Non-Technical Summary

Crises affect financial institutions differently. Some may be more affected, becoming weaker or even going bankrupt. Others may be better prepared, leveraging their advantages and strengthening their positions. These changes in the financial system impact *market power* in non-trivial ways: a bank's ability to raise prices (interest rates) beyond competitive levels without losing clients, thus generating above-average profits. This paper proposes a methodology to assess how the COVID-19 pandemic affected bank market power in local credit markets and applies this methodology to the Brazilian banking system.

Brazilian municipalities vary significantly in terms of economic and financial development, climate, and demography, potentially resulting in a wide variety of local market power profiles. In addition, the COVID-19 pandemic hit municipalities at different times, beginning in the most populous capitals with large airports and then spreading to inland municipalities. Furthermore, the federal government's efforts to combat the economic effects of COVID-19 have been broadly consistent among municipalities. The contrasting differences between, on the one hand, the diversity of municipal profiles and their associated timing to experience COVID-19 cases and, on the other hand, the uniform economic measures taken by the government to counteract the COVID-19 provide ideal conditions for assessing the pandemic's influence on the market power in local credit markets empirically.

We explore this cross-sectional variation of COVID-19 prevalence over Brazilian localities and use bank branch, individual, and firm-level databases to assess how the pandemic affected the two components of market power: *the effective price* (effective interest rate includes the contractual rate plus taxes and other fees and is net of losses) and *the marginal cost* (additional cost of the bank to grant another unit of credit). We eliminate confounding factors arising from changes in bank-specific credit supply by comparing the *same* bank operating *across* similar localities with *different* COVID-19 prevalence levels.

We show the COVID-19 pandemic had little effect on the effective price (credit income over the volume of credit concessions): bank branches compensate for the decline in credit income by also decreasing the volume of credit concessions. However, COVID-19 increased marginal costs because bank branches cannot easily adjust their costs in response to the reduction in credit concessions. As a result, COVID-19 reduced the bank's market power in local credit markets more affected by the virus, primarily through the marginal cost channel. However, IT played a critical role during the COVID-19 outbreak: bank branches that invested more in IT before the COVID-19 outbreak were less impacted, as they could more easily replace local borrowers with remote ones. Consequently, they suffered less from the adverse economic effects of the pandemic and ended up leveraging their position in terms of market power compared to other bank branches.

Sumário Não Técnico

Crises afetam instituições financeiras de forma diferente. Algumas podem ser mais afetadas, se enfraquecendo ou indo até à falência. Outras podem estar mais bem preparadas e saírem fortalecidas. Essas mudanças no sistema financeiro impactam o poder de mercado de forma não trivial, ou seja, o poder que um banco tem de fixar preços (taxas de juros) acima do nível competitivo sem perder clientes, obtendo assim lucro acima da média. Este trabalho propõe uma metodologia para avaliar como a crise da pandemia da Covid-19 impactou o poder de mercado dos bancos no mercado de crédito local e aplica essa metodologia ao sistema bancário brasileiro.

Os municípios brasileiros são muito diferentes no que se refere ao desenvolvimento econômico e financeiro, ao clima e à demografia, permitindo perfis muito distintos de poder de mercado local. Além disso, a pandemia de Covid-19 atingiu os municípios de forma não simultânea, começando pelas capitais mais populosas com grandes aeroportos e se espalhando para as cidades do interior. Ainda, as medidas que o governo federal tomou para combater os efeitos econômicos da Covid-19 são as mesmas para todos os municípios. O contraste entre, de um lado, a diversidade dos municípios e do momento em que foram atingidos pela pandemia e, de outro, a uniformidade das medidas econômicas adotadas em todo o país fornece as condições ideais para a avaliação empírica do impacto da Covid-19 no poder de mercado no crédito local.

Nós exploramos essa variedade da prevalência da Covid-19 entre municípios brasileiros e usamos diversas bases de dados em nível de agências bancárias, indivíduos e firmas para avaliar como a pandemia afetou as duas componentes do poder de mercado: o preço efetivo (a taxa de juros efetiva inclui a taxa contratual, impostos e outras taxas, e é líquida de perdas) e o custo marginal (custo adicional do banco para conceder um real a mais de crédito). Para eliminar fatores que surgem de mudanças na oferta de crédito de um banco específico, comparamos um mesmo banco operando em localidades semelhantes, mas com diferentes níveis de prevalência da Covid-19.

Nós mostramos que a pandemia da Covid-19 não impactou de forma significativa o preço efetivo (renda de crédito sobre o volume de concessões de crédito): as agências bancárias compensam a queda nas receitas de crédito com uma redução na concessão de crédito. No entanto, a Covid-19 aumentou os custos marginais principalmente porque as agências bancárias não conseguem ajustar rapidamente seus custos em resposta à redução nas concessões de crédito. Portanto, a Covid-19 reduziu o poder do banco em mercados locais de crédito mais afetados pela pandemia, principalmente pelo canal do custo marginal. No entanto, TI teve um papel crucial na pandemia: agências bancárias que gastaram mais em TI antes da pandemia de Covid-19 foram menos impactadas, pois conseguem substituir mais facilmente os tomadores locais por remotos. Consequentemente, elas sofreram menos com os efeitos adversos da pandemia e acabaram melhorando seu posicionamento em termos de poder de mercado em relação a outras agências bancárias.

