_{b,l,t}, \tag{6}$$

Table VI reports the coefficient estimates of (6) for the following dependent variables: local funding costs (Specs. I–II), local tax costs (Specs. III–IV), local labor costs (Specs. V–VI), and local other administrative costs (Specs. VII-VIII). To establish a baseline on how COVID-19 affected specific cost factors, we run (6) with (even-numbered specs) and without (odd-numbered specs) the interactions with the IT cost share.

Consistent with our previous findings regarding local total costs, each cost factor also does not respond to different levels of local COVID-19 intensity. However, we observe a shift in the cost structure for more digitalized banks during the COVID-19: they reduce funding costs (Spec. II) at the expense of increased labor (Spec. VI) and other administrative costs (Spec. VIII). Given that more digitalized banks can reduce total costs compared to less digitalized banks (Spec. VI of Table IV), the decrease in funding costs dominates the increase in the other two cost components. One potential explanation for lower funding costs may arise from the convenience provided by digital services. If customers cannot access digital services easily, they may perceive as important the need to carry physical money. In contrast, if they can pay and manage their financial needs electronically via internet banking or cellphones, they may hold money in banking accounts, thereby lowering the bank's funding costs. One possible reason

TABLE VI. *Benefits of IT (cost flexibility): through which cost factor does digitalization provide cost flexibility?*

Dependent Variables:	Funding Costs		Tax Costs		Labor Costs		Other Adm. Costs	
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Variables of interest								
$\text{COVID-19}_t \cdot \text{COVID-19 Intensity}_l$	0.0124	0.0241	0.0085	0.0096	-0.0044	-0.0035	-0.0049	-0.0066
	(0.0145)	(0.0156)	(0.0071)	(0.0081)	(0.0044)	(0.0055)	(0.0056)	(0.0072)
$\text{COVID-19}_t \cdot \text{COVID-19 Intensity}_l$		-0.0390***		-0.0055		0.0138***		0.0173***
$\cdot$ % IT Cost_b		(0.0082)		(0.0057)		(0.0053)		(0.0061)
Controls								
$\text{COVID-19}_t \cdot \text{Emergency Aid Volume/GDP}_l$	-0.0515	-0.0443	-0.0319	-0.0310	-0.0176	-0.0200	-0.0085	-0.0115
	(0.0430)	(0.0424)	(0.0245)	(0.0242)	(0.0183)	(0.0182)	(0.0192)	(0.0191)
$\text{COVID-19}_t \cdot \text{\% SMEs}_l$	0.1015***	0.0997***	0.0610***	0.0607***	0.0305**	0.0313***	0.0146	0.0156
	(0.0293)	(0.0291)	(0.0157)	(0.0157)	(0.0119)	(0.0118)	(0.0128)	(0.0127)
$\text{COVID-19}_t \cdot \text{Distance to Capital}_l$	0.0062	0.0072	-0.0030	-0.0029	-0.0010	-0.0015	-0.0001	-0.0006
	(0.0249)	(0.0248)	(0.0133)	(0.0133)	(0.0099)	(0.0099)	(0.0124)	(0.0126)
$\text{COVID-19}_t \cdot \text{Population}_l$	-0.0514	-0.0476	0.0206	0.0210	-0.0070	-0.0073	0.0038	0.0028
	(0.0642)	(0.0630)	(0.0228)	(0.0229)	(0.0097)	(0.0098)	(0.0162)	(0.0167)
$\text{COVID-19}_t \cdot \text{Average Market Share}_{bl}$	0.0030	0.0057	-0.0117	-0.0114	0.0269***	0.0261***	0.0293***	0.0282***
	(0.0163)	(0.0164)	(0.0109)	(0.0109)	(0.0078)	(0.0077)	(0.0101)	(0.0101)
$\text{COVID-19}_t \cdot \text{Average Provision/Credit}_{bl}$	-0.0051	-0.0043	0.0012	0.0012	0.0042	0.0050	-0.0045	-0.0041
	(0.0116)	(0.0117)	(0.0052)	(0.0053)	(0.0037)	(0.0040)	(0.0047)	(0.0046)
$\text{COVID-19}_t \cdot \text{Average Credit Maturity}_{bl}$	-0.2047***	-0.2072***	0.0210	0.0207	-0.0285	-0.0278	0.0257	0.0268
	(0.0436)	(0.0435)	(0.0257)	(0.0258)	(0.0223)	(0.0224)	(0.0237)	(0.0237)
$\text{COVID-19}_t \cdot \text{Average Credit Ticket}_{bl}$	0.0082	0.0084	0.0216***	0.0217***	0.0116	0.0116	0.0327***	0.0326***
	(0.0076)	(0.0077)	(0.0082)	(0.0082)	(0.0091)	(0.0091)	(0.0087)	(0.0087)
Fixed effects and controls								
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Macrolocality · *Per capita* GDP(3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls and interactions?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,788	7,788	7,788	7,788	7,788	7,788	7,788	7,788
R^2	0.8700	0.8710	0.9138	0.9138	0.9132	0.9136	0.9217	0.9218

Note: This table reports coefficient estimates for variations of the specification in Equation (6) using semiannual data from 2019 to 2020 at the bank-locality-time level. We use the following bank-branch-specific cost factors: funding costs (Specs. I–II), which include costs from deposits, securities and bonds; tax costs (Specs. III–IV); labor costs (Specs. V–VI); and other administrative costs (Specs. VII–VIII), which is the remaining administrative costs after deducting labor costs. Even-numbered (odd-numbered) specifications do (do not) include terms with the IT share cost variable. In even-numbered specifications, we make triple interactions of our local COVID-19 intensity measure, the step variable COVID-19, and the national bank's IT spending as a share of its total cost before the COVID-19 outbreak (% IT Cost_b). We add controls for the local intensity of government programs to combat the economic effects of COVID-19 (Emergency Aid Volume / GDP_l and Share of SMEs_l) and the locality's distance and population. We add all low-order interactions and marginal terms for covariates appearing in a higher-order interaction that are not collinear with the fixed effects. We also introduce ex-ante controls for the bank-branch-specific market share, provision/credit, credit maturity, and credit ticket by taking their averages across credit modalities weighted by the credit volume in the pre-pandemic period. We add locality and time-bank-macrolocality-*per capita* GDP (discretized in terciles) fixed effects. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

for increased labor costs for more digitalized banks may arise from their specific distribution of job roles than traditional banks. More digitalized banks are more likely to have job roles more prone to teleworking (such as IT-related), which were less affected by public policies aimed at combating the COVID-19 economic effects.

IT and lending flexibility: IT development enables financial transactions, including credit, electronically with borrowers regardless of their locality. Precisely banks that spent more on IT before the COVID-19 are likely to have more developed and trustworthy online banking systems, enabling these remote transactions to a larger extent. If that is the case, we should expect that banks with more developed IT systems could more easily replace or complement borrowers in localities more affected by COVID-19 with other remote borrowers. That is, IT could provide lending flexibility for more digitalized banks than traditional banks, which may have been especially useful during the COVID-19 pandemic, which affected certain localities more than others. Since credit concessions decreased in more affected localities (Spec. V of Table III), more digitalized banks in localities heavily affected by COVID-19 could rearrange their credit portfolio, potentially away from local borrowers.

If our hypothesis sustains, we should observe a shift in the borrower's locality concentration: the share of borrowers outside (inside) the bank branch's physical locality should increase (decrease) for more digitalized bank branches in localities more affected by COVID-19. We test this hypothesis by running through loan-level data in the SCR, inspecting the bank branch's and borrower's locations of each credit operation. SCR contains the bank branch's CEP (or ZIP code). We can determine the borrower's location by matching its tax identifier with the *Receita Federal do Brasil* dataset.

We test the shift in the borrower's locality concentration of bank branches using the same specification as in (6) but changing the dependent variables. We also report our results without interactions with the level of IT spending as a share of total costs to establish a baseline. Table VII reports the coefficient estimates for the following dependent variables: share of credit to borrowers (Specs. I–II) and share of distinct borrowers (Specs. III–IV) living outside the bank branch's physical locality. Bank branches in localities more affected by COVID-19 reduce credit concessions to non-local borrowers (Spec. I) relative to branches of the same bank in less affected but similar localities. The number of non-local clients is insensitive to the local COVID-19 intensity (Spec. III). However, more digitalized bank branches increased the share of clients living outside the bank branch's locality after the COVID-19 outbreak, suggesting IT development facilitated credit reallocation between local and remote borrowers. Our results highlight the role of digitalization in allowing bank branches to be less sensitive to local borrowers' conditions. Section 7.4 examines to which localities are more digitalized bank branches expanding during COVID-19.

IT and local market power: the cost and lending flexibility provided by digitalization may enable banks to continue lending relative more than traditional banks in areas more affected by COVID-19, where quarantine and restrictions of economic activities were fiercer. This feature may have favored digitalized banks by improving their positioning in the credit market in terms of market power. We test this hypothesis by augmenting our baseline specification at the bank-modality-locality-time level in Eq. (3) with the bank-level IT spending as a share of total costs in the pre-pandemic period as follows:

$$\begin{aligned} y_{b,m,l,t} = \alpha_{b,m,g(l),t} + \alpha_l + \beta \cdot \text{COVID-19}_t \cdot \text{Intensity}_l + \lambda \cdot \text{COVID-19}_t \cdot \text{Intensity}_l \cdot \%\ \text{IT Cost}_b + \\ + \gamma^T \cdot \text{Controls}_{b,m,l} + \varepsilon_{b,m,l,t}. \end{aligned} \tag{7}$$

Table VIII reports the coefficient estimates of (7) using the following dependent variables: average effective price (Spec. I), marginal cost (Spec. II), Lerner index (Spec. III), credit income (Spec. IV), the volume of credit concessions within the half-year (Spec. V), provisions as a share of the outstanding credit (Spec. VI), and contractual prices (Spec. VII). Compared to traditional banks, more digitalized banks can lend more (Spec. V) and collect more credit income (Spec. IV) in localities more affected by COVID-19 than the same bank operating in other similar and less affected localities. The increase

TABLE VII. *Benefits of IT (lending flexibility): digitalized banks become less sensitive to local borrowers' conditions.*

Dependent Variables:	% Credit Outside Locality		% Clients Outside Locality	
Model:	(I)	(II)	(III)	(IV)
Variables of interest				
COVID-19_t · COVID-19 Intensity_l	-0.0350**	-0.0385***	-0.0121	-0.0149
	(0.0137)	(0.0146)	(0.0087)	(0.0096)
COVID-19_t · COVID-19 Intensity_l · % IT Cost_b		0.0373***		0.0198**
		(0.0132)		(0.0093)
Controls				
COVID-19_t · Emergency Aid Volume/GDP_l	-0.0045	-0.0116	-0.0092	-0.0130
	(0.0313)	(0.0308)	(0.0340)	(0.0341)
COVID-19_t · % SMEs_l	-0.0062	-0.0044	0.0053	0.0062
	(0.0143)	(0.0143)	(0.0134)	(0.0135)
COVID-19_t · Distance to Capital_l	-0.0177	-0.0188	-0.0078	-0.0085
	(0.0241)	(0.0240)	(0.0174)	(0.0177)
COVID-19_t · Population_l	0.0108	0.0082	0.0019	0.0003
	(0.0086)	(0.0086)	(0.0044)	(0.0051)
COVID-19_t · Average Market Share_{bl}	-0.0216	-0.0245	-0.0182	-0.0200
	(0.0275)	(0.0275)	(0.0200)	(0.0200)
COVID-19_t · Average $\text{Provision/Credit}_{bl}$	-0.0124	-0.0126	0.0086	0.0082
	(0.0191)	(0.0190)	(0.0104)	(0.0108)
COVID-19_t · Average Credit Maturity_{bl}	0.0784**	0.0802**	0.0020	0.0033
	(0.0391)	(0.0391)	(0.0238)	(0.0238)
COVID-19_t · Average Credit Ticket_{bl}	0.0056	0.0057	-0.0052	-0.0054
	(0.0242)	(0.0243)	(0.0084)	(0.0083)
Fixed effects and controls				
Locality	Yes	Yes	Yes	Yes
Time · Bank · Macrolocality · *Per capita* GDP(3)	Yes	Yes	Yes	Yes
Other controls and interactions?	Yes	Yes	Yes	Yes
Observations	7,788	7,788	7,788	7,788
R^2	0.6559	0.6568	0.7123	0.7124

Note: This table reports coefficient estimates for variations of the specification in Equation (6) using semiannual data from 2019 to 2020 at the bank-locality-time level. We use the following bank-branch-specific variables: share of credit to borrowers (Specs. I–II) and share of distinct borrowers (Specs. III–IV) living outside the bank branch's physical locality. Even-numbered (odd-numbered) specifications do (do not) include terms with the IT share cost variable. In even-numbered specifications, we make triple interactions of our local COVID-19 intensity measure, the step variable COVID-19, and the national bank's IT spending as a share of its total cost before the COVID-19 outbreak (% IT Cost_b). We add controls for the local intensity of government programs to combat the economic effects of COVID-19 (Emergency Aid Volume / GDP_l and Share of SMEs_l) and the locality's distance and population. We also introduce ex-ante controls for the bank-branch-specific market share, provision/credit, credit maturity, and credit ticket by taking their averages across credit modalities weighted by the credit volume in the pre-pandemic period. We add all low-order interactions and marginal terms for covariates appearing in a higher-order interaction that are not collinear with the fixed effects. We add locality and time-bank-macrolocality-*per capita* GDP (discretized in terciles) fixed effects. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

in credit concessions, combined with the fact that digitalized banks expanded their credit concessions to borrowers outside the bank branch's physical location, suggests that more digitalized banks *complemented* rather than *substituted* their local borrower *clientele* with remote borrowers.

Effective prices of more digitalized banks are not different from traditional banks (Spec. I) when comparing their values for the same credit modality in more affected against less affected localities. This finding suggests that the increase in credit income is a mechanical consequence of increased credit concessions and not higher interest rates (Spec. VII) or changes in borrowers' riskiness profiles (Spec. VI).

More digitalized banks can mitigate the increase in marginal costs in localities more affected by

TABLE VIII. *How does COVID-19 affect local market power and lending behavior for more digitalized bank branches?*

Dependent Variables:	Effective Price_{bmlt}	Marginal Cost_{bmlt}	Lerner_{bmlt}	Credit Income_{bmlt}	Granted Credit_{bmlt}	$\frac{\text{Provision}_{bmlt}}{\text{Credit}_{bmlt}}$	Contractual Price_{bmlt}
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Variable of interest							
COVID-19_t · COVID-19 Intensity_l	-0.0055	0.0221***	-0.0251***	-0.0075**	-0.0259***	0.0133*	0.0067***
	(0.0043)	(0.0066)	(0.0077)	(0.0033)	(0.0060)	(0.0078)	(0.0026)
COVID-19_t · COVID-19 Intensity_l · % IT Cost_b	0.0049	-0.0171***	0.0146**	0.0090**	0.0119**	-0.0025	-0.0022
	(0.0044)	(0.0061)	(0.0071)	(0.0043)	(0.0057)	(0.0068)	(0.0027)
Controls							
COVID-19_t · Emergency Aid Volume/GDP_l	-0.0114	-0.0279*	0.0112	-0.0012	0.0105	-0.0210	-0.0084
	(0.0110)	(0.0169)	(0.0194)	(0.0059)	(0.0095)	(0.0165)	(0.0056)
COVID-19_t · % SMEs_l	0.0035	0.0254***	-0.0233***	0.0070*	-0.0352***	-0.0002	0.0008
	(0.0041)	(0.0077)	(0.0090)	(0.0039)	(0.0061)	(0.0069)	(0.0022)
COVID-19_t · Distance to Capital_l	0.0013	-0.0050	0.0056	0.0041	-0.0027	0.0058	0.0005
	(0.0063)	(0.0104)	(0.0107)	(0.0048)	(0.0085)	(0.0098)	(0.0032)
COVID-19_t · Population_l	0.0011	0.0147**	-0.0033	-0.0159***	0.0074	0.0002	0.0033***
	(0.0019)	(0.0059)	(0.0065)	(0.0043)	(0.0155)	(0.0039)	(0.0011)
COVID-19_t · Market Share_{bl}	0.0220***	0.0410***	-0.0465***	-0.0193***	-0.0114*	0.0085	0.0052
	(0.0069)	(0.0074)	(0.0097)	(0.0063)	(0.0069)	(0.0136)	(0.0046)
COVID-19_t · Provision/Credit_{bl}	-0.0036	-0.0234**	0.0102	-0.0027	-0.0094**	-0.3297***	0.0104**
	(0.0104)	(0.0099)	(0.0100)	(0.0047)	(0.0044)	(0.0229)	(0.0049)
COVID-19_t · Credit Maturity_{bl}	-0.0254	0.0428*	-0.0203	0.0337*	0.0377**	0.0157	0.0708***
	(0.0200)	(0.0257)	(0.0415)	(0.0189)	(0.0191)	(0.0329)	(0.0087)
COVID-19_t · Credit Ticket_{bl}	-0.0017	0.0037	-0.0200	-0.0396*	-0.0403	-0.0014	-0.0013
	(0.0025)	(0.0061)	(0.0181)	(0.0231)	(0.0479)	(0.0025)	(0.0011)
Fixed effects and controls							
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Modality · · Macrolocality · *Per capita* GDP(3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls and interactions?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	78,535	78,535	78,535	78,535	78,535	78,535	78,362
R^2	0.9242	0.7674	0.7691	0.7999	0.7495	0.9094	0.9731