COVID-19 and Local Market Power in Credit Markets

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Abstract

This paper investigates how COVID-19 affected the local market power of Brazilian credit markets. Despite extensive research on financial crises, the mechanisms by which a pandemic might influence local market power remain unclear. We first propose a new methodology to estimate bank market power at the local level. We design a local and data-intensive version of the Lerner index by developing heuristics to reallocate national-level bank resources across local inputs, products, and costs for each of its branches by leveraging many rich data sources. We then exploit the cross-sectional exogenous variation of COVID-19 prevalence over Brazilian localities to analyze how it influenced local market power through the effective price and marginal cost channels. Despite reducing the economic activity substantially in more affected localities, COVID-19 did not significantly impact the effective price channel: bank branches offset the decrease in credit income with a corresponding reduction in the volume of credit concessions. However, COVID-19 raised marginal costs primarily because bank branches were unable to rapidly adjust their costs in response to the decrease in volume of credit concessions, highlighting the stickiness of cost factors as a result of economic rigidities and legal and financial frictions. Consequently, COVID-19 reduced the local market power of bank branches in areas more affected by COVID-19 via the marginal cost channel. Bank branches that spent more on IT before the COVID-19 outbreak suffered less: they could more easily replace local borrowers with remote ones. Cost adjustment frictions reduce, and they enjoy higher local market power. We also design a bank-specific measure of exposure to COVID-19 by exploiting the bank-specific credit dispersion across localities before the outbreak and the associated localities' COVID-19 prevalence. Banks more exposed to COVID-19 increased their local market power mainly via the effective price channel, which operated through a negative supply shock and not increased credit income. The paper provides new insights as to how crises can affect local market power in non-trivial ways.

Keywords: COVID-19, market power; competition; Lerner index; IT.

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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 bank market power for different banks and localities and apply it to the Brazilian banking sector by leveraging the use of many rich microdata sets.

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, while 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 containment measures were implemented, the sectoral composition and structure of their economies, 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

[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, 2003; 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] del 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).

crisis, like a financial crisis, slowed economic growth, increased 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 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 developed

[7] Health crises are more complex than financial crises. COVID-19 is extremely contagious and can be fatal, necessitating governments to take drastic measures to contain the outbreak and mitigate its economic consequences. Due to the severity of its effects, 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 leverage 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.

IT systems *ex-ante* the pandemic improved their positioning in terms of market power.

Bank market power is an important topic for policymakers and academia because it directly impacts the real economy. A more competitive banking system can lower loan interest rates and increase the returns on deposits, boosting savings and investment. Thus, it promotes economic development. However, it can exacerbate adverse selection and moral hazard problems and reduce the credit availability to more opaque borrowers, the diversification of business risk, and the benefits of 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]

Bank market power assessment is typically at the national level, generally because of the lack of microdata to estimate the banks' local production function. In addition, bank branches may have limitations in their choices due to the organizational structure of financial institutions. First, bank headquarters can centralize business decisions and establish guidelines for standardizing operational tasks across locations, limiting the competence of bank branches (i.e., local branches would not necessarily be optimizing costs). Second, banks may centralize certain inputs, such as funding, in specific offices, which decide how to redistribute them to individual branches. This governance structure makes it challenging to measure input costs at the local level. Third, local characteristics—such as court efficiency, environmental risks, economic dynamism, and diversification of economic activities—may impact compliance with the bank headquarters' guidelines regarding local supply and pricing of banking products. It is often not possible to account for these local differences when measuring market power.

We overcome these limitations 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 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.

The Lerner 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] This means that banks with greater market power can extract higher profits, as an increase in credit

[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. Banks can mitigate increased credit risk by raising capital or implementing measures to mitigate risks.

[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.

prices results in a comparatively lower decrease in the demand for loans. 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.[14] We improve this definition in this paper. First, we do not use the bank's outstanding credit, which potentially contains old credit operations that do not necessarily capture the current competitive market conditions. Instead, we explicitly separate new credit grants from old credit 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.[15] This limitation biases credit prices upwards materially if there is a substantial volume of very short-term credit. To correct this problem, we resort to (billions of) *daily* loan-level income data with balance position and cash flows before and after every repayment. Third, we estimate marginal costs for each bank branch and credit modality using a translog 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. Local market power in the Lerner sense can change via two channels: *the effective price channel* and *the marginal cost channel*. All else equal, increases in the first (second) lead to higher (lower) market power.

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,[16] 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 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. Additionally, we consider the following factors in our empirical analysis: (i) we have detailed datasets, (ii) bank branches can offer credit

[14] *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.

[15] As an example, consider a \$100 credit operation that matures in one week and began 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.

[16] 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.

in markets outside their physical location,[17] and (iii) we are interested in measuring the channels through which market power can change.

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.[18] First, the virus hit heavily state capitals, which are the most populous areas and host all core airports, before spreading significantly to inland municipalities. The substantial differences in how COVID-19 has affected different places provide us with exogenous variation across localities to understand how it has changed local market power in Brazilian credit markets. 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.[19]

We use this cross-sectional variation to investigate how COVID-19 has affected the effective price and marginal cost channels that, together, shape local market power in Brazilian localities. Localities with a higher COVID-19 prevalence are more likely to implement public health measures, such as horizontal social distancing, lockdown, and quarantines. These measures affect economic activities, notably those relying on an in-site labor force and consumption. Using data on firm income from credit and debit card transactions, invoices, wire transfers, and exports, we first show localities with higher COVID-19 prevalence had lower local economic activity than similar localities with lower levels of COVID-19 prevalence. A one-standard-deviation increase in the share of the local population affected by COVID-19 (4%) causes a loss of approximately R$ 272 million in the locality-level firm income, or around 19% of the sample average, highlighting the substantial economic impact. The decline in local output has implications for the credit market and has a non-trivial

[17] A bank branch can be physically located in one location and lend to companies or individuals in another location. With the advance of digitalization, this behavior has become more common, and the exact physical boundaries of local markets that concentration measures require have become blurred.

[18] 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 populous and located closer to core airports—before moving on to inland municipalities (Paul et al., 2020; Wang et al., 2020b).

[19] Our local COVID-19 prevalence measure is unrelated to the localities' size, preponderant economic activities, and distance to capital if we compare localities of similar wealth levels and geographically close to each other.

effect on local market power through the effective price and marginal cost channels.[20]

To address how COVID-19 has affected local market power through these channels, we resort to a within-bank and across-locality empirical strategy. This setup enables us to eliminate confounding factors arising from changes in bank-specific credit supply while letting locality-specific conditions vary. Our COVID-19 prevalence measure provides exogenous variation across localities. To mitigate concerns with omitted-variable biases, we compare across localities geographically close to each other and with similar wealth levels.[21] 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.

Despite the significant impact of COVID-19 on local economic activity, we find that it does not substantially affect the effective price channel for localities more affected by the pandemic. We then investigate the effective price components: (i) credit income and (ii) granted credit. We expect lower economic activity to reflect lower income levels, which should reduce credit income either through increased non-performing loans or increased postponements of bank debt repayment enabled by the introduction of government programs to combat the effects of COVID-19. This hypothesis is indeed the case: a one-standard-deviation increase in the local COVID-19 prevalence reduces the locality-level credit income by R\$ 0.98 million or 19% of the sample average following the COVID-19 outbreak. Simultaneously, granted credit decreases by R\$ 2.81 million or 18.6% of the sample average.[22] Therefore, the substantial decrease in credit income was offset by a similar decrease in local credit granting, resulting in a roughly similar effective price in localities with more COVID-19 prevalence when comparing branches of the same bank. We conclude the effective price channel is not a substantial component that affected banks' local market power across localities during the pandemic.

We find economically significant results for the marginal cost channel. A one-standard-deviation increase in the local COVID-19 prevalence (4%) increases banks' marginal costs by one cent during the COVID-19 pandemic. This value is expressive as the marginal costs' sample mean is 5.9 cents. If banks could adjust their total costs based on their output volumes frictionlessly, we would not expect changes in their marginal costs. Theoretically, decreases in granted credit should be accompanied by reductions in bank branches' total costs. We find that bank branches' total costs do not change in localities more affected by the COVID-19, suggesting banks cannot reduce their

[20] 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. We run a robustness test only on non-financial firms without branches and obtain qualitatively the same results.

[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, 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 *per capita* GDP levels.

[22] We also find the borrowers' riskiness (provisions as a share of the outstanding credit) and contractual prices increase. While we cannot fully insulate credit demand in this empirical specification because we do not use loan-level data, the decrease in credit volume and the increase in interest rates suggest a potential supply shock. We will elaborate on this further in the following paragraphs.

total costs in the short term, despite the relative reduction in credit grants. This finding highlights the short-term stickiness of many cost factors due to economic, 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. The reduction in local market power is pervasive: it occurs for credit modalities for non-financial firms and individuals, and for modalities that typically mature in the short and long term.

The COVID-19 pandemic highlighted the importance of IT in the banking sector. Bank branches that spent more on IT *ex-ante* the COVID-19 experienced fewer frictions arising from adjustments in their total costs. IT development enables credit transactions electronically with borrowers regardless of their locality and provides flexibility for credit operations. Bank branches that spent more on IT before COVID-19 are likely to have more developed online banking systems, enabling remote transactions to a greater extent. We find empirical evidence that bank branches that spent more on IT before 2020 could more easily replace borrowers in localities more affected by COVID-19 with remote borrowers outside the locality. This feature permitted bank branches to be less sensitive to local borrowers' conditions. Therefore, bank branches better positioned in terms of IT spending *ex-ante* the COVID-19 outbreak are less affected and can maintain their local market power through rearrangements of their borrowers' portfolios, potentially focusing on areas less affected by COVID-19.

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.