Note: This table reports coefficient estimates for the specification in Equation (7) using semiannual data from 2019 to 2020 at the bank-modality-locality-time level. We use the following dependent variables: effective price (Spec. I), marginal cost (Spec. II), Lerner (Spec. III), credit income of within-half-year granted credit (Spec. IV), within-half-year granted credit (Spec. V), provisions as a share of the outstanding credit (Spec. VI), and contractual price or interest rate (Spec. VII). All specifications have two sets of control variables. The first set comprises controls for government policies introduced to combat the economic effects of COVID-19: the total emergency aid volume received by residents in the locality during 2020 as a share of the local GDP and the share of SMEs in the locality (firms with up to three employees) by the end of 2019. The second set encompasses *ex-ante* bank-modality-locality controls (fixed with December 2019 values) encompassing: local market share (bank outstanding credit as a share of the locality-level outstanding credit), provisions as a share of the outstanding credit, average maturity and average ticket. We add all low-order interactions and marginal terms for covariates appearing in a higher-order interaction that are not collinear with the fixed effects. We also introduce locality and time-bank-modality-macrolocality-*per capita* GDP (discretized in terciles) fixed effects. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

COVID-19 than traditional banks (Spec. II). This finding is consistent with the fact that digitalization enabled increased credit concessions and provided cost and lending flexibility in relation to traditional banks, reducing frictions of adjusting the bank branch's cost structure in the short term. As a result, the adverse effects of COVID-19 on marginal costs were attenuated. Therefore, digitalized banks experienced an attenuated loss (or even an increase for high-tech banks) in their market power in local credit markets relative to traditional banks. Digitalization enabled banks to adjust their credit portfolio quickly and re-balance credit across localities facing distinct levels of COVID-19 intensity.

7 Additional empirical evidence

7.1 COVID-19 and local economic activity

Localities with a higher COVID-19 prevalence are more likely to implement public health measures such as horizontal social distancing, lockdown, and quarantines. Such measures may impact a wide variety of economic activities, most notably those relying on in-site labor force and consumption. This section shows that an increase in local COVID-19 prevalence caused a decrease in local economic activity. This piece of evidence rationalizes many of the empirical findings discussed in the previous section, such as reduced credit concessions and income in more affected localities.

A first challenge is the lack of recent data on economic activity at the local level. The natural candidate in Brazil is data from the IBGE, which contains estimates of the Brazilian municipalities' local GDP. However, this data has a lag of three to four years. Therefore, we resort to payment transactions received by firms in Brazil. We use firm-specific inflows as a proxy for the firm income. In Brazil, firms can receive payments in several ways. We attempt to encompass many of these income streams in our empirical exercises by analyzing electronic transactions from the following confidential datasets:[39]

- Transactions from credit and debit cards from open array operations reported by accreditors.[40] In Brazil, individuals and firms typically settle small-valued transactions using credit and debit cards. Therefore, this is an important income source for sectors in the retail market. In 2019 and 2020, 3.5 million firms received funds from debit or credit cards. In 2019 (2020), these firms were recipients of 1.67 (1.68) billion operations with an aggregate value of R$ 1.51 (1.62) trillion, equating to 20% of Brazil's 2019 GDP (22% of Brazil's 2020 GDP).

- Invoices or "*Boletos*" from the *Câmara Interbancária de Pagamentos* (CIP), which is a not-for-profit association that is part of the Brazilian Payments System (SPB). Invoices are a document widely used in Brazil as a payment instrument for a product or service. In 2019 and 2020, 1.80 million firms received funds from invoices. In 2019 (2020), these firms were recipients of 2.58 (2.81) billion operations with an aggregate value of R$ 3.79 (3.75) trillion, equating to 51% of Brazil's 2019 GDP (50% of Brazil's 2020 GDP).

- Wire transfers or *Transferência Eletrônica Disponível* (TED) from the *Sistema de Transferência de Reservas* (STR) and the *Sistema de Transferência de Fundos* (CIP-Sitraf), both part of the

[39] We exclude funds received from financial institutions or investment funds. We also eliminate transactions within the same firm economic group, a typical operation among firms with multiple plants for internal liquidity management purposes. We also remove transactions from the public sector; international representative bodies, such as embassies; and sectors that deal with water supply and sanitation activities, which are likely to be financed by local governments. Even though we use these data sources as a proxy for the firm income, we should acknowledge that there may be some potential mismatches between our proxy and the *de facto* firm income. First, our data is based on a cash basis of accounting, whereas firm income accounting is formally based on an accrual basis of accounting. Second, we do not have transactions settled with cash, checks, direct deposits into accounts, or automatic debit transactions (typical for paying water and electricity, telephone, TV, and Internet in Brazil). Third, we lack data on businesses where the buyer uses the good as part of payment, such as automobile dealerships and agriculture. Fourth, we do not have registries of foreign operations' income. Last, we do not include PIX (instant payment scheme that enables its users to send or receive payment transfers in few seconds at any time, including non-business days) operations because they only began operating in November 2020 for the corporate sector.

[40] The dataset does not include private label and flagged private label cards because these operations run through the merchant's network. In addition, we do not have operations from other closed arrangements, such as meal vouchers and single-ticket.

SPB and maintained by the BCB.[41] We end up with 6.74 million firms in our sample during 2019 and 2020. In 2019 (2020), there were 192.78 (258.73) million firm-to-firm operations with an aggregate value of R$ 3.88 (4.38) trillion, equating to 52% of Brazil's 2019 GDP (59% of Brazil's 2020 GDP).

- Exports. We proxy the firm's exports using the Foreign Exchange System or *Sistema de Câmbio* maintained by the BCB. The system captures foreign exchange market operations in Brazil at the transaction level in high frequency.[42] In 2019 and 2020, 25 thousand firms received funds from exports. In 2019 (2020), these firms were recipients of 19.86 (20.39) thousand operations with an aggregate value of R$ 0.20 (0.19) trillion, equating to 3% of Brazil's 2019 GDP (3% of Brazil's 2020 GDP).

We aggregate these firm-specific income streams to the locality level using information from the firm's geographical position from the *Receita Federal do Brasil*, the Brazilian IRS. We run the following locality-time econometric specification:

$$\text{Income}_{l,t} = \alpha_l + \alpha_{g(l),t} + \beta \cdot \text{COVID-19}_t \cdot \text{COVID-19 Intensity}_l + \varepsilon_{l,t}, \tag{8}$$

in which l and t index locality and time (January 2019 to June 2021, monthly). We use the following locality-level income of firms as the dependent variable: (i) aggregate of all streams mentioned above, (ii) credit and debit cards, (iii) invoices, (iv) exports, and (v) wire transfers. The variable COVID-19 Intensity$_l$ follows (2), and COVID-19$_t$ is a dummy variable that assumes the value of one when the year is 2020 or 2021, and zero otherwise. The term α_l represents locality fixed effects that absorb any time-invariant, non-observable, and locality-specific characteristic. We use the time-variant fixed effects $\alpha_{g(l),t}$ to make within-comparisons of localities within the same macrolocality *and* with similar *per capita* GDP (discretized in terciles) levels, as in our baseline regressions. We cluster errors at the locality level, which coincides with the level of variation of our COVID-19 intensity measure. We apply a standardization procedure in all numeric variables. The variable $\varepsilon_{l,t}$ is the error term.

Our coefficient of interest is β in (8). We interpret the coefficient as the *relative effect* of a one-standard-deviation increase in the COVID-19 intensity on the locality-level income compared to other localities within the same macrolocality and similar *per capita* GDP levels.

Specifications I–V of Table IX report the coefficient estimates of (8). A one-standard-deviation increase in the COVID-19 intensity (4%) causes a reduction of 0.0248 standard deviation in the locality's

[41] STR and CIP-Sitraf are real-time gross settlement payment systems that record electronic interbank transactions between two economic agents in Brazil. These are high-frequency datasets that provide information on the transaction's exact time, the identification and location of the payer and receiver of the money, and the transaction's purpose, among others. Our analysis removes payments among branches of the same firm conglomerate, as they are likely to increase when a firm branch is experiencing liquidity issues.

[42] We exclude intercompany operations as they are more related to liquidity or investment opportunities managed by the firm conglomerate. The *Sistema de Câmbio* is only able to capture operations in which there are inflows of funds from abroad to Brazil. Therefore, we do not observe financial resources maintained (paid by the importer) abroad in international accounts. Since we do not have information about the money destination, we may also include receipts unrelated to purchases, such as capitalization of companies by partners or third parties, sale of non-operational assets, and marketplace operations.

income when we consider all income streams (Spec. I). This effect is economically significant, corresponding to a decrease of $0.0248 \cdot$ R\$ 10,918 million $\approx$ R\$ 272 million or around 19% of the sample average. Even though a higher COVID-19 prevalence negatively affects all firm income channels, its effect is statistically significant only for credit and debit cards and invoices, which have widespread use by households to settle purchases with businesses. While common in the corporate segment, wire transfers are used by households only for relatively large-valued operations. Exports are frequently limited to firms.

TABLE IX. *How does COVID-19 affect local economic activity?*

Sample:	All Firms					Firms without Branches				
Dependent Variables (Inflow):	All	Cred/Deb Cards	Invoices	Exports	Wire Transfers	All	Cred/Deb Cards	Invoices	Exports	Wire Transfers
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables										
COVID-19$_t$	-0.0248***	-0.0092***	-0.0098***	-0.0083	-0.0059	-0.0215***	-0.0161***	-0.0123***	-0.0220	-0.0074
$\times$ COVID-19 Intensity$_l$	(0.0058)	(0.0034)	(0.0032)	(0.0172)	(0.0038)	(0.0055)	(0.0049)	(0.0045)	(0.0281)	(0.0058)
Fixed effects and controls										
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Macrolocality · *Per capita* GDP(3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls?	Yes	Yes	Yes	Yes	Yes					
Fit statistics										
Observations	13,514	13,514	13,514	9,359	13,514	13,514	13,514	13,514	6,184	13,514
R^2	0.9920	0.9971	0.9982	0.9147	0.9929	0.9934	0.9973	0.9975	0.9229	0.9945

Note: This table reports coefficient estimates of the specification in (8) using monthly data from January 2019 to June 2021 at the locality-time level. The dependent variable takes the aggregate firm income considering the following inflow streams: (i) all streams (Specs. I and VI), (ii) credit and debit cards (Specs. II and VII), (iii) invoices (Specs. III and VIII), (iv) exports (Specs. IV and IX), and (v) wire transfers (Specs. V and X). We report results when we aggregate all firms within the locality (Specs. I–V) and only firms without branches (Specs. VI–X). The variable COVID-19 Intensity$_l$ is the average number of COVID-19 infectious residents as a share of the locality's population in 2020, and COVID-19$_t$ is a dummy variable that assumes the value of one when the year is equal to 2020 and zero, otherwise. We use locality and time-macrolocality-discretized *per capita* GDP fixed effects in all specifications. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

We also provide a case study of the time-varying COVID-19 effect on the locality's income to examine the parallel trends assumption. For that, we replace the step variable COVID-19$_t$ in (8) with monthly pulse dummies. Figure 9 depicts the β coefficient for each month from January 2019 to June 2021. Overall, the differences are statistically insignificant before 2020, corroborating the similarities between the compared groups. There is a strong break in the trend of credit and debit cards in March–April 2020, coinciding with the implementation of social distancing and quarantine health measures by local authorities to mitigate the COVID-19 spreading.

We assign the income to the locality of the firm's headquarters. However, it is reasonable to assume that large firms could centralize income in a specific plant to enjoy gains of scale while offering products and services in a decentralized way. Ideally, we would like to assign the income to the locality in which the firm produced the good or service. While we lack such type of information, we can mitigate this concern by running regressions only with firms without branches. We again use information from the *Receita Federal do Brasil* to identify the number of branches for each active Brazilian non-financial firm. Then, we only retain firms without branches before aggregating income at the locality level. Specifications VI–X rerun (8) using only firms without branches. Results remain unchanged. The reduction in credit and debit cards and invoices is even stronger for these firms, which mainly deal with

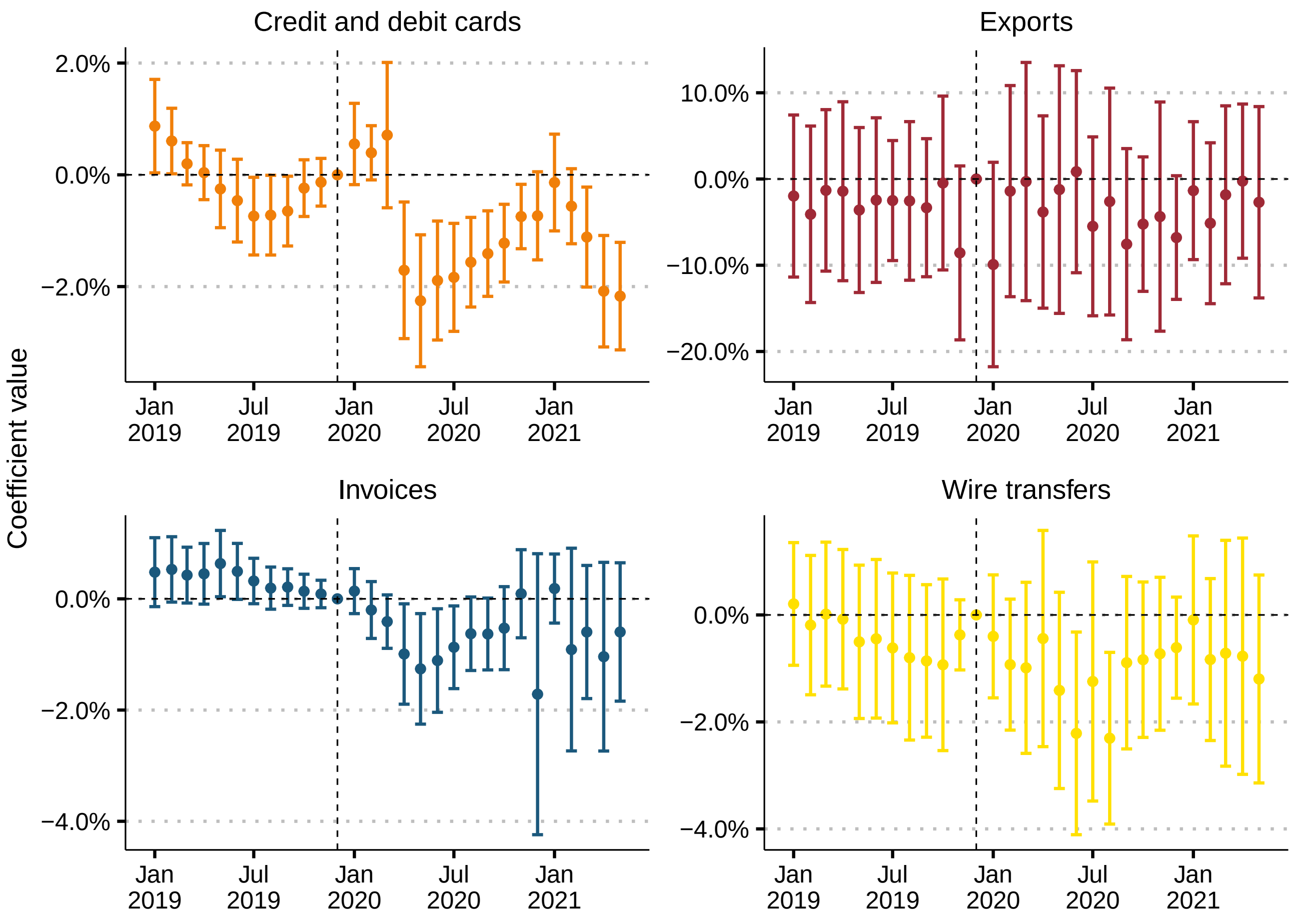


Figure 9. Time-varying effects of COVID-19 prevalence in Brazilian localities for credit and debit cards (upper left), invoices (bottom left), exports (upper right), and wire transfers (bottom right). We run the specification in (8) but changing the step variable COVID-19$_t$ for monthly pulse dummies. Each point represents the β coefficient for a specific month from January 2019 to May 2021. Vertical bars denote the 95% confidence interval.

final consumers who settle their purchases with such payment media.