The previous analysis does not allow us to understand how COVID-19 affected *different* banks. To do so, we also perform a within-locality and across-bank analysis. This empirical strategy enables us to control for any locality-specific factor that could drive our results, such as COVID-19 local prevalence. To obtain exogenous variation across banks, we construct a measure of bank-specific exposure to COVID-19 by averaging the locality-specific COVID-19 prevalence in places where the bank has credit weighted by the bank's outstanding credit in 2019 in that locality. [23] Even though the measure is unrelated to bank size, we opt to compare banks of similar size within a locality because the Brazilian government introduced many programs to incentive credit to combat the effects of the pandemic that large banks operationalized, which could distort our results. This strategy also enables us to control for any size-specific changes in banking regulation, such as the

[23] We show this measure is unrelated to bank-level liquidity (Liquidity Coverage Ratio), solvency (capitalization level), bank size and control.

introduction of the prudential segmentation framework in Brazil.[24] Our variation comes from banks of similar size operating in the *same* locality and *same* credit modality but with *different* levels of exposure to COVID-19.

We find a one-standard-deviation increase in the bank's exposure to COVID-19 (1%) raises the effective price by 1.13 p.p. after the COVID-19 outbreak compared to a bank of similar size operating in the same locality and credit modality. This effect is economically relevant (8.3% of the sample average). Effective prices increase primarily as a result of decreased credit granting, and not increased credit income. Contractual prices also increased in 2020 for banks more exposed to COVID-19. Put together, our findings indicate COVID-19 caused a negative credit supply shock in more exposed banks. Banks more exposed to COVID-19 also reduced their credit portfolio riskiness following the COVID-19 outbreak. This deleveraging indicates more exposed banks searched for less risky borrowers following the negative credit supply shock.

We do not find evidence of the bank's exposure to COVID-19 affecting local marginal costs when comparing banks of the same size within the same locality and credit modality. The net effect is an increase in the local market power of banks more affected by COVID-19 through the effective price channel. The effective price increases due to a negative supply shock and not increased credit income.

We also perform many additional tests. We find banks with higher local market shares before 2020 charged even higher effective prices following the COVID-19 outbreak, suggesting local concentration plays a role in shaping local market power primarily via the effective price channel. This empirical finding is in line with Joaquim et al. (2019). In contrast, banks with more liquidity before 2020 charged relatively lower effective prices during 2020, suggesting financial constraints influenced the effective price channel during the pandemic. This result highlights the existence of common effects on market power between pandemics and financial crises, similar to the findings of Cubillas and Suárez (2018).

The paper proceeds as follows. Section 2 discusses the related literature. Section 3 introduces the baseline model, datasets, and definition of the productive process for Brazilian bank branches. Section 4 analyzes the local competition in credit markets. Section 5 explores how the COVID-19 pandemic affected local credit markets and banks. Section 6 concludes. The Appendices contain additional analysis of variables and interesting correlations.

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).

[24] The Resolution n. 4.553/2017 of the National Monetary Council introduced the concept of prudential segmentation, which establishes an increasing set of rules proportional to the size of the bank, integration with international markets, and importance to the domestic economy. The strategy of comparing banks of similar size controls for time-varying changes in this size-specific regulation.

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).[25] 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 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., 2020a). 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

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

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. We believe this is the first study on how COVID-19 affected local market power using comprehensive data for an important emerging market country.

3 Methodology

3.1 Model definition

In this paper, we evaluate banks' local credit market power using Lerner indices. We define a local credit market in terms of a credit product, a time period, and the credit location, regardless of the borrower's location. Although a bank may operate over the entire national territory, we consider that each bank in each locality is a local firm, subject to local input prices, offering prices and quantities of products locally and optimizing costs locally.

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 (unobservable 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:

$$L_{blt}^{(j)} = \frac{p_{blt}^{(j)} - MC_{blt}^{(j)}}{p_{blt}^{(j)}}, \tag{1}$$

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.

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.[26] 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

[26] 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.

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 of banking competition.

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}):

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

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 N inputs and produces M products. In (2), the total cost TC_{blt} and input prices $W_{blt}^{(1)}$, $i \neq 1$, are divided by the price $W_{blt}^{(1)}$ to ensure the linear homogeneity of the estimated cost function.[27] 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 unobservable 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.[28] The term ε_{blt} is the stochastic error.

We differentiate the total cost function in (2) 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.:

$$MC_{blt}^{(j)} = \frac{\partial TC_{blt}}{\partial Q_{blt}^{(j)}} = \left(\frac{CT_{blt}}{Q_{blt}^{(j)}}\right)\left(\beta_j + \beta_{jj} \ln Q_{blt}^{(j)} + \sum_{k=2}^{N} \beta_{jk} \ln Q_{blt}^{(k)} + \sum_{i=2}^{M} \gamma_{ji} \ln\left(\frac{W_{blt}^{(i)}}{W_{blt}^{(1)}}\right)\right). \tag{3}$$

The marginal cost in (3) 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 (2) locally. This information usually is present at the national bank level. We overcome this limitation by constructing heuristics to reallocate national-

[27] 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 ($W_b lt(1)$) 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.

[28] 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 unobservable shocks, such as the effect of local public policies on regional economic activity, the local court efficiency, environmental risks and the local diversification of economic activities.

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.

3.2 Setup and datasets for the Brazilian case

We first define the term *locality* used in this paper. Brazil has 5,570 municipalities in 2021, many of which have strong economic and financial relationships with neighboring municipalities. For instance, it is common to have a job and bank accounts in a neighboring municipality. Therefore, we believe the effective circumscription of credit markets is broader than a municipality's boundaries in Brazil. In this sense, we delimit the locality as the Immediate Geographic Region, as defined and published by the Brazilian Institute of Geography and Statistics (IBGE).[29] 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.[30] We use the location of bank branches instead of borrowers when estimating banks' total cost functions in (2). This stems directly from our choice of banks as the market participants for whom we are computing market power. The computation of a local production function for a bank in a location must consider the products from that bank at that location, thus it is necessary to include all the credit granted by that bank at the location, including that granted to borrowers from other localities.[31]

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 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. Using these design choices, for instance, we evaluate the total cost TC_{blt} in (2) for bank b in the immediate geographic region l during the semiannual period t.

We describe the data used in this paper as we use that information to support our methodologies and analyses. In this section, we show an overview of the data required for evaluating the market power of banks in local credit markets, along with the databases from which we extract them. In Section 4.1, we get into more detail regarding these data, specifying data sources and treatment procedures employed before the computations and analyses, closing the section with an

[29]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.

[30]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.

[31]This feature results from the growing importance of IT, enabling banks to operate remotely. Considering the location of borrowers instead of bank branches can lead to important distortions. 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 Southeast Region, these amounts were maximal: 36.2% of the outstanding credit and 49.8% of the borrowers.

overview of bank local credit markets elaborated from these data. Finally, in Section 5, we reference the additional data required for the analyses conducted in that Section regarding the effects of the COVID-19 pandemic on local credit markets. The data listed below is used to compute local input prices and outputs to be used in the banks' local production functions. We use the following datasets:

- 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 locations (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).

3.3 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 (2).

Input prices ($W_{blt}^{(i)}$): Table 1 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

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

[33]IT enables a bank branch to grant credit regardless of the borrower's location.

Table 1: *Bank input prices ($W_{blt}^{(i)}$) used to estimate the total cost function in (2).*

i	Price of input $\mathbf{W_{blt}^{(i)}}$	Name and Rationale
1	$W_{blt}^{(1)} = \frac{\text{Funding Costs}_{bt}}{\text{Total Funding}_{bt}}$	**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	$W_{blt}^{(2)} = \frac{\text{Tax Costs}_{bt}}{\text{Total Assets}_{bt}}$	**Tax prices**. We assume the local taxation price is approximately uniform across localities since taxation costs refer mainly to federal taxes in Brazil.[32] 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	$W_{blt}^{(3)} = \frac{\text{IT Costs}_{bt}}{\text{Volume of Credit Granted}_{bt}}$	**IT prices**. We compute the price of information technology (IT), communication, and data processing resources allocated to credit operations based on these IT costs as a share of the bank branch's volume of credit granted during the period t, regardless of the borrower's physical location.[33] The expenses variable IT Costs$_{bt}$ (Cosif) is the proportion of the bank b's IT, communication, and data processing costs in period t computed for the ratio of the gross outstanding credit to the bank's usual assets.
4	$W_{blt}^{(4)} = \frac{\text{Labor Costs}_{blt}}{\text{Number of Employees}_{blt}}$	**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.
5	$W_{blt}^{(5)} = \frac{\text{Other Admin. Costs}_{bt}}{\text{Total Assets}_{bt}}$	**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 IT (Cosif) and labor (RAIS/Caged) costs, all of which relative to bank b in period t.

branch level. Brazil is not an exception to this as well.[34] 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 (2), as we would need to break down total costs in specific factors such as funding, tax costs, IT, labor, and other administrative costs.

[34]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.

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 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 2 shows the five 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.[35]

Table 2: *Components of the bank's local total costs (TC_{blt} in (2)). 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, other administrative costs and amortization, except those related to IT, communication, and data processing costs and labor 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	IT, communication, and data processing costs allocated to credit operations.	Proportion of within-half-year credit originated by the bank branch regardless of the borrower's location (SCR) relative to the bank's national within-half-year aggregate.
5	Labor costs.	Proportion of the bank branch's payroll (RAIS / Caged) relative to the bank's national payroll.

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:[36] credit operations (SCR), bonds and securities (ESTBAN), and operations with other assets[37] (ESTBAN). Within

[35]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 $l = 2$, $LC_{b2t} = 130 * 70/100 = 91$.

[36]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.

[37]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

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 3 lists the considered credit modalities in terms of the product segment: households or non-financial firms.[38]

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 stock of credit operations and has this potential problem in their marginal cost estimates. This limitation may have its roots because these works rely 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 competition.

Table 3: *Credit modalities considered as credit-related banking products when evaluating (2). 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.

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 3; (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.

3.4 Effective price of credit products

This paper focuses 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 (2). The banking literature normally uses the ratio between revenue from credit operations and the volume of credit as

subtracted from the value of current assets and long-term assets.

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

a proxy for the *average credit price*.[39] This effective price is net of losses due to credit default, since this strategy effectively measures the income that is received by the bank in its credit operations. It differs from the contractual interest rate, which incorporates default and other risk factors. For comparability purposes, we follow this literature and take the average effective price of the credit product m granted by bank b during period t at location l as the ratio of the effective income flow from credit grants within the half-year (SCR) and the volume of credit grants within the half-year (SCR).