7.2 Other market power measures as alternatives to the local Lerner index

This paper proposes a local version of the Lerner index, which is very data-intensive and requires some assumptions about the functional form of the bank branches' local total costs function. This section revisits our baseline regressions reported in Specs. III of Tables III (without IT covariates) and VIII (with IT covariates) but using alternative measures that are less data-intensive and require less assumptions. This analysis aims at giving a sense of the marginal value of using the local Lerner index over other simpler approaches. Additionally, it allows understanding the implications of using measures that are easier to compute but conceptually less appropriate. We hold our sample constant as in the baseline results to enable comparability of both approaches.

Table X reports coefficient estimates for two alternative measures for market power as dependent variables: the bank branch's local market share in a specific credit modality (Specs. I–II) and the HHI of these local market shares across bank branches in a specific locality (Specs. III–IV). The higher the local market share and HHI (more concentrated), the higher the local market power tends to be. We apply the same empirical specifications as in Spec. III of Tables III and VIII for the first measure, because it also varies at the bank-locality-modality-time level. The second measure varies at the modality-locality-time level because we aggregate across bank branches. Therefore, we create a locality-specific measure of IT readiness by using the average IT spending as a share of the total costs of banks operating in that locality weighted by their local volume of credit. Additionally, we exchange the fixed effects time-bank-macrolocality-*per capita* GDP for time-modality-macrolocality-*per capital* GDP (terciles).

TABLE X. *Robustness tests: using alternative measures of market power to the local Lerner index.*

Dependent Variables:	Credit Market Share$_{bmlt}$		Credit HHI$_{mlt}$	
Model:	(I)	(II)	(III)	(IV)
Variables				
COVID-19$_t$				
× COVID-19 Intensity$_l$	-0.0080**	-0.0112***	-0.0141**	-0.0118*
	(0.0040)	(0.0042)	(0.0072)	(0.0064)
× COVID-19 Intensity$_l$ · % IT Cost$_b$		0.0102*		
		(0.0061)		
× COVID-19 Intensity$_l$ · Locality's IT Readiness$_l$				-0.0057
				(0.0072)
Fixed effects and controls				
Locality	Yes	Yes	Yes	Yes
Time · Bank · Modality · Macrolocality · *Per capita* GDP(3)	Yes	Yes	No	No
Time · Modality · Macrolocality · *Per capita* GDP(3)	No	No	Yes	Yes
Other controls and interactions?	Yes	Yes	Yes	Yes
Fit statistics				
Observations	78,500	78,500	43,164	43,164
R^2	0.8968	0.8968	0.8127	0.8127

Note: This table reports coefficient estimates for variations of the specifications in Equation (3) (Spec. I and III) and (7) (Specs. II and IV) using semiannual data from 2019 to 2020. We use the following dependent variables: the bank branch's local market share in a specific credit modality (Specs. I–II) and the HHI of these local market shares across bank branches in a specific locality (Specs. III–IV). All controls (coefficients not shown) for the empirical setup in Specs. I and III (II and IV) follow Spec. III of Table III (Table VIII). Locality's IT Readiness is the average IT spending as a share of the total costs of banks operating in that locality weighted by their local volume of credit. Fixed effects of Specs. I and II follow Spec. III of Table III. Fixed effects of Specs. III and IV are similar except that time-bank-macrolocality-*per capita* GDP is changed for time-modality-macrolocality-*per capital* GDP (terciles). Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

We find that the bank branch's local market shares decrease in localities more affected by COVID-19 when compared to the same bank operating in other but similar localities in the same credit modality market (Specs. I and II). Credit becomes more diversified (less concentrated) in localities more affected by COVID-19 than other similar localities (Specs. III and IV). Both results suggest a decrease in the local market power in localities more affected by COVID-19, which is consistent with our baseline results. However, these simpler measures do not tell us about the channels through which market power can change. This feature is a substantial advantage of the local Lerner index over these measures one may have to ponder when deciding on using complex or more straightforward measures to evaluate market power. On the one hand, the local Lerner index provides insightful information on the main drivers of local market power changes, which may be critical for policymaking. On the other hand, it requires microdata and assumptions over the bank branch's production functions.

7.3 Alternative less saturated specifications

This section revisits our baseline regressions reported in Specs. I–III of Tables III (without IT) and VIII (with IT) but dropping controls or employing less saturated regressions. We hold our sample constant as in the baseline results to enable comparability of both approaches. Table XI reports coefficient estimates for these baseline regressions when we remove the original controls (Specs. I–VI) and use a less saturated set of fixed effects (Specs. VII–XII). In the second case, we retain only time-bank fixed effects, such that we still examine how the *same* bank changes its financial outcomes across localities. Our results remain qualitatively the same, implying they are not dependent on controls, which can be noisy, or a comprehensive set of fixed effects.

TABLE XI. *Robustness tests: how does COVID-19 affect local market power and its components? How does digitalization change these results?*

Robustness Test Type:	No controls, same fixed effects						Same controls, less fixed effects					
Dependent Variables:	Price_{bmlt}		$\text{Marginal Cost}_{bmlt}$		Lerner_{bmlt}		Price_{bmlt}		$\text{Marginal Cost}_{bmlt}$		Lerner_{bmlt}	
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Variables												
COVID-19_t												
× $\text{COVID-19 Intensity}_l$	-0.0028	-0.0049	0.0225***	0.0261***	-0.0293***	-0.0327***	-0.0026	-0.0002	0.0152***	0.0170***	-0.0241***	-0.0240***
	(0.0036)	(0.0041)	(0.0070)	(0.0073)	(0.0086)	(0.0087)	(0.0037)	(0.0045)	(0.0051)	(0.0051)	(0.0063)	(0.0061)
× $\text{COVID-19 Intensity}_l \cdot \text{\% Local IT Cost}_{bl}$		0.0040		-0.0216***		0.0192**		-0.0034		-0.0156***		0.0112*
		(0.0042)		(0.0066)		(0.0081)		(0.0033)		(0.0049)		(0.0062)
Fixed effects and controls												
Other Controls?	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Locality	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Time · Bank · Modality · · Macrolocality · *Per capita* GDP(3)	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Fit statistics												
Observations	79,782	79,782	79,782	79,782	79,782	79,782	79,052	79,052	79,052	79,052	79,052	79,052
R^2	0.9237	0.9238	0.7645	0.7646	0.7681	0.7681	0.1481	0.1482	0.0494	0.0496	0.0711	0.0714

Note: This table reports coefficient estimates for robustness tests in which we remove controls (Specs. I–VI) and use only time-bank fixed effects (Specs. VII–XII) from the baseline regressions in Specs. I–III of Tables III (without IT, odd-numbered specifications in this table) and VIII (with IT, even-numbered specifications in this table). All remaining empirical setup follows those tables. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

7.4 Where are more digitalized bank branches expanding during COVID-19?

Our previous results showed that more digitalized bank branches could expand lending outside their physical locations in terms of volume and number of clients during COVID-19. This feature gave these bank branches an upper hand in maintaining their operational activities, reflecting in relative lower marginal costs and improved local market power compared to other local bank branches. This section analyzes where these more digitalized banks expanded in the first year of the pandemic.

The original empirical setup employs microdata on the bank's financial outcomes over a semiannual period in a specific locality for a credit modality. It does not discriminate the credit destination, i.e., the borrower's locality. We also need information on the borrower's location to understand the expansion of digitalized banks during the COVID-19. Therefore, we go back to the SCR dataset and reconstruct the dataset but now segregate the bank's financial outcomes over a semiannual period for both the bank branch's and borrower's locations. We only have information on the volume of credit concessions and the number of distinct clients. We end up with bank-specific interlocal lending networks, where vertices are localities. An edge connecting two localities represents credit concession from the bank branch in the edge's originating locality to a borrower in the edge's ending locality. We only keep edges that connect different localities, i.e., we remove self-loops in the network. Additionally, we remove singleton vertices that are localities where none of the bank branches lend outside the locality.

Our identification strategy relies on the exogenous variation of COVID-19 intensity across similar borrowers' locations, i.e., within the same macrolocality and with similar *per capita* GDP (discretized in terciles). The data in network format enables us to compare lending across borrower's locations for the *same* bank branch (within-bank-branch analysis), thereby allowing us to isolate any time-variant supply shocks at the bank branch level. For instance, this approach controls for different local COVID-19 intensity at the lender side. Differences in local COVID-19 intensity can vary only at the borrower's side. Similar to our baseline setup, we interpret COVID-19 intensity in this configuration as a local credit demand shock in the borrower's locality.

To gain interpretability, we use the *difference* rather than the level of local COVID-19 intensity in the borrower's locality concerning that in the bank branch's locality (ΔIntensity). Therefore, positive (negative) values in this difference indicate that COVID-19 intensity is stronger (weaker) in the borrower's location than in the bank branch's location. We operationalize this empirical strategy with the following specification:

$$y_{b,l,d,t} = \alpha_{b,l,g(d),t} + \alpha_d + \lambda \cdot \text{COVID-19}_t \cdot \Delta\text{Intensity}_{ld} \cdot \%\ \text{IT Cost}_b + \gamma^T \cdot \text{COVID-19}_t \cdot \text{Controls}_{b,d} + \varepsilon_{b,l,d,t}, \tag{9}$$

in which b indexes the bank, l is the bank branch's locality (credit origination), d is the borrower's locality (credit destination), and t is the period (semiannual from 2019 to 2020). Table XII reports coefficient estimates of (9) for the following dependent variables: the bank branch's number of distinct clients (Spec. I) and volume of credit concessions in a specific locality d (Spec. II). To save up space, we only show the coefficient λ, which indicates how bank digitalization affects remote lending in localities more affected by COVID-19 than other less but similar localities. More digitalized bank branches reduce the number of distinct clients (Spec. I) and volume of credit concessions (Spec. II) in remote localities relatively more affected by COVID-19 than traditional bank branches. Our results indicate that digitalized bank branches prefer allocating credit in localities less affected by the own bank branch's locality during COVID-19.

We now analyze to which types of remote localities bank branches prefer to expand. For that, we augment (9) by adding a quadruple interaction (and all other lower-order interactions) between the terms COVID-19$_t$, Δ COVID-19 Intensity$_{ld}$, % Local IT Cost$_b$, and the difference between an observable transmission factor of the borrower's and the bank branch's locality (Transmission Factor$_{bld}$). By interacting the Transmission Factor$_{bld}$ with the three covariates, we can understand how bank branches choose among remote localities with the *same* relative level of local COVID-19 intensity. This feature is important because our baseline results show that digitalized bank branches move away from remote localities more affected by COVID-19 than their own localities. We use the following relative transmission factors (difference between observables of the borrower's and bank branch's localities): (i) bank-branch-specific differences, such as local Lerner indices and market shares and (ii) locality-specific differences, such as *per capita* GDP, population, and IT readiness. Bank branches prefer expanding to remote localities in which they have relatively higher market power (Spec. III) and to remote localities that are less

TABLE XII. Where are more digitalized bank branches expanding during COVID-19?

Dependent Variables:	#Clients$_{bldt}$	Granted Credit$_{bldt}$					
Transmission Factor:	—	—	ΔLerner$_{bld}$	ΔMark. Share$_{bld}$	Δ*Per cap.* GDP$_{ld}$	ΔPopulation$_{ld}$	ΔIT Readiness$_{ld}$
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Variables							
COVID-19$_t$ $\times$ Δ COVID-19 Intensity$_{ld}$	-0.0089***	-0.0188***	-0.0178***	-0.0183***	-0.0204***	-0.0138***	-0.0193***
$\times$% Local IT Cost$_b$	(0.0030)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0033)	(0.0032)
COVID-19$_t$ $\times$ Δ COVID-19 Intensity$_{ld}$			0.0042**	0.0009	-0.0049**	0.0065***	0.0007
$\times$% Local IT Cost$_b$ $\times$ Transmission Factor$_{bld}$			(0.0017)	(0.0022)	(0.0020)	(0.0022)	(0.0025)
Fixed effects and controls							
Borrower's Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Bank's Locality ·	Yes	Yes	Yes	Yes	Yes	Yes	Yes
· Borrower's Macrolocality ·							
· Borrower's *Per capita* GDP(3)							
Other controls and interactions?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	1,177,031	1,177,031	1,177,031	1,177,031	1,177,031	1,177,031	1,177,031
R^2	0.8688	0.8179	0.8181	0.8179	0.8183	0.8185	0.8183

Note: This table reports coefficient estimates for the specification in Equation (9) using semiannual data from 2019 to 2020 at the bank-bank branch's locality-borrower's locality-time level. We use the following dependent variables: the bank branch's number of distinct clients (Spec. I) and volume of credit concessions in a specific locality d (Specs. II–VII). To save space, we only report the coefficient λ in (9) and also the quadruple interactions in Specs. III to VII. The variables in differences Δ COVID-19 Intensity$_{ld}$ and the transmission factors ΔLerner$_{bld}$, ΔMark. Share$_{bld}$, Δ*Per cap.* GDP$_{ld}$, ΔPopulation$_{ld}$, and ΔIT Readiness$_{ld}$ are taken from observed values in borrower's locality minus that from the bank branch's locality. We add controls for the local intensity of government programs to combat the economic effects of COVID-19 (Emergency Aid Volume / GDP$_l$ and Share of SMEs$_l$) and the locality's distance and population, all with respect to the borrower's location. We add all low-order interactions and marginal terms for covariates appearing in a higher-order interaction that are not collinear with the fixed effects. We add borrower's locality and time-bank-bank branch's locality-borrower's macrolocality-borrower's-*per capita* GDP (discretized in terciles) fixed effects. Coefficients represent the change in the dependent variable in terms of standard deviations for a one-standard-deviation increase of the independent variable. One-way (borrower's locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

wealthy (Spec. V) and more populated (Spec. VI). Relative differences in market share (Spec. IV) and IT readiness (Spec. VII) do not drive lending decisions to remote localities.

8 Conclusions

This paper investigates how the COVID-19 pandemic and the digitalization of banks—the ratio of their IT spending to their total costs in the pre-pandemic period—affected their market power in credit markets in Brazil using a multi-product bank Lerner index. The main advantage of the Lerner index is that it allows investigating through which channels market power can change: effective prices or marginal costs.

We adapt this index to perform estimations of banking competition in each credit modality market at a local level. Studies on banking competition typically consider the bank at the national level as the unit of analysis. This choice stems from the lack of microdata required to estimate banks' local production functions and may compromise conclusions about competition in credit markets. We attempt to overcome this limitation by using microdata from various proprietary and public sources and designing resource allocation heuristics to estimate each bank's inputs, outputs, and costs in each locality and credit modality. The estimation of competition at more granular levels has several advantages. First, it permits us to understand possible competitive relationships among credit modalities, localities, and banks. Second, it enables us to identify apparently similar localities but with substantially different levels of local competition. Understanding these relationships can support policies that promote competition in regional credit markets.

The pandemic in Brazil started in large urban centers and later spread to smaller inland municipalities in very distinct ways. We exploit this cross-sectional exogenous variation and use our local version of the Lerner index to investigate how COVID-19 influenced market power in local credit markets through the effective price and marginal cost channels. Before the pandemic, the financial system was undergoing a heavy digitalization process. The introduction of public health measures to contain the COVID-19 spread accelerated this process even further. In this paper, we investigate if the market power of more digitalized banks has increased.

We resort to a within-bank, across-locality empirical strategy to carry out our analyses. To further mitigate the effects of any issues with differences in the bank's credit composition portfolio in different localities, we also compare the same bank operating in the same credit modality market across similar localities. We also control for government programs designed to combat the economic effects of the pandemic since they can influence the decision of credit-taking. This empirical setup views the COVID-19 shock as a local credit demand shock.

We find that COVID-19 does not affect effective prices. However, there are substantial changes in their components: credit income and concessions. The reduction in credit concessions offset the decrease in credit income, resulting in unaltered effective prices. We also find that the pandemic increases banks' marginal costs. The decline in granted credit and the increase in marginal costs suggest banks cannot reduce their total costs. We test this hypothesis and confirm that bank branches in localities more affected by COVID-19 cannot adjust their local total cost in the short term due to economic stickiness and legal and financial frictions. We conclude that the pandemic reduced the local market power of Brazilian banks through the marginal cost channel. We also perform robustness tests with alternative, less data-intensive measures than the Lerner index.