There are two important distinctions of our paper 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 competitive 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 the effective credit income and outstanding credit volume. In this approach, we would observe the credit income at the end-of-month financial statement but not the outstanding credit volume. Hence, effective prices would be biased upwards. If there is a significant volume of very short-term credit, then the distortion could be substantial.[40]

To correct this problem, instead of calculating the average effective price using end-of-month financial accounts, we resort to *daily* loan-level income data from the SCR. We have information on credit operations' cash flows daily— including whether it is a payment of interest or the principal—and the outstanding credit volume immediately *before* every payment. We evaluate bank b's average effective price in location l during half-year t by summing up all credit incomes (I) and their associated outstanding credit volumes *before* these payments (V) from the beginning of the credit operation up to the end of the half-year or the credit liquidation, whichever occurs first.[41] Mathematically, the average effective price is:

$$p_{blt}^{(m)} = 6\frac{\sum_{k \in \mathscr{S}_t} I_{blk}^{(m)}}{\sum_{k \in \mathscr{S}_t} V_{blk}^{(m)}}, \tag{4}$$

in which $\mathscr{S}_t$ is the set of all days within half-year t, $I_{blk}^{(m)}$ indicates the sum of interest inflows of credit modality m that bank b at locality l received during day k, and $V_{blk}^{(m)}$ is the outstanding credit volume before these payments at the same day. We multiply the ratio of credit income and outstanding

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

[40] 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.

[41] This is a general approach that also accounts for multiple in-month payments. If we pay in advance a bank credit twice in a specific month, there will be two entries in that operation's cash flow records. For each of these, the associated inflows and outstanding credit enter the computation of the average effective price in the numerator and denominator of (4), respectively.

credit by six to convert the average monthly rate to a semiannual basis.[42]

4 Local competition in credit markets in Brazil: an exploratory analysis

Local competition and its determinants have a large room for exploration in the literature. This section provides a comprehensive analysis of this theme using Brazilian data. We first provide an overview of the data required to estimate the local Lerner index. Appendix A complements this analysis with detailed summary statistics. Then, we examine the evolution of local average effective prices, marginal costs, and Lerner indices across Brazilian localities. Appendix B provides additional empirical evidence of the local correlates of competition in Brazil. Finally, we investigate how bank branches' cost factors—funding, tax, labor, IT, and other administrative costs—changed after the COVID-19 outbreak. This analysis sheds light on the main cost factors that influence banks' total costs before and after the pandemic. At this point, we obtain partial correlations that may help further identify the economic meaning backing our causal estimates in Section 5.

4.1 Data and overview of bank credit local markets

This work requires a large amount of data to estimate competition locally. We begin by discussing the data sources, extraction strategies, and data treatment procedures. We finalize this section with an overview of local bank credit markets.

4.1.1 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. Since our methodology requires evaluating credit income and outstanding credit immediately before the payment to compose the effective prices of credit modalities, we need to run through every loan operation in the data set. In total, we process 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 CEP or 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 (4).

[42]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.

- Cosif. We use information of monthly banks' consolidated financial statements and supervisory variables to compute input prices and total bank local costs, according to Section 3.3. We then take the semiannual average of balance variables[43] 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 monthly. Similar to what we do for the Cosif database, we re-base this information on a semiannual basis. After this, we aggregate this information geographically to the bank-locality level using the IBGE Geographic database. We use bank-locality ratios of the local ESTBAN variable and the aggregate ESTBAN amount to apportion the bank-level Cosif variables. We use this strategy because, most of the time, there is no direct correspondence between the accounting aggregates extracted from the ESTBAN database and 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.[44] We also aggregate this information to the bank-locality level.

4.1.2 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 (2)). 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 4 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.

[43] Balance variables are those that refer to outstanding positions. For instance, total assets and total funding.

[44] We take the average of the bank branch's number of employees considering the number of months available 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.

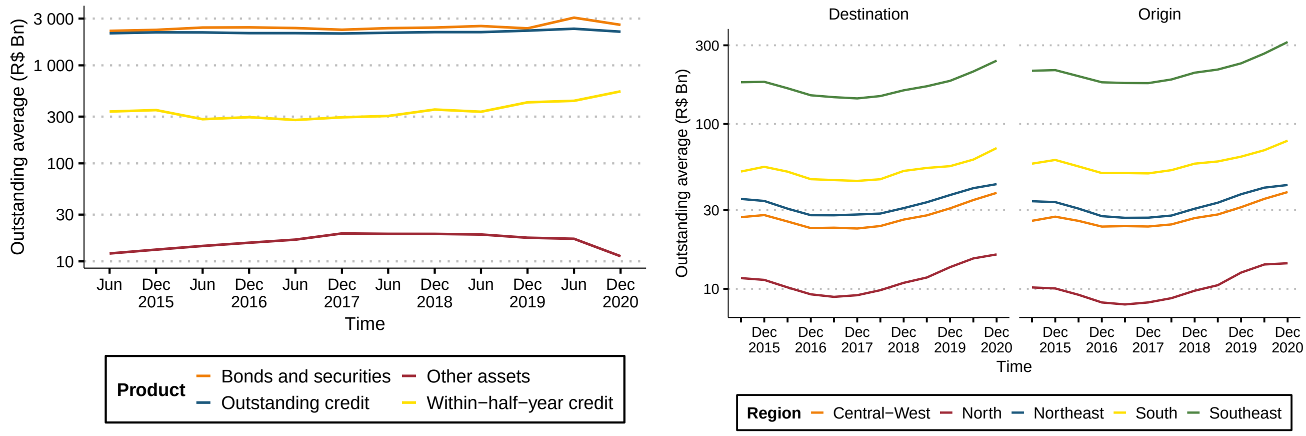
Table 4: *Number of banks with positive outstanding credit in the whole country and in each region from 2015 to 2020. The same bank may appear more than once when it operates in more than a single region.*