We go further in our analyses and examine whether there is cost flexibility gain for banks that rely more on a specific cost factor, namely, local factors–funding, tax, labor, and other administrative–and digitalization. We find that local factors are unrelated to bank branchs' ability to adjust their local total costs more efficiently during the pandemic. In contrast, more digitalized banks can reduce local costs. We also investigate through which channels digitalization enables local costs reduction. We also investigate how each of the four local cost factors—funding, tax, labor, and other administrative costs—behaves during the pandemic for banks with different levels of digitalization. During the COVID-19, more digitalized banks reduced funding costs at the expense of increased labor and other administrative costs. However, the decrease in funding costs dominates the increase in the other two cost components.

Additionally, we check whether digitalization provides lending flexibility. We find that bank branches in localities more affected by COVID-19 reduce credit concessions to non-local borrowers relative to branches of the same bank in less affected but similar localities. The number of clients does not change. However, more digitalized bank branches increase the credit volume and the share of clients living outside the bank branch's locality after the COVID-19 outbreak. We also find that bank branches expand to remote localities with relatively higher market power and to remote localities that are less wealthy and more populated.

Finally, we investigate whether the cost and lending flexibility provided by digitalization have favored more digitalized banks by improving their market power in local credit markets. We find digitalized banks mitigate the increase in marginal costs caused by COVID-19. Compared to traditional banks, more digitalized banks expand credit concessions and receive more credit income in localities more affected by COVID-19 than the same bank operating in similar or less affected localities. The increase in credit concessions and the fact that digitalized banks also expanded their credit to borrowers outside the bank branch's physical location suggests that more digitalized banks complemented rather than substituted their local borrower clientele with remote borrowers. We conclude that digitalized banks experienced an attenuated loss (or even an increase, for high-tech banks) in their market power in local credit markets relative to traditional banks.

Our results highlight the role of digitalization in allowing cost and lending flexibility during times of distress, enabling credit reallocation between local and remote borrowers, and facilitating bank expansion. These features alleviate the impact of shocks in the market power of banks that are more digitalized.

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Appendix A Data and overview of bank credit local markets

A large amount of data is required to estimate competition locally. This appendix initially provides details on data processing: sources, extraction strategies, treatment procedures. Then, using these data, we bring an overview of local bank credit markets that contextualize our results of competition across Brazilian localities.

A.1 Data treatment

We collect data from January 2015 to December 2020. We compile and transform them into semiannual variables, as of June and December of each year. We perform the following data treatments:

- SCR. We use SCR data to compute credit product quantities $Q_{blt}^{(m)}$ and effective prices $p_{blt}^{(m)}$ of bank b for the credit modality m in the locality l during the semiannual period t. Our methodology computes effective prices of credit modalities in each period from credit income and outstanding credit immediately before lenders receive repayments, requiring information for all open loan operations in these periods. In this paper, we have processed 10.8 billion records of outstanding positions of individual credit operations. We then group these credit operations by semiannual period, bank, locality of the *bank branch that granted the credit* (according to bank branch's ZIP code), credit modality, and an indicator of the credit grant having occurred within the half-year under analysis or before it. For each of these groups, we compute semiannual outstanding amounts (product quantities) and effective prices from the available monthly information. For product quantities, we consider the average of the monthly amounts. For effective prices, we use Equation (13).

- Cosif. We use information of monthly banks' consolidated financial statements and supervisory variables to compute input prices and total bank local costs, according to Table B1 in Section B.2. We then take the semiannual average of balance sheet variables and the sum of the expenses variables within the half-year to compute the costs. All of this information is available at the bank level.

- ESTBAN. This database contains monthly records of summarized balance-sheet information at the bank-municipality level. Similar to what we do for the Cosif database, we rebase this information to a semiannual basis. After this, we aggregate geographically this municipality-level information to the corresponding bank-locality level using the IBGE Geographic database. Finally, we use bank-locality ratios of the local ESTBAN variable to the country-level aggregate ESTBAN amount to apportion the bank-level Cosif variables. We use this strategy because, most of times, accounting aggregates extracted from the ESTBAN database are not the same as those from Cosif.

- IBGE Geographic data. This database has information on geographic units of the Brazilian territory. It serves to map municipalities into their respective Immediate Geographical Region (our unit of locality in this work), a more appropriate unit of analysis for analyzing competition locally.

- RAIS and Caged. These datasets have monthly employment relationships for all bank branches in Brazil. Similar to the previous transformations, we re-base this information on a semiannual basis. We sum the bank's payroll and average the number of employees within the half-year.[43] We also aggregate this information to the bank-locality level.

A.2 Overview of bank credit markets

This section shows an overview of the bank credit market from 2015 to 2020, exploring the bank production function variables used in our translog model (Equation (11)). We intend to provide information on the relative relevance of each input and output, with a particular focus on credit modalities.

Our data encompasses commercial and universal banks operating in Brazil, including private (35 in December 2020), state-owned (9), and foreign banks (30). In December 2020, they corresponded to roughly 83% of the overall credit market (banking and non-banking credit). Table A1 reports the number of banks with positive outstanding credit in Brazil and in each region. Despite the slight decrease in the number of banks, large banks are equally present in all regions throughout the sample period. Smaller banks concentrate in the Southeast, the most developed region in Brazil.

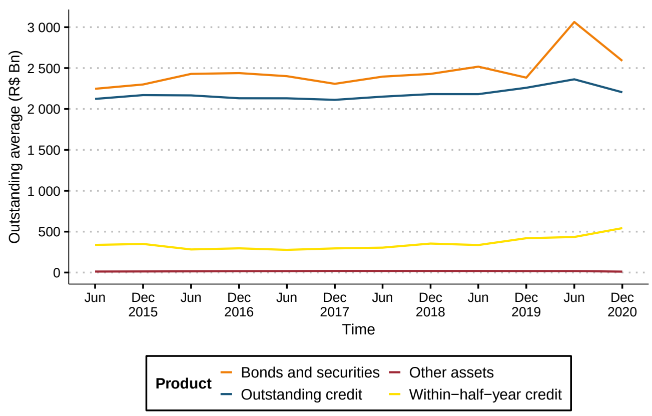
TABLE A1. *Number of banks with positive outstanding credit in the whole country and in each region from 2015 to 2020. The same bank may appear more than once when it operates in more than a single region.*

Size	2015	2016	2017	2018	2019	2020
Country	*79*	*78*	*78*	*76*	*75*	*74*
Large	6	5	5	5	5	5
Medium-sized	6	6	6	6	5	5
Small	28	27	29	30	30	29
Micro	39	40	38	35	35	35
Central-West	*20*	*20*	*19*	*19*	*18*	*16*
Large	6	5	5	5	5	5
Medium-sized	4	4	4	4	3	2
Small	7	8	7	7	7	7
Micro	3	3	3	3	3	2
North	*12*	*11*	*11*	*11*	*10*	*10*
Large	6	5	5	5	5	5
Medium-sized	1	1	1	1	0	0
Small	4	4	4	4	4	4
Micro	1	1	1	1	1	1
Northeast	*20*	*19*	*19*	*18*	*17*	*16*
Large	6	5	5	5	5	5
Medium-sized	5	5	5	4	3	2
Small	6	6	6	6	6	6
Micro	3	3	3	3	3	3
South	*26*	*25*	*24*	*23*	*20*	*21*
Large	6	5	5	5	5	5
Medium-sized	5	5	5	5	4	4
Small	7	8	7	6	5	7
Micro	8	7	7	7	6	5
Southeast	*69*	*69*	*70*	*69*	*68*	*67*
Large	6	5	5	5	5	5
Medium-sized	6	6	6	6	5	5
Small	25	24	27	28	28	27
Micro	32	34	32	30	30	30

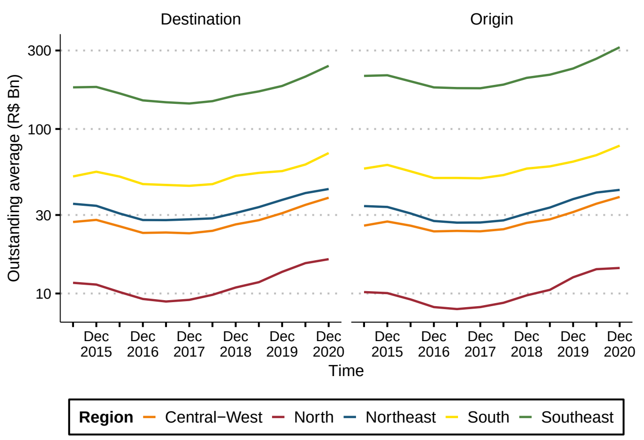
[43] We take the average of the bank branch's number of employees considering the number of months for which there are data within the half-year. The Kendall correlation between the average number of employees and the outstanding bank credit of the entire sample is 0.68. This correlation is sensitive to the region: 0.55 (North), 0.70 (Northeast), Central-West (0.62), Southeast (0.70), and South (0.69). Therefore, there is not a trivial relationship between the amount of outstanding credit and the number of local employees in bank branches.

Our model that estimates local Lerner indices assumes banks are minimizing the costs related to their production function. Although we focus on credit products, the production function has to include all banking products: credit (within and before the half-year), bonds and securities, and operations with other assets. Figure A1a displays the evolution of semiannual outstanding averages for these products. Bonds and securities have roughly the same volume as the aggregation of all credit products. Stocks of operations with other assets are relatively negligible. Within-half-year granted credit corresponds to 15 to 20% of the overall credit stock. The large volume of operations before the current half-year highlights the importance of focusing on most recent operations—those within the half-year—to better capture the current conditions and more reliably estimate competition.

Another modeling choice we need to make is to select the geographic point-of-view of credit operations. We can aggregate them by the borrower's (credit destination) or the bank branch's (credit origin) location. Figure A1b portrays the within-half-year credit volume across regions using the credit destination and origin perspectives. There are differences mainly in the Southeast, where the credit origin is higher than the credit destination perspective, perhaps because of the large concentration of banking activities in this region that channel credit throughout the country. We adopt the credit origin perspective because of several factors. First, it is more consistent with the production function approach: the resources and the costs related to producing credit are those from the branch originating the resources. Second, the credit origin perspective lets us capture electronic transactions originating in a specific bank branch regardless of the borrower's location. Such a feature is important because online banking operations have increased substantially in Brazil.[44] Third, we are measuring local bank branches market power, therefore we need to define the markets in which we perform these measurements to include, for each credit product and local bank, all of its transactions with its customers, regardless of their localities.



(a) Bank products



(b) Within-half-year credit with different aggregation criteria

Figure A1. *Country-level bank products over time. (a) Evolution of the volume of bank products: outstanding credit (total and within-half-year), bonds and securities, and other assets. (b) Comparison of regional outstanding within-half-year credit volumes using the credit destination (borrower) and credit origin (bank branch) perspectives. Vertical axes are in log scale.*

We focus on within-half-year credit products, thus we now describe the relative importance of within-half-year credit modalities. Figures A2 and A3 exhibit the within-half-year credit volume by

[44] Appendix C.1 uses data from the Central Bank of Brazil and shows the evolution of the number of local against remote transactions and the number of transactions per channel (ATM, branches, call center, correspondent, internet banking, and mobile banking) in Brazil from 2010 to 2019. Remote transactions have been increasing substantially in the last years, mainly through the internet and mobile banking. Remote transactions have surpassed face-to-face transactions since 2014.

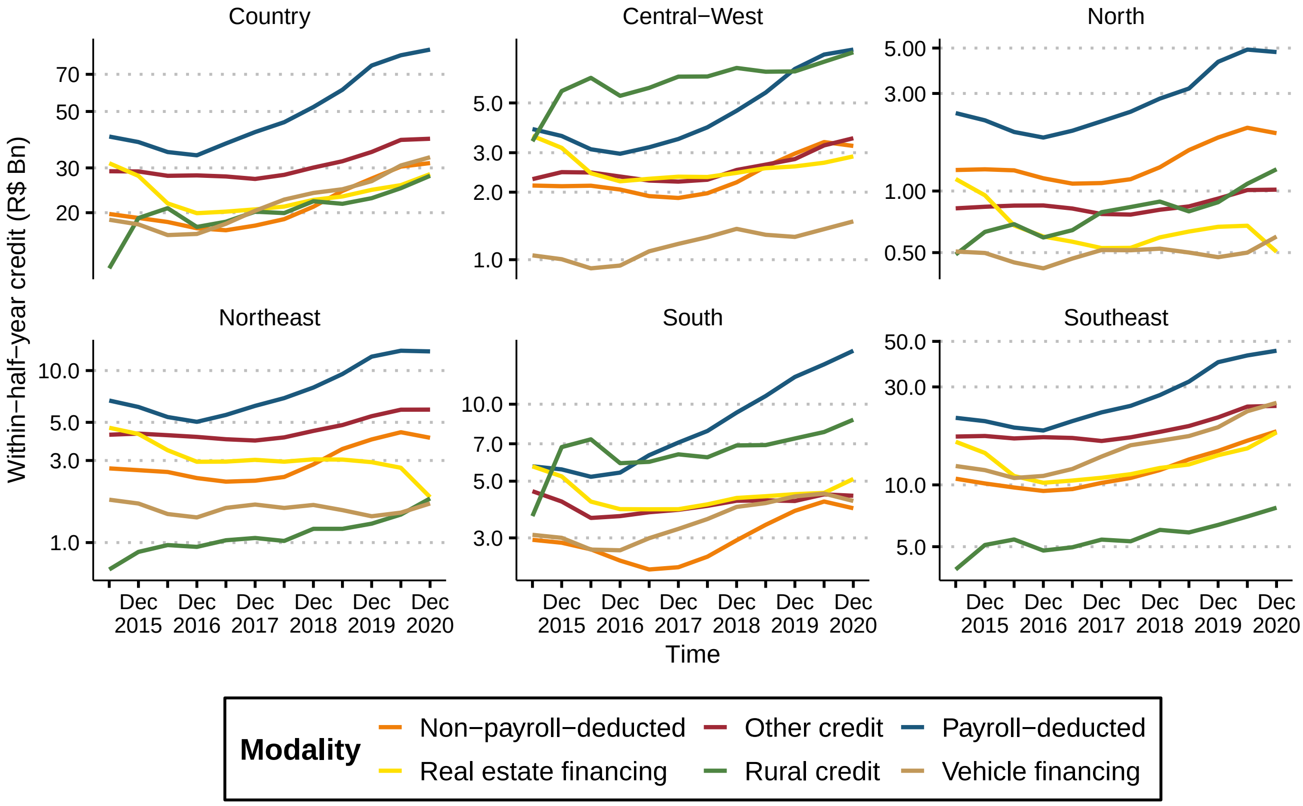


Figure A2. *Outstanding position of within-half-year credit granted in each region for credit modalities for individuals. Vertical axes are in log-scale.*

credit modality for individuals and non-financial firms, respectively. The within-half-year credit volume for individuals has increased for all modalities since 2017 at the country level. Payroll-deducted credit has the highest outstanding position in all regions, except in the Central-West, where prevails rural credit. The within-half-year credit volume for non-financial firms had a steep increase in 2020, probably due to the effects of the COVID-19 pandemic. Working capital and account receivables are the modalities with the highest within-half-year outstanding volumes.