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

Our model that estimates local Lerner indices assumes banks minimize their costs through a production function. Although we concentrate on credit products, we need to include all banking products in the production function: credit (within and before the half-year), bonds and securities, and operations with other assets. Figure 1a displays the evolution of semiannual outstanding averages for these products. Bonds and securities have roughly the same volume as 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 newer 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 1b 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.[45] Third, we understand that the competition conditions are those at the credit origin locality rather than those at the borrower (credit destination) locality, especially for smaller banks.



***(a)** Bank products*

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

***Figure 1:** 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.*

Since our focus is on within-half-year credit products when estimating competition, we now describe the relative importance of within-half-year credit modalities. Figures 2 and 3 exhibit the within-half-year credit volume by 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.

We now look at the input prices of banks' production functions. We also aggregate these variables at the regional level for visualization purposes. For a specific semiannual period, we compute a region-specific input price variable by averaging over the local values of that variable across bank branches in the region weighted by the corresponding bank branch's local total cost as a share of the banking system's aggregate total costs in that region. Figures 4a–4e show the evolution of local average input prices across Brazilian regions. According to Table 1, funding, tax and IT prices are bank-specific variables and do not vary across localities. In contrast, labor and other administrative prices are local variables. Therefore, in the case of funding, tax and IT prices, regional differences cannot be attributed to local differences. They are due exclusively to differences in the group of banks in each region granting credit and to their regional costs' shares. Conversely,

[45] Appendix C uses data from the Central Bank of Brazil and shows the evolution of the number of face-to-face 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.