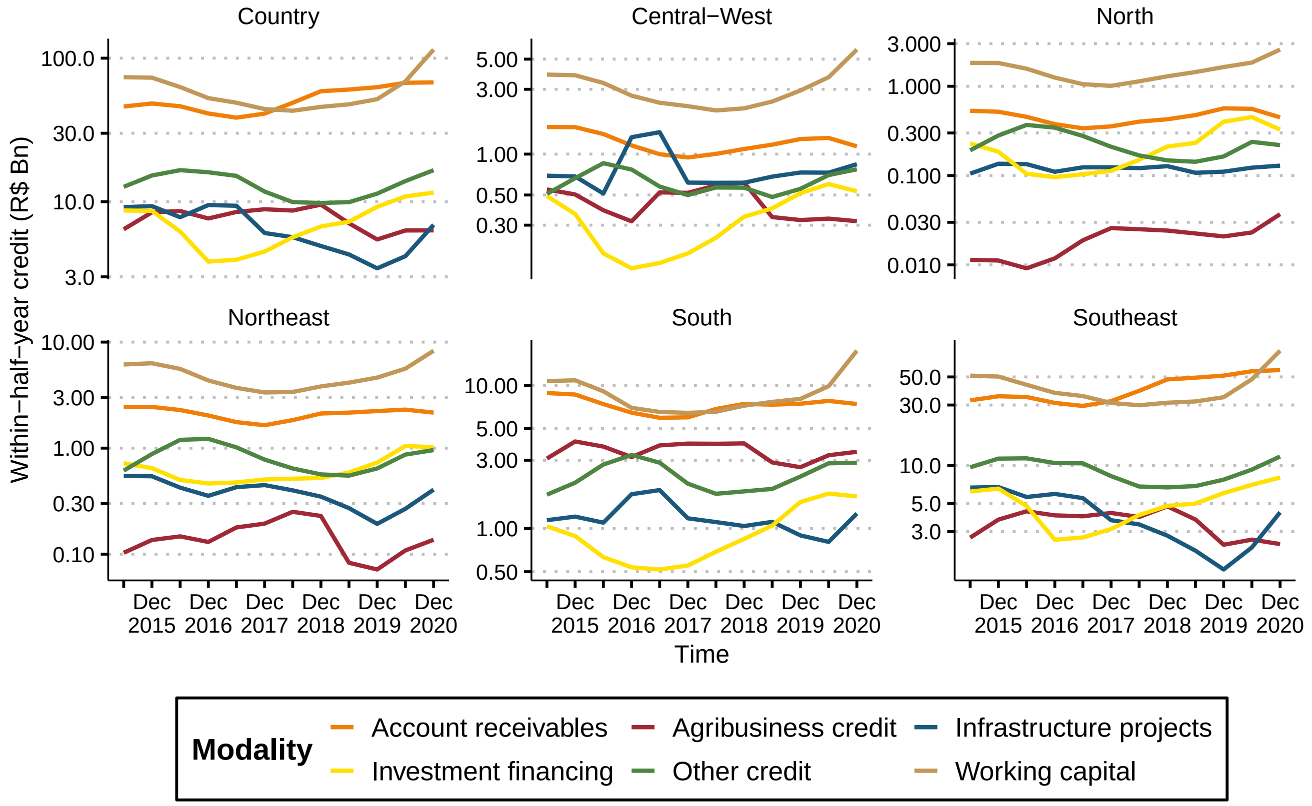


Figure A3. *Outstanding position of within-half-year credit granted in each region for credit modalities for non-financial firms. Vertical axes are in log-scale.*

Appendix B Estimation of local competition in credit markets in Brazil

Estimating local market power in credit markets and identifying its determinants are fields in the literature with much room for exploration. This appendix proposes a methodology for estimating local Lerner indexes for the banking credit market and applies it to Brazilian data.

B.1 Model definition

We evaluate banks' local credit market power using data-intensive version of the Lerner index. We use the definition of local markets described in Section 4 to provide a framework for the model and the interpretation of results.

We need two pieces of information to estimate the Lerner index of a specific bank in a given market: (i) the effective price (observable variable) and (ii) the marginal cost (non-observable variable) of the product. We can evaluate the Lerner index of bank b at location l in period t for the banking product j using the following expression:

$$L_{blt}^{(j)} = \frac{p_{blt}^{(j)} - MC_{blt}^{(j)}}{p_{blt}^{(j)}}, \tag{10}$$

in which $p_{blt}^{(j)}$ and $MC_{blt}^{(j)}$ are the average effective price and marginal cost of bank b at location l at time t relative to banking product j, respectively.

After computation, prices, marginal costs and Lerner indexes for each period and market (bank, credit modality, locality) can be aggregated to represent information on broader markets over time, for instance, the Lerner index aggregated for all banks and credit modalities in a locality, or the marginal cost aggregated for the credit modalities to non-financial firms, all banks, in a country region (for further details, see Section B.4).

The banking literature uses a total cost function to estimate the marginal cost. The cost function assumes a transcendental logarithmic functional form (translog) and takes a set of banks' inputs and products as arguments.[45] Then, the derivative of the cost function with respect to a specific product is used to estimate the product's marginal cost. We follow this procedure and estimate the marginal cost using a cost function. However, we differ from the literature in the dimension in which the estimation takes place. While the banking literature assesses marginal cost at the (national) bank-time level, we use bank-locality-time data. In this way, we can identify local idiosyncrasies in bank market power.

Considering that banks may operate across localities differently, we saturate the total cost function with fixed effects. In this way, we can control for non-observable bank-specific institutional settings in each location and location-specific shocks. This approach is vital because the cost function assumes that banks have the same production function and, therefore, the cost-related parameters are the same for all banks, locations, and time. We use the following empirical specification for the bank b's total cost in location l at time t (TC_{blt}):

$$\ln\left(\frac{TC_{blt}}{W_{blt}^{(1)}}\right) = \alpha_{bl} + \alpha_{lt} + \sum_{j=1}^{N}\beta_j \ln Q_{blt}^{(j)} + \frac{1}{2}\sum_{j=1}^{N}\sum_{k=1}^{N}\beta_{jk}\ln Q_{blt}^{(j)}\ln Q_{blt}^{(k)} + \sum_{i=2}^{M}\delta_i \ln\left(\frac{W_{blt}^{(i)}}{W_{blt}^{(1)}}\right) + \\ + \frac{1}{2}\sum_{i=2}^{M}\sum_{k=2}^{M}\delta_{ik}\ln\left(\frac{W_{blt}^{(i)}}{W_{blt}^{(1)}}\right)\ln\left(\frac{W_{blt}^{(k)}}{W_{blt}^{(1)}}\right) + \sum_{j=1}^{N}\sum_{i=2}^{M}\gamma_{ji}\ln Q_{blt}^{(j)}\ln\left(\frac{W_{blt}^{(i)}}{W_{blt}^{(1)}}\right) + \varepsilon_{blt}, \qquad (11)$$

in which $W_{blt}^{(i)}$ and $Q_{blt}^{(j)}$ represent the price of the i-th input and the quantity produced of the j-th product by bank b at location l during period t. The bank uses M inputs and produces N products. In (11), the total cost TC_{blt} and input prices $W_{blt}^{(i)}$, $i \neq 1$, are divided by the price $W_{blt}^{(1)}$ to ensure the linear homogeneity of the estimated cost function.[46] In addition, $\beta_{jk} = \beta_{kj}$, $\forall j,k$, and $\delta_{ik} = \delta_{ki}$, $\forall i,k$. We introduce bank-locality effects α_{bl} to capture non-observable characteristics of bank b in location l that are time-invariant, and time-locality effects α_{lt} to absorb locality-specific factors that affect banks over time.[47] The term ε_{blt} is the stochastic error.

[45] In this approach, one assumes that banks are optimizing costs taking input prices and quantities to be produced as given. It is well-suited for estimating bank costs, that are non-observable, from observed data.

[46] The linear homogeneity assures the same cost function when prices and costs are multiplied by a constant and the other parameters remain unchanged. We choose the funding price ($W_{blt}^{(1)}$) as the divisor for numerical stability. First, it has a reasonable magnitude (not too small like the tax price and not too large as the labor price) and standard deviation. Second, the literature also uses funding as the divisor due to banks' traditional financial intermediation role.

[47] The bank-locality fixed effects (α_{bl}) capture the average effects of the strategic positioning of each bank regarding local market niches and organizational choices both at the bank and at the bank branch level. The time-locality fixed effects (α_{lt}) absorb locality-specific non-observable shocks, such as the effect of local public policies on regional economic activity, the

We differentiate the total cost function in (11) with respect to the quantity produced of product j to obtain the local marginal costs associated with the same product j by bank b in location l during period t ($MC_{blt}^{(j)}$), i.e.:

$$MC_{blt}^{(j)} = \frac{\partial TC_{blt}}{\partial Q_{blt}^{(j)}} = \left(\frac{TC_{blt}}{Q_{blt}^{(j)}}\right)\left(\beta_j + \beta_{jj}\ln Q_{blt}^{(j)} + \sum_{k=2}^{N}\beta_{jk}\ln Q_{blt}^{(k)} + \sum_{i=2}^{M}\gamma_{ji}\ln\left(\frac{W_{blt}^{(i)}}{W_{blt}^{(1)}}\right)\right). \tag{12}$$

The marginal cost in (12) is the monetary amount spent by bank b to increase the banking product j in locality l during period t by *one* monetary unit.

The empirical challenge in evaluating competition at the local level is to estimate bank-specific input prices and the quantity of each product in (11) locally. This information usually is present at the national bank level. We overcome this limitation by constructing heuristics to reallocate national-level bank resources across local inputs, products, and costs for each of its branches using several proprietary and public data sources from Brazil. We first discuss these datasets and then present the reallocation heuristics.

B.2 Productive process: the bank's local total cost function

This section details the components of the total cost function that we evaluate for each location according to (11).

Input prices ($W_{blt}^{(i)}$): Table B1 shows the definition of input prices of the local total cost function.

Local total cost (TC_{blt}): While it is common for central banks to have consolidated financial statements of banks to pursue their institutional goals, it is unusual to have information at the bank branch level. Brazil is not an exception to this as well.[49] While the BCB has detailed data on the total costs of each financial institution in Brazil through the Cosif dataset, there is no information on specific cost factors for each bank branch. The latter would require complete financial statements at the bank branch level. One potential option would be to use ESTBAN. However, ESTBAN contains information on balance sheet accounts with an intermediate level of detail and only summarized information on income statement accounts. It only contains the aggregate income statement accounts total costs and total revenues. This information is insufficient to evaluate the required information on banks' inputs in (11), as we would need to break down total costs in specific factors such as funding, tax costs, labor, and other administrative costs.

We overcome this limitation by constructing heuristics to allocate national-level bank-specific costs across their branches. Our strategy is to allocate the high-quality and detailed national-level costs of each bank from the Cosif dataset to every branch across localities using other datasets with useful local

local court efficiency, environmental risks and the local diversification of economic activities.

[48] The federal tax burden of Brazilian financial institutions was approximately 79% of all the collected taxes between 2015 and 2020.

[49] The BCB receives financial statements and many other datasets to pursue its institutional goals of ensuring the stability of the currency purchasing power, fostering a sound, efficient and competitive financial system, and promoting the economic well-being of society. Specifically, financial institutions report their financial statements monthly to the BCB. This information is subject to many quality and accounting controls allowing the BCB to use such information to monitor the minimum prudential requirements (such as liquidity and capital requirements) for every bank.

TABLE B1. Bank input prices ($W^{(i)}_{blt}$) used to estimate the total cost function in (11).

i	Price of input $\mathbf{W^{(i)}_{blt}}$	Name and Rationale
1	$W^{(1)}_{blt} = \dfrac{\text{Funding Costs}_{bt}}{\text{Total Funding}_{bt}}$	**Funding prices**. We assume the local funding price is uniform for the same bank in different locations, as the bank's funding strategy normally follows centralized internal governance. The expenses variable Funding Costs$_{bt}$ (Cosif) and the Total Funding$_{bt}$ variable (Cosif) are the bank b's funding expense in period t and the average outstanding funding in period t, respectively.
2	$W^{(2)}_{blt} = \dfrac{\text{Tax Costs}_{bt}}{\text{Total Assets}_{bt}}$	**Tax prices**. We assume the local taxation price is approximately uniform across localities since taxation costs refer mainly to federal taxes in Brazil.[48] The expenses variable Tax Costs$_{bt}$ (Cosif) and stock variable Total Assets$_{bt}$ (Cosif) are the bank b's tax costs in period t and its total assets.
3	$W^{(3)}_{blt} = \dfrac{\text{Labor Costs}_{blt}}{\text{Number of Employees}_{blt}}$	**Labor prices**. We take the price of labor resources as the local average salary. The expenses variable Labor Costs$_{blt}$ (RAIS/Caged) and the Number of Employees$_{blt}$ variable (RAIS/Caged) are the bank b's total labor costs in t and the *average* number of employees at location l during period t.
4	$W^{(4)}_{blt} = \dfrac{\text{Other Admin. Costs}_{bt}}{\text{Total Assets}_{bt}}$	**Other administrative prices**. We consider the price of other administrative resources, such as rental expenses, depreciation, amortization and cost of supplies required for running the bank's operational infrastructure, uniform across locations due to data unavailability. The expenses variable Other Admin. Costs$_{bt}$ is the sum of administrative (Cosif), depreciation (Cosif) and amortization (Cosif) costs minus labor (RAIS/Caged) costs, all of which relative to bank b in period t.

bank branch information, such as the ESTBAN or SCR. The combination of local information data with Cosif guarantees that the sum of all bank branches' costs coincides with the aggregate financial statement of that bank.

Table B2 shows the four cost components that we employ to estimate each bank's local total costs. In each line, we report the aggregate base value from Cosif and the heuristics for allocation of that value across bank branches.[50]

Quantity of products ($Q^{(j)}_{blt}$): In this study, we define banks' products by choosing the two largest earning assets categories and a residual category, which results in these outputs:[51] credit operations (SCR), bonds and securities (ESTBAN), and operations with other assets[52] (ESTBAN). Within credit operations, our granular data enables us to subdivide it into credit modalities. The composition of banks' credit portfolios may substantially vary across municipalities and can be a source of potential differences in market power. In this way, we opt to model credit products in terms of their modalities. Table B3 lists

[50]For instance, suppose that bank b has branches in two localities and that, for the computation of total costs TC_{blt} we need to allocate personnel expenses to each locality. We have the bank's aggregate labor cost (Cosif) = 130, the bank's aggregate payroll (RAIS / Caged) = 100 and the branches' total payroll. For locality $l = 1$, it is 30, while for $l = 2$, it is 70. Thus, we will allocate labor costs LC_{blt} as follows. For $l = 1$, $LC_{b1t} = 130 * 30/100 = 39$, and for $l = 2$, $LC_{b2t} = 130 * 70/100 = 91$.

[51]This product list is line with the literature. Shaffer and Spierdijk (2020) provide a list with an overview of recent banking studies that use the Lerner index computed from a translog cost function. The list has about 50 studies from which 10 consider loans and securities as products.

[52]We evaluate operations with other assets in a residual form: cash and cash equivalents, interbank investments, bonds and securities, interbank relationships, interdependence relationships and credit, and leasing operations are subtracted from the value of the sum of current assets and long-term assets.

TABLE B2. *Components of the bank's local total costs (TC_{blt} in (11)). For each cost component, we divide national-level cost components of a bank (second column) across its bank branches using an heuristics for allocation (third column).*

Comp.	**Aggregate base value (Cosif)**	**Heuristics for allocation (location-specific)**
1	Funding costs, except those related to bonds and securities.	Proportion of the outstanding credit originated by the bank branch regardless of the borrower's locality (SCR) in relation to the bank's national aggregate.
2	Funding costs related to bonds, securities, and repo operations at the interbank market.	Proportion of the sum of [interbank and liquidity applications with securities (ESTBAN)] and [derivative financial instruments (ESTBAN)] in the locality relative to the bank's national aggregate.
3	Sum of tax costs, administrative costs excluding labor, and amortization and depreciation costs.	Proportion of the sum of [outstanding credit operations originated by the bank branch regardless of the borrower's locality (SCR)] + [interbank and liquidity applications (ESTBAN)] + [securities and derivative financial instruments (ESTBAN)] + [leasing and other securities and assets (ESTBAN)] in the locality relative to the bank's national aggregate.
4	Labor costs.	Proportion of the bank branch's payroll (RAIS / Caged) relative to the bank's national payroll.

the considered credit modalities in terms of the product segment: households or non-financial firms.[53]

Some credit modalities typically have long maturities. In this way, a bank's stock of credit operations may include active operations originated a long time before, under market conditions potentially different from those observed in the current period. Research in this area usually considers the whole stock of credit operations and has this potential problem in their marginal cost estimates. This limitation may result from these works be relying solely on (national-level) banks' financial statements, which do not permit the identification of new grants and previous outstanding credit. In order to better capture the competitive market conditions in each period (a half-year), we subdivide the credit volume into that granted *within* the half-year and that granted *before* the half-year. To the best of our knowledge, this is the first work that considers this feature to better estimate market power.

Therefore, in our model, each bank can produce thirty products: (i) fourteen products referring to credit operations granted within the half-year of the modalities listed in Table B3; (ii) fourteen for operations before the half-year of those modalities; (iii) one for operations with bonds and securities; and (iv) one for operations with other assets.

B.3 Effective price of credit products

We focus on credit products granted within a half-year. We explicitly index these products with an m superscript. Formally, it is a subset of all j bank products as in (11). The banking literature normally uses the ratio between the revenue from credit operations and the volume of credit as a proxy for the *average credit price*.[54] This effective price is net of losses due to credit default, since this measure is

[53]The division roughly follows the credit modalities published in the Financial Stability Report of the BCB.

[54]Shaffer and Spierdijk (2020) evaluate market power in multi-product banks using the Lerner index. They state that in these computations banks' output price is typically calculated as the average revenue, given by the total revenue divided by

TABLE B3. Credit modalities considered as credit-related banking products when evaluating (11). Each credit modality is represented by two banking products: operations that occurred within and before the half-year under analysis.

Credit modality for individuals	Credit modality for non-financial firms
1. Payroll-deducted personal credit	1. Working capital credit
2. Non-payroll-deducted personal credit	2. Revolving working capital credit
3. Real estate financing	3. Infrastructure financing
4. Rural credit	4. Real estate financing
5. Vehicle financing	5. Investment credit
6. Other credit	6. Account receivables credit
	7. Agribusiness credit
	8. Other credit

Note: The "other credit" modality in each segment refers to an aggregation of credit modalities with a small share in the segment's outstanding credit. In the credit segment for non-financial firms, the modalities below may have non-standard characteristics compared to credit modalities available in other countries. Infrastructure financing refers to earmarked credit for financing infrastructure projects. Investment credit is non-earmarked and is used for financing firm investment projects. Finally, account receivables credit refers to the anticipation of receivables, given as collateral, such as promissory notes, bills, checks, and credit card bills.

based on the income that is received by the bank in its credit operations. It differs from the contractual interest rate, which incorporates expected default and other risk factors. Ideally, the average effective price of a portfolio of a credit product m granted by bank b during period t at location l should be computed as the internal interest rate of its cash flow. However, due to the unavailability of complete cash flow data (cash flow dates and amounts), we resort to a proxy in line with the literature: we compute the portfolio's average effective price as the ratio of the sum of monthly income flows from credit grants within the half-year I (SCR) and the 6-month average of monthly outstanding credit averages within the half-year V (SCR).[55] The portfolio's average effective price, expressed in terms of semiannual interest rate, is:

$$p_{blt}^{(m)} = \frac{\sum_{k \in \mathscr{H}_t} I_{blk}^{(m)}}{\frac{1}{6} \sum_{k \in \mathscr{H}_t} V_{blk}^{(m)}}, \tag{13}$$

in which $\mathscr{H}_t$ is the set of all months within half-year t, $I_{blk}^{(m)}$ indicates the portfolio sum of income inflows of each operation of credit modality m granted in t, computed by the accrual method, that bank b at locality l received during month k, and $V_{blk}^{(m)}$ is the sum of monthly outstanding credit average for these operations at the same month.[56]

There are two important distinctions of our methodology to the literature. First, we focus on credit operations within a half-year when evaluating their effective price, instead of the entire credit portfolio of a bank. This approach enables us to better measure the current market conditions. Second, we explicitly take into account very short-term credit, i.e., operations that mature in less than one month. The traditional approach taken in the literature is to consider end-of-month accounting data to retrieve

total assets. Studying regional competition in US banking, Erler et al. (2017) also adopt this method to compute credit prices.

[55]Monthly income flows are obtained from the SCR database for single operations. They are computed by the accrual method and reflect daily effects of the contractual interest rate and outstanding credit. Additionally, loans in default receive zero income. Regarding monthly outstanding credit averages, due to lack of data, we proxy them as the sum of the outstanding amount in the beginning of the month to new credit grants during the month, if any.

[56]We are simplifying the computation by assuming a simple compounding over months. This simplification does not distort the results because we are looking at a short horizon.

the effective credit income and outstanding credit volume. In this approach, for a single operation we would find the credit income computed at the end-of-month financial statement but the outstanding credit volume would be zero. Hence, after aggregating these operations with others in the portfolio, effective prices would be biased upwards. If there is a significant volume of very short-term credit, then the distortion could be substantial.[57] In turn, our approach of computing the portfolio's average effective price as the ratio of the sum of monthly income flows from credit grants within the half-year (SCR) and the average of monthly outstanding credit averages within the half-year (SCR) mitigates this problem.[58]

B.4 Evolution of local effective prices, marginal costs, and Lerner indices

This section provides a comprehensive view of local market power across Brazilian localities. Since the literature normally looks at national aggregates, this information is entirely novel. We report average effective prices (not contractual prices) and the estimation of marginal costs and local Lerner indices across Brazilian localities. Our model's outputs yield these three variables for each bank for a specific credit product in a locality during a semiannual period. Our focus is on within-half-year credit products listed in Table B3. We display these variables at different levels of aggregation: localities, regions, and the whole country.[59]

Table B4 shows summary statistics of variables used in the estimation of local Lerner indices.

[57] In fact, along the semiannual periods in the data sample, operations that mature in less than 30 days correspond to 7% to 12% of the average overall outstanding credit in these periods. However, these operations are concentrated in shorter-term (and higher price) modalities, which impose a much larger distortion on prices computed for these modalities.

[58] However, substituting the monthly outstanding credit averages in the denominator by the sum of the outstanding amount in the beginning of the month and the new credit grants during the month as we do will bias effective prices down. This bias may become of low relevance after aggregating all the operations of credit product m granted by bank b in locality l during period t.

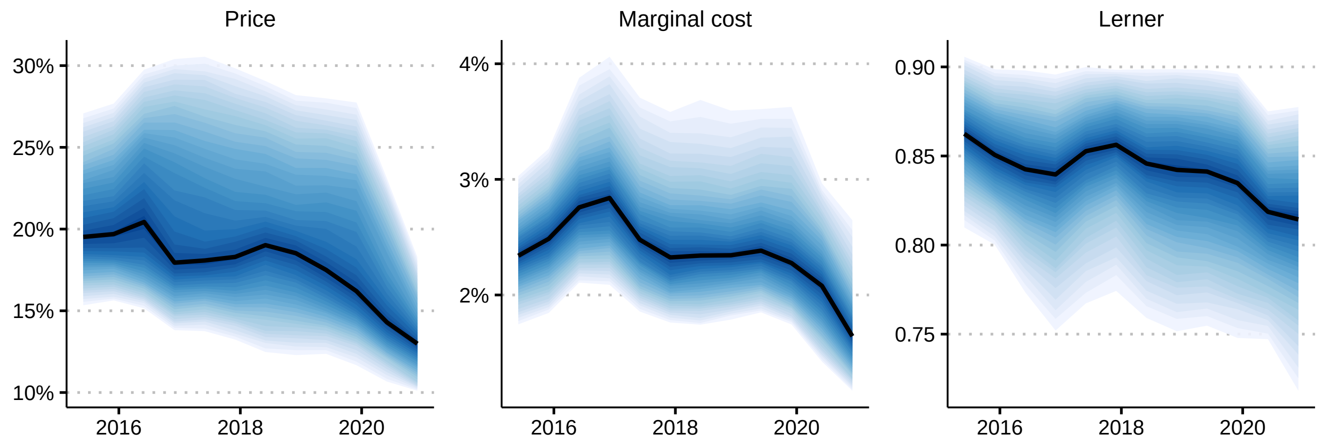
[59] Shaffer and Spierdijk (2020) demonstrate we can aggregate multi-product banks Lerner indices consistently by using the credit income as a weighing strategy. We follow this guideline and use the bank's credit modality income. This paper uses this procedure to aggregate Lerner indices, marginal costs, and effective prices of different banks for different credit modalities and localities.

TABLE B4. *Summary statistics of variables used in the estimation of local Lerner indices. Semiannual data, from 2015 to 2020. Local total costs are sums of monthly accrued amounts. The other variables are averages over a half-year.*

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
A. Local total cost in a half-year (in log R$)								
Local cost	32,975	16.439	1.448	13.784	15.406	16.269	17.278	20.515
B. Input prices (in log R$)								
Funding	32,975	−3.477	0.653	−6.737	−3.683	−3.408	−3.057	−2.535
Tax	32,975	−6.153	0.346	−6.861	−6.436	−6.151	−5.953	−5.202
Labor	32,975	10.618	0.385	9.718	10.399	10.611	10.88	11.485
Administrative (other)	32,975	−4.288	0.448	−5.342	−4.499	−4.279	−4.104	−3.065
C. Non-credit products (in log R$)								
Bonds and securities	32,975	2.506	5.945	0	0	0	0	27
Operations (other)	32,975	5.740	6.393	0	0	0	11.7	22
D. Credit granted to individuals within the half-year (modality outstanding average in log R$)								
Payroll-deducted	32,975	13.835	4.666	0.000	13.907	15.189	16.177	22.225
Non-payroll-deducted	32,975	13.487	3.640	0.000	12.944	14.277	15.339	21.825
Real estate	32,975	9.604	6.732	0	0	12.7	14.6	22
Rural	32,975	7.202	7.532	0.000	0.000	0.000	14.775	20.999
Vehicle	32,975	10.319	5.640	0.000	9.718	12.425	13.842	23.253
Other	32,975	13.754	3.268	0.000	12.895	14.198	15.543	22.721
E. Credit granted to non-financial firms within the half-year (modality outstanding average in log R$)								
Working capital	32,975	13.597	4.376	0.000	13.116	14.573	15.833	23.570
Revolving working capital	32,975	11.628	4.525	0.000	9.865	12.759	14.647	21.921
Infrastructure	32,975	8.404	6.340	0.000	0.000	11.545	13.495	21.456
Real estate	32,975	0.457	2.451	0	0	0	0	19
Investment	32,975	8.335	6.127	0.000	0.000	11.107	13.083	21.917
Account receivables	32,975	11.668	5.372	0.000	10.906	13.392	14.970	23.109
Agribusiness	32,975	2.913	5.875	0	0	0	0	22
Other	32,975	11.153	4.716	0.000	10.279	12.524	14.000	21.849
F. Credit granted to individuals before the half-year (modality outstanding average in log R$)								
Payroll-deducted	32,975	15.364	4.853	0.000	15.413	16.812	17.706	23.463
Non-payroll-deducted	32,975	14.690	3.495	0.000	14.188	15.380	16.373	22.081
Real estate	32,975	13.127	7.025	0.000	13.068	15.657	17.636	24.725
Rural	32,975	10.691	7.750	0.000	0.000	14.256	16.848	22.942
Vehicle	32,975	12.467	5.680	0.000	12.548	14.374	15.620	24.182
Other	32,975	14.866	3.313	0.000	14.291	15.423	16.424	23.277
G. Credit granted to non-financial firms before the half-year (modality outstanding average in log R$)								
Working capital	32,975	15.067	4.013	0.000	14.499	15.803	16.980	24.225
Revolving working capital	32,975	12.636	3.966	0.000	11.888	13.480	14.758	21.555
Infrastructure	32,975	12.536	6.364	0.000	12.060	14.899	16.525	23.909
Real estate	32,975	3.135	6.103	0	0	0	0	23
Investment	32,975	11.740	5.274	0.000	11.376	13.331	14.806	23.751
Account receivables	32,975	10.766	5.117	0.000	9.666	12.281	14.108	22.241
Agribusiness	32,975	5.424	7.179	0	0	0	13.5	23
Other	32,975	12.912	4.826	0.000	12.582	14.287	15.561	23.854
H. Credit effective prices of modalities for individuals (in % per half-year)								
Payroll-deducted	30,115	12.636	4.599	0.214	9.292	11.333	16.181	144.894
Non-payroll-deducted	31,258	27.087	9.870	0.245	20.197	26.842	34.344	199.026
Real estate	22,553	4.537	3.387	0.107	3.143	3.848	4.602	64.736
Rural	16,056	4.622	3.269	0.104	2.958	3.853	5.650	95.905
Vehicle	26,036	12.766	6.277	0.290	7.926	10.351	17.200	97.634
Other	31,857	26.442	15.820	0.113	12.109	22.643	40.033	155.509
I. Credit effective prices of modalities for non-financial firms (in % per half-year)								
Working capital	30,442	14.510	7.131	0.141	9.383	13.803	18.781	169.255
Revolving working capital	30,172	34.342	15.546	0.156	22.768	33.807	46.216	176.428
Infrastructure	21,411	5.400	5.343	0.128	2.924	4.144	6.064	80.212
Real estate	1,140	4.808	4.406	0.118	2.749	3.997	5.636	59.406
Investment	21,959	10.383	5.681	0.153	6.924	9.507	12.853	191.624
Account receivables	28,012	8.928	3.395	0.134	6.515	8.757	11.153	43.592
Agribusiness	6,593	3.448	2.916	0.104	2.556	3.192	3.881	93.275
Other	28,809	13.256	9.654	0.101	7.961	11.306	16.621	194.948

Figure B1 shows the distribution of the effective price, marginal cost, and Lerner over time aggregated by locality[60] for the overall credit market in each locality. The black line denotes the median

[60]We compute these distributions by firstly obtaining a local aggregate for each variable weighing bank-modality observations within the same locality and time (semiannual period) by local credit income. Then we display the distributions of



(a) *(b)* *(c)*

Figure B1. *Distributions of effective prices, marginal costs and Lerner indices over time at the locality level.*

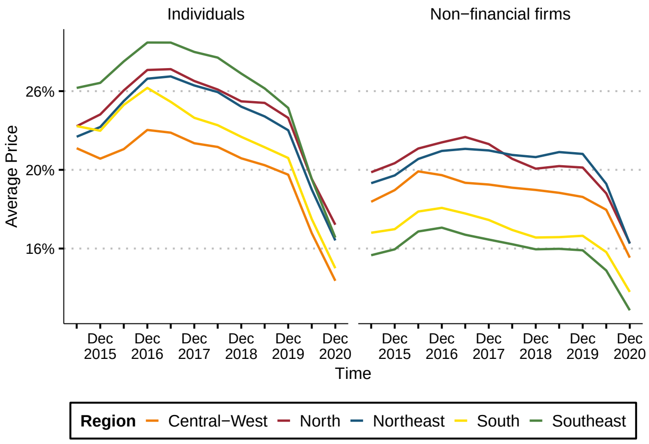
of the variables and the distribution is plotted for the range of percentiles 25 to 75%. There is a large dispersion of these variables across localities. This fact suggests national-level analysis may overlook many important aspects of market power across localities, reinforcing the need of developing methods to estimate market power locally. Effective prices decrease over time, with a substantial reduction of its dispersion after the COVID-19 outbreak. Marginal costs have an inverted U-shaped behavior, with similar dispersion across the sample period. Lerner decreases over time, with increasing dispersion. The similar trends of the effective price and Lerner indicate the effective price channel (and not the marginal cost channel) dictates the Lerner index in the aggregate level.

We now look at average effective price, marginal cost, and Lerner for individuals and non-financial firms across Brazilian regions. Figure B2a shows the average effective price of operations of credit to individuals was higher than to non-financial firms across Brazilian regions. In 2020, there was a significant drop in the average effective price in both segments, mainly for credit to individuals. This fall may be correlated with the effects on the economic activity of the COVID-19 pandemic and the debt renegotiation measures that took place in the period, which directly reduced the credit income flow of credit operations.

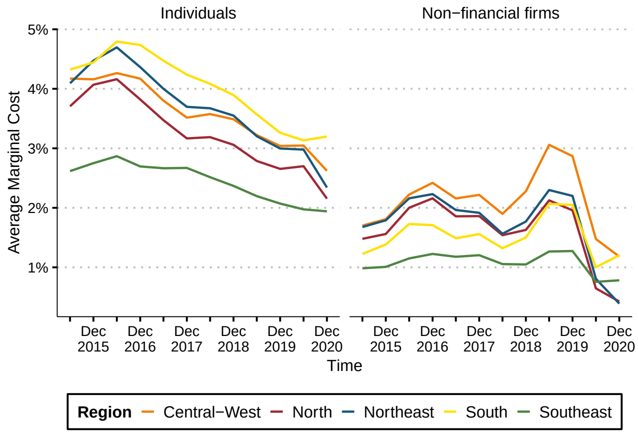
Figure B2b shows the marginal cost of credit to non-financial firms was lower than that to individuals across Brazilian regions. Marginal costs of individuals credit consistently decreased over time. They remain steady for firms until 2018 when marginal costs start rising until the end of 2019. After the COVID-19 outbreak, marginal costs of individuals and non-financial firms credit decreased, notably for non-financial firms and less developed regions (North, Northeast, and Central-West).

Figure B2c exhibits the local Lerner indices for credit to individuals and to non-financial firms across Brazilian localities. Until 2019, the Lerner indices increased for individuals while they decreased for non-financial firms. The increase in local market power of banks in credit to individuals suggests that, despite the decrease in effective prices, the reduction in marginal costs was dominant. Conversely, the Lerner index decrease for credit to non-financial firms indicates the increase in marginal costs prevailed over the effective price channel. Despite the Southeast and South being the most developed regions in Brazil, they have different patterns for the Lerner index: the Southeast has the highest Lerner index

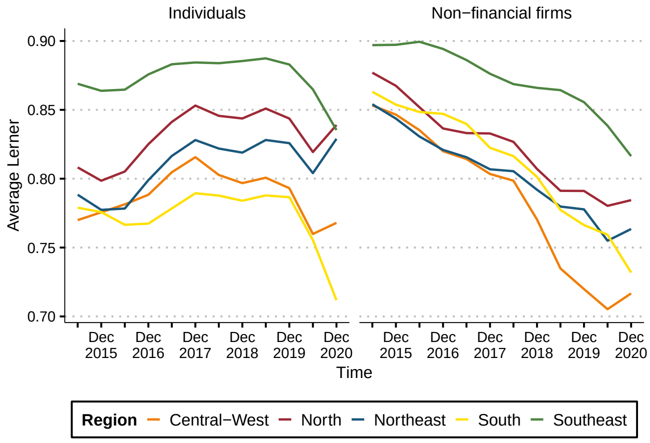
these local aggregates for each date, for each variable.



(a) Effective Price



(b) Marginal Cost



(c) Lerner

Figure B2. *Evolution of effective prices, marginal costs and Lerner indices aggregated by region and segment (individuals and non-financial firms).*

(because of the lowest marginal costs), and the South has one of the lowest (one of the highest marginal costs).

Part of the heterogeneity we observe in the results may arise from different shares of credit modalities in each region. To mitigate this issue, we now further drill down our results and look at the credit modality level across Brazilian regions. Figures B3 and B4 display the average effective price of each credit modality for individuals and non-financial firms, respectively, across Brazilian regions. While the effective price trend seems similar across regions, the relative effective price ordering within a credit modality changes across regions, suggesting there is no dominance of a particular region in terms of pricing. Overall, there is a decrease of effective prices in Brazil for individuals and non-financial firms, consistent with our finding at the aggregate level in Figure B1a.[61]

Effective prices of payroll-deducted credit are very similar across regions and are, on average, 10–15 p.p. lower than non-payroll-deducted credit. Both modalities have stable effective prices until December 2017, when they consistently fall. There is a higher dispersion of non-payroll-deducted across regions, with lower effective prices in the Central-West and South. Even though collateralized, vehicle financing

[61] The fan charts in Figure B1 are less affected by large banks than the averages we report in Figure B2. Even though they show the same finding, they offer complementary views: the results are pervasive to all banks and are not only driven by large banks.

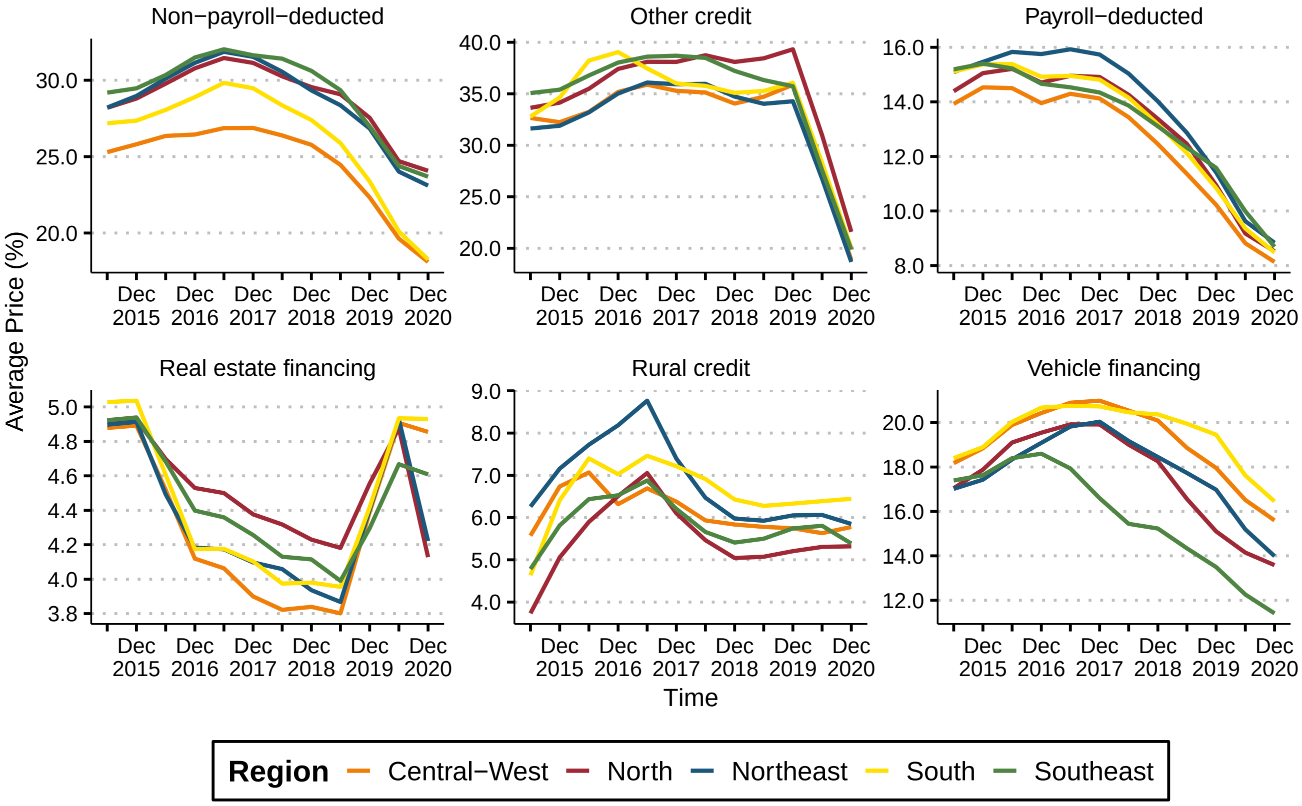


Figure B3. *Evolution of the average effective price of each credit modality for individuals aggregated to the regional level from 2015 to 2020.*

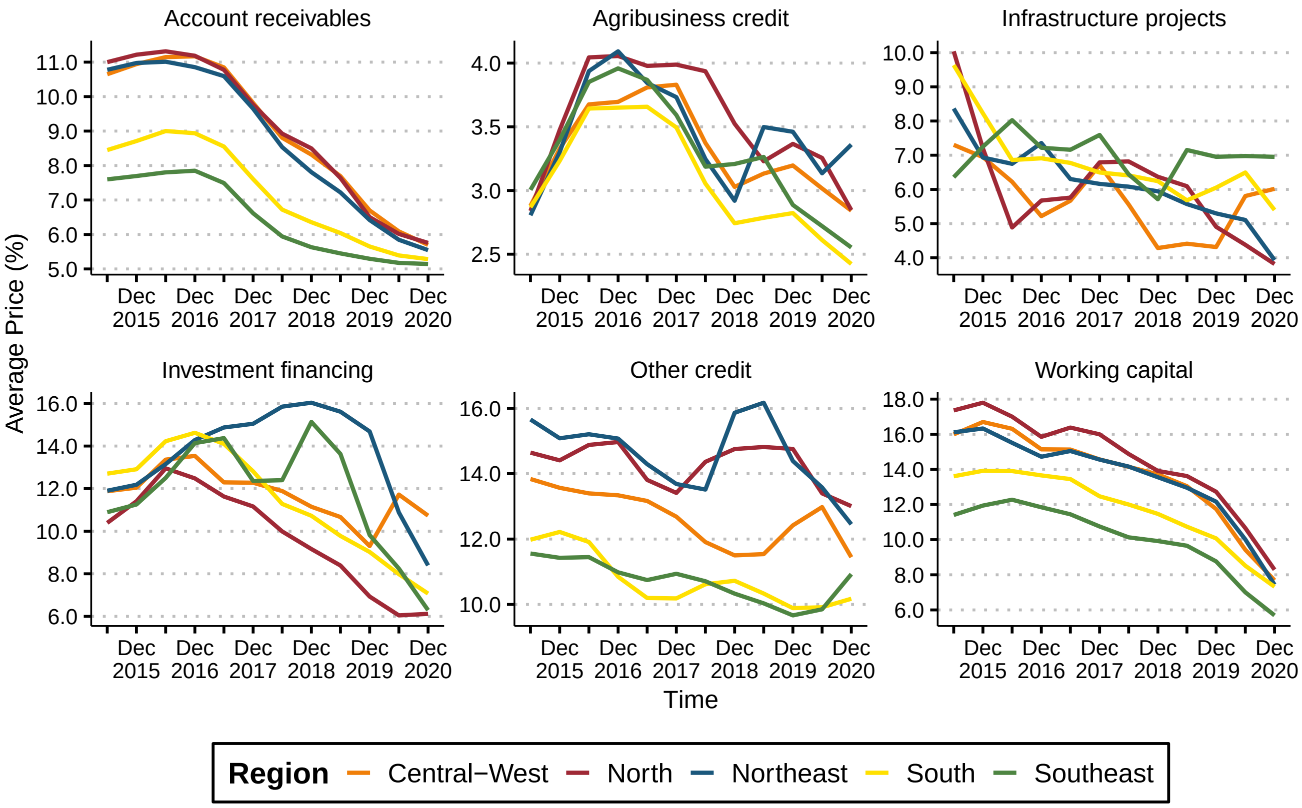


Figure B4. *Evolution of the average effective price of each credit modality for non-financial firms aggregated to the regional level from 2015 to 2020.*

shows increasing dispersion over time, with the lowest effective prices in the Southeast. The "other credit" modality includes overdraft operations.[62] The significant decrease in effective prices of this modality may be a combined effect of the COVID-19 outbreak and a new regulation[63] introduced in January 2020 that established a maximum cap for the interest rate in overdraft operations.

Short-term credit for non-financial firms, such as working capital and account receivables, has lower effective prices in more developed regions. These modalities have roughly the same (higher) effective price in less developed regions. Effective prices of working capital decreased substantially in 2020, reflecting the government's credit programs to mitigate the effects of the pandemic. Effective prices of agribusiness credit are the lowest in the South, a region with developed rural activities.

Figures B5 and B6 display the marginal cost of each credit modality for individuals and non-financial firms, respectively, across Brazilian regions.[64, 65] Overall, marginal costs are falling in the pre-pandemic period and increasing during the pandemic for individuals. One exception is vehicle financing, whose evolution pattern is the opposite. Marginal costs for individuals are typically the lowest in the Southeast region, which is consistent with the concentration of bank headquarters in the region and potential gains of scale. Although being an economically developed region, marginal costs in the South are usually high, especially for payroll-deducted and non-payroll-deducted credit.

Marginal costs for non-financial firms are typically constant in the pre-pandemic period. During the pandemic, in most cases they increase in the first half-year of 2020 and then drop in the second half-year. However, marginal costs end up 2020 with higher levels compared to pre-pandemic values. Exceptions are working capital in less developed regions and investment financing in the South and Central-West. Again, marginal costs are usually the lowest in the Southeast region. The gap in marginal costs of the Southeast to the remainder regions is substantial for working capital and account receivables, modalities with the highest within-half-year credit volumes.

Figures B7 and B8 exhibit the Lerner index of each modality of credit to individuals and non-financial firms, respectively, across Brazilian regions. Generally, Lerner indices increase for most modalities of credit to individuals in the pre-pandemic period and then fall after the COVID-19 outbreak. Since both effective prices and marginal costs fall, the increase in the Lerner index indicates the marginal cost channel prevails over the effective price channel. Vehicle financing has an opposite temporal pattern. The Lerner index for rural credit changes less following the COVID-19 pandemic. Both COVID-19 and changes in the overdraft regulation may drive the decrease of the Lerner index for the "other credit" modality.

[62] In 2019, overdraft operations accounted for 17.9% of "other credit" modality, whereas in 2020, this share was 11.7%.

[63] Resolution n. 4,765 of October 27$^{\text{th}}$, 2019, of the Central Bank of Brazil, that came into effect in January, 6$^{\text{th}}$, 2020.

[64] Shaffer and Spierdijk (2017) discuss the existence of negative marginal costs and Lerner index in estimations of the translog specification. One reason is that the translog functional form may be too restrictive, causing economically implausible marginal costs and associated Lerner indices. We face the same problem in the estimation, as we deal with many outputs at a very granular level (bank-locality). For instance, marginal costs for vehicle financing are negative in Figure B5 during 2015 and 2020 in the Central-West. Nonetheless, the shares of negative marginal costs and Lerner are not relevant.

[65] A comparison among the marginal cost levels of credit modalities in each segment suggests that they are negatively related to their average tickets.

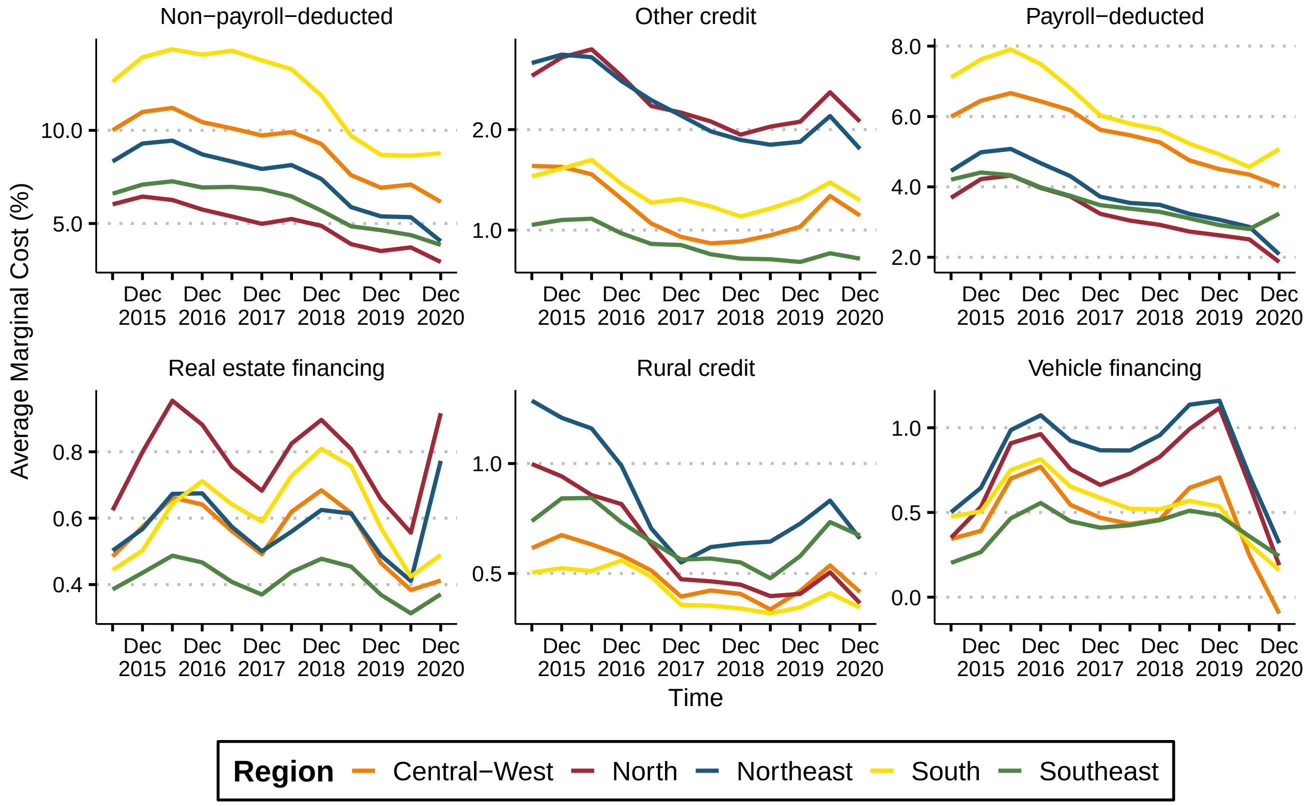


Figure B5. *Evolution of the marginal cost of each credit modality for individuals aggregated to the regional level from 2015 to 2020.*

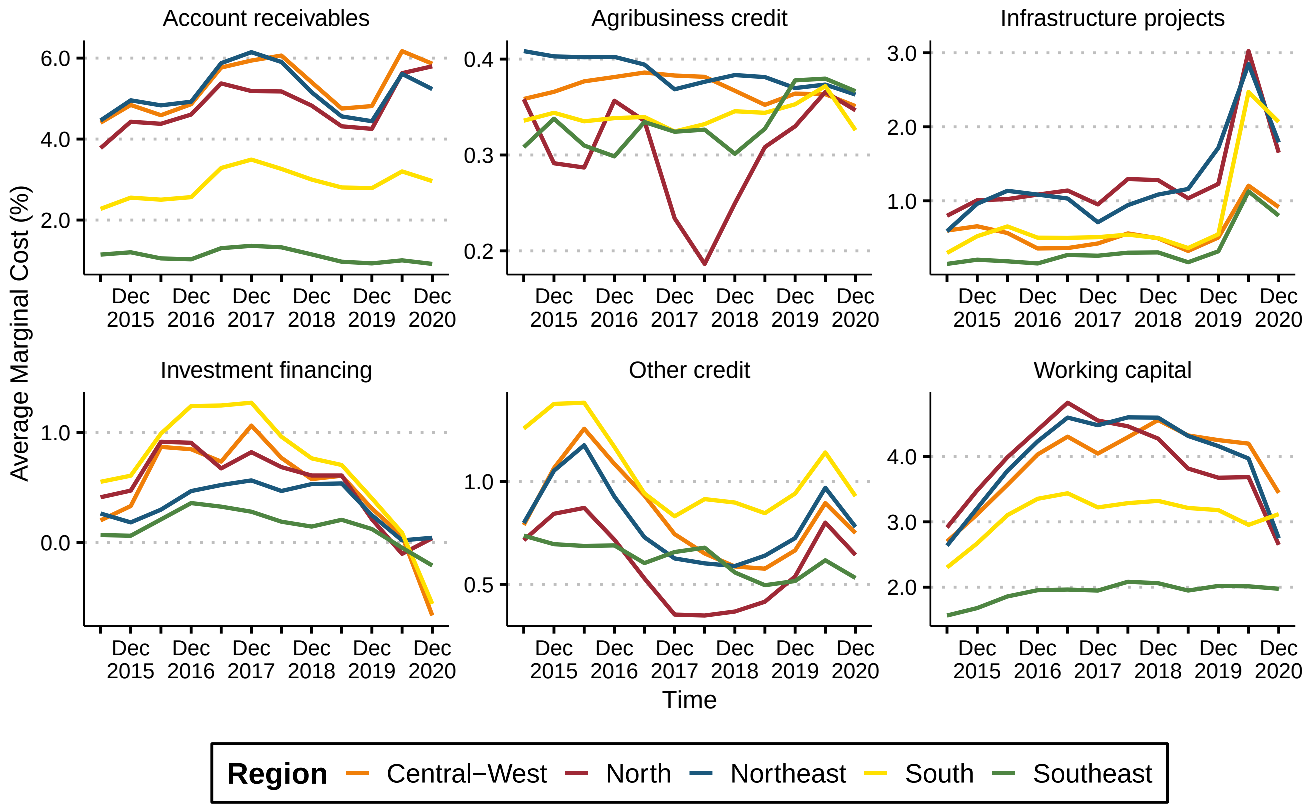


Figure B6. *Evolution of the marginal cost of each credit modality for non-financial firms aggregated to the regional level from 2015 to 2020.*

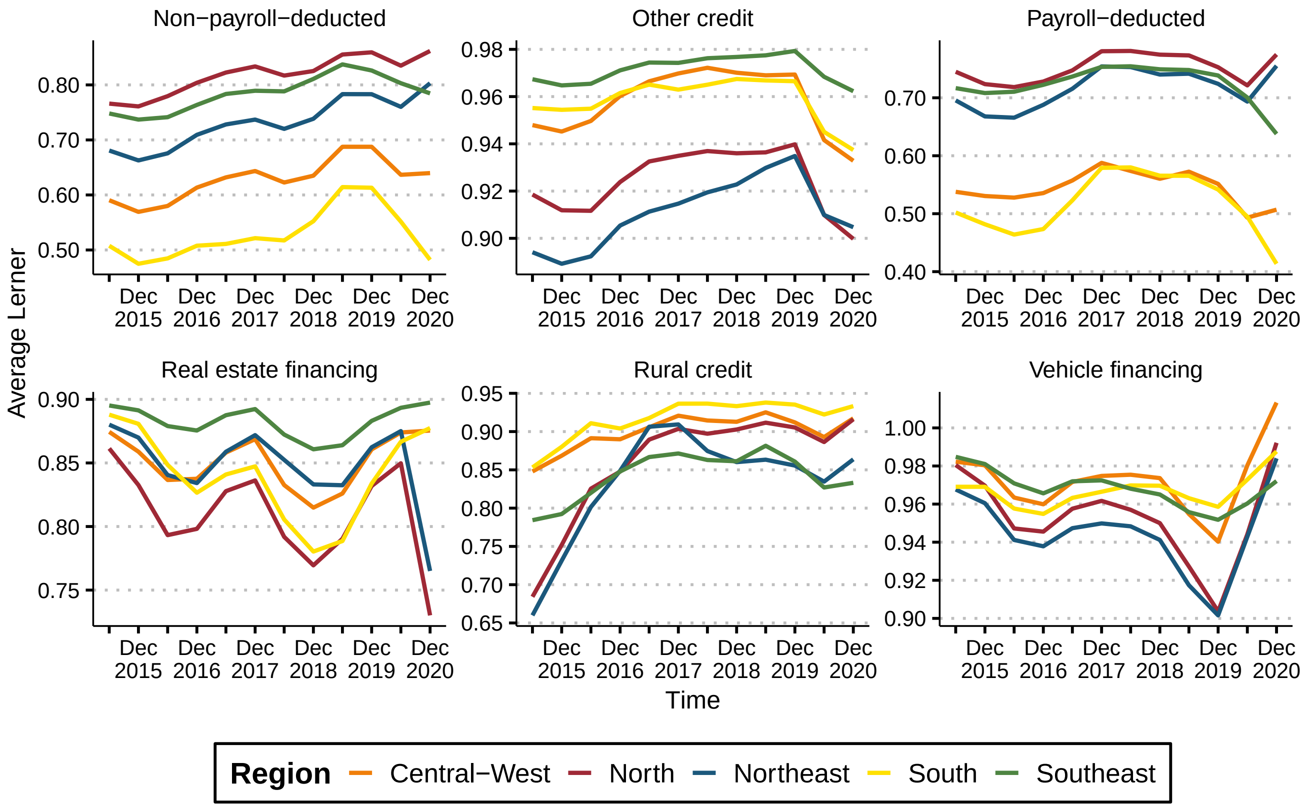


Figure B7. *Evolution of the Lerner index cost of each credit modality for individuals aggregated to the regional level from 2015 to 2020.*

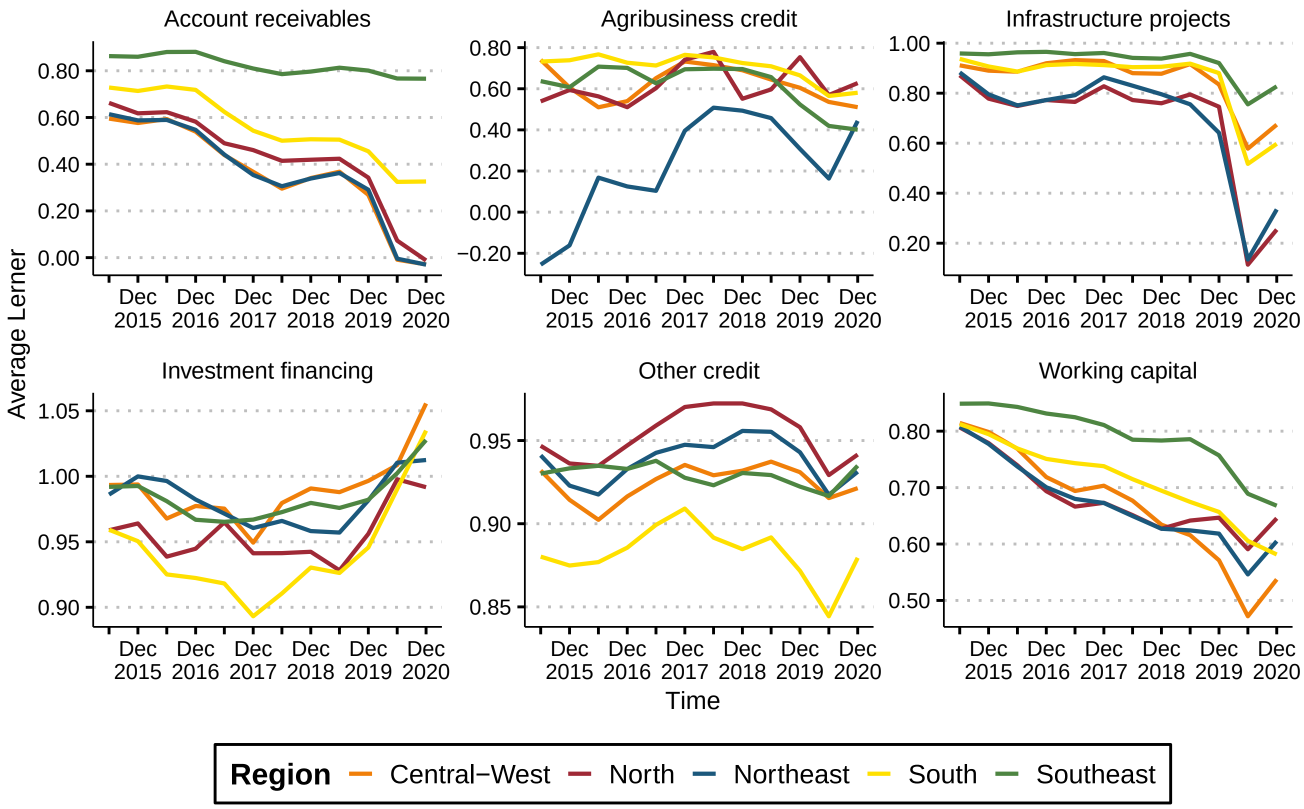
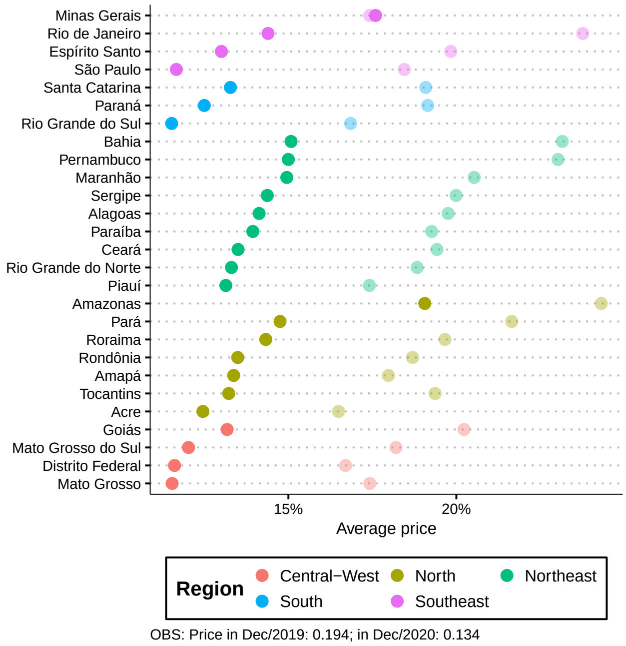


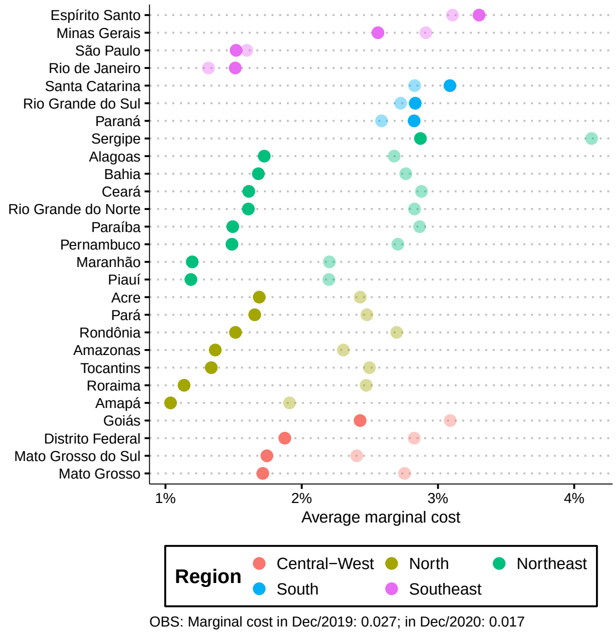
Figure B8. *Evolution of the Lerner index cost of each credit modality for non-financial firms aggregated to the regional level from 2015 to 2020.*

There is a mixed pattern in the evolution of the Lerner index of credit modalities to non-financial firms. For working capital and account receivables, in general, the Lerner index decreases in both pre-pandemic and during the pandemic. An exception is working capital in less developed regions. The decrease in effective prices is the primary driver of decreases in the Lerner index of these modalities. While roughly constant during the pre-pandemic period, the Lerner index of infrastructure projects falls substantially during the pandemic. The sharp increase in marginal costs drives this increase. The Lerner index of investment financing increases over time, and there is no dominance of effective prices nor marginal costs in explaining the Lerner index for this modality.

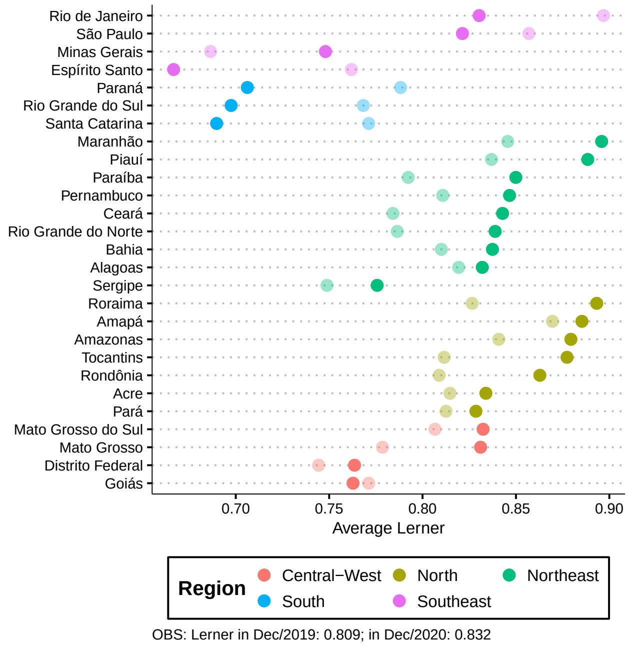
Figure B9 shows a comparison of average effective prices, marginal costs, and Lerner indices when we aggregate these measures at the state level. These results suggest competition at a national level may overlook many important local aspects of local credit markets. The proposition of our methodology attempts to contribute to the literature in this direction.



(a) Effective Price



(b) Marginal Cost

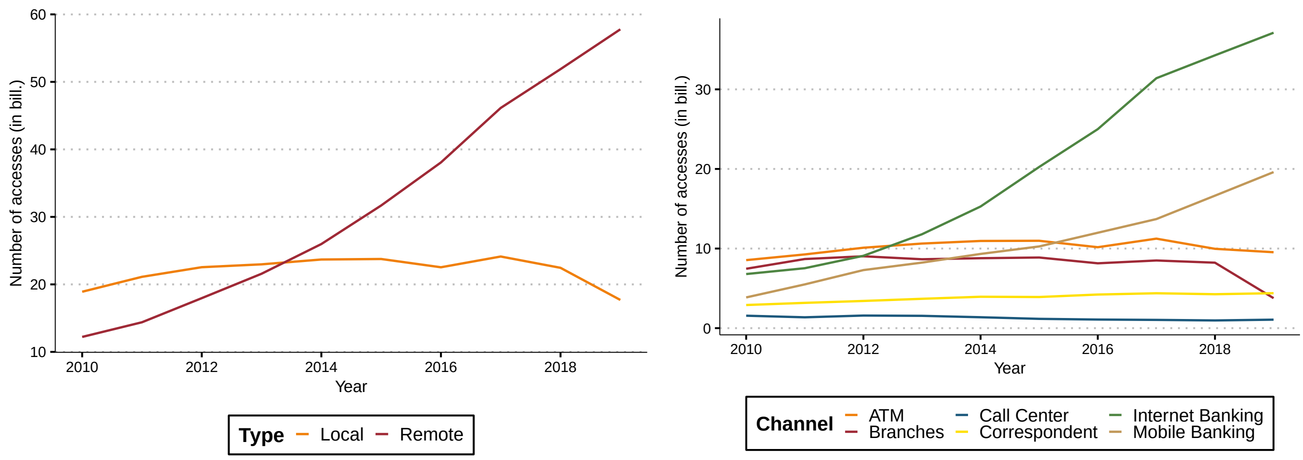


(c) Lerner

Figure B9. *Average effective prices, marginal costs, and Lerner indices for Brazilian states in the pre-pandemic (December 2019, more transparent disks) and during the pandemic (December 2020, more opaque disks). We aggregate bank-modality-locality observations within the same state.*

Appendix C Additional material

C.1 Local and remote transactions in Brazil



(a) *Local vs. remote transactions*

(b) *Transactions by access channels*

Figure C1. *Number of transactions in Brazil from 2010 to 2019. (a) Local vs. remote transactions. (b) Transactions for each access channel (ATM, bank branch, call center, banking correspondents, internet banking, mobile banking). Transactions include invoice payment, deposits, transfers, loans, withdraw, financial statement queries, other financial and non-financial transactions. Data is public and comes from the Central Bank of Brazil (access here > Financial Inclusion > Relationship with the NFS > Transaction > [“Number of transactions by type” (a) and “Type of transactions per access channel” (b)].*

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