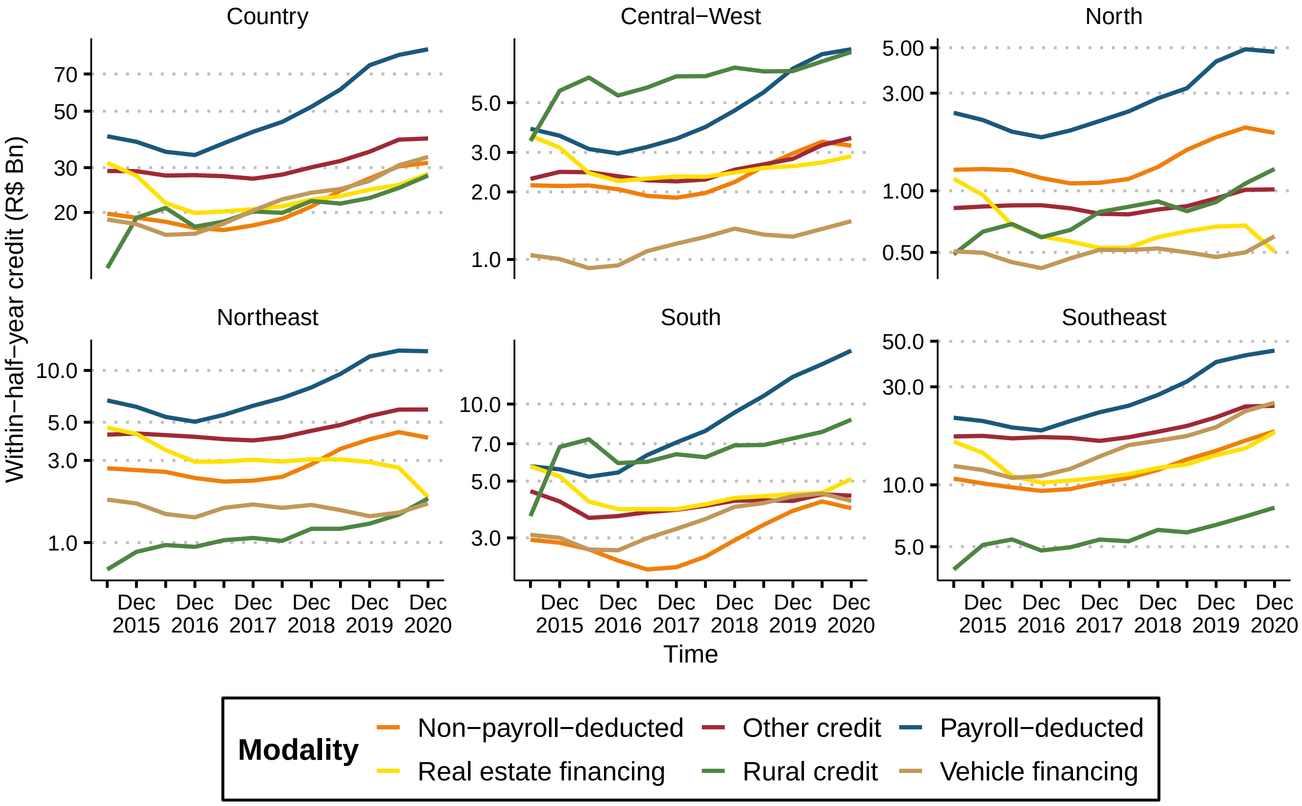


Figure 2: *Outstanding position of within-half-year credit granted in each region for credit modalities for individuals. Vertical axes are in log-scale.*

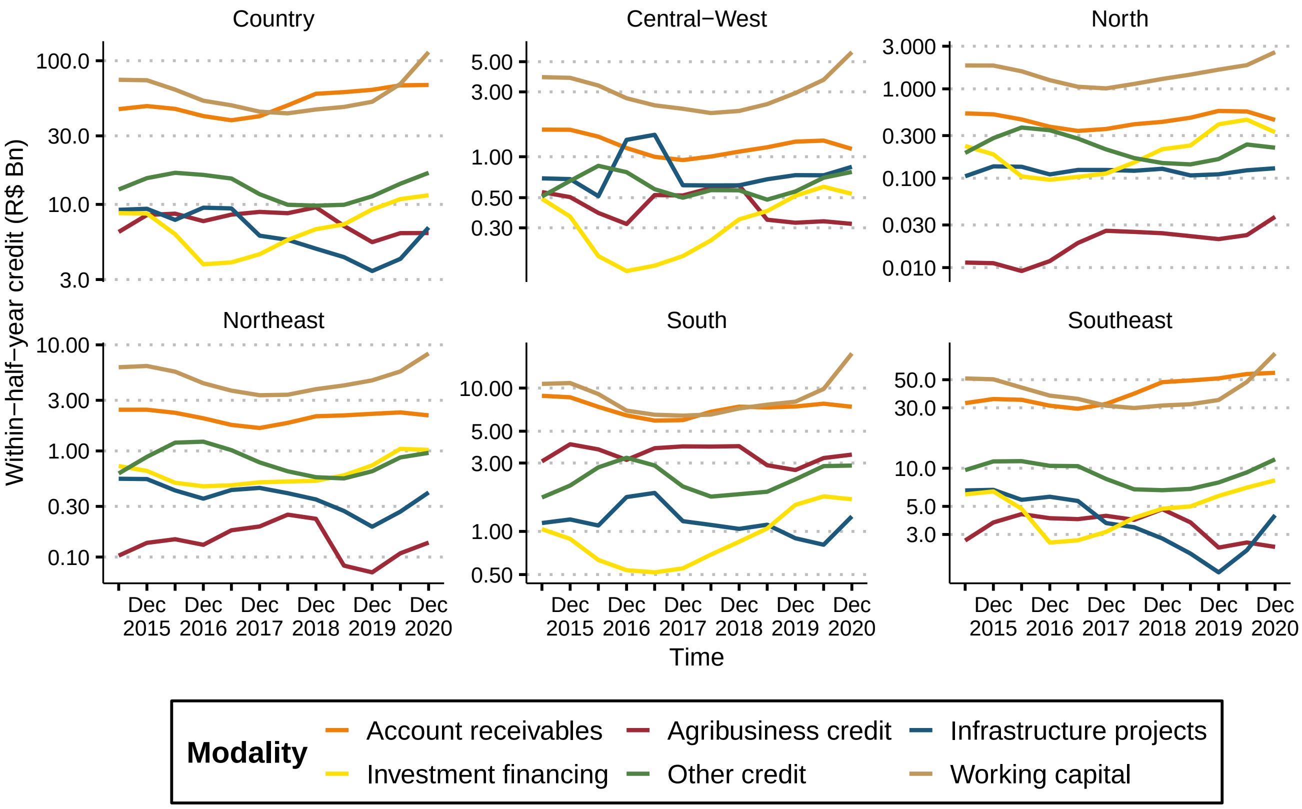


Figure 3: *Outstanding position of within-half-year credit granted in each region for credit modalities for non-financial firms. Vertical axes are in log-scale.*

regional differences among labor and other administrative prices represent real local differences.

Funding, tax, and IT prices in the North region follow the prices faced by large banks, the most prevalent in these regions. In the Southeast region, they relate more to the country's average. Funding price decreases from June 2016 onwards, reflecting the fall in the domestic interest rate along that period. However, there is a spike in June 2020 amidst the COVID-19 pandemic, which could be due to liquidity restrictions, although the domestic interest rate was at its lowest level in the study period. Tax rates significantly decrease during 2020, primarily because of the tax-related measures to combat the pandemic.[46] IT prices—which we interpret in terms of IT-related expenses by a unit of granted credit—fell from 2016 to the end of 2019. In 2020, due to changes in banks' business models related to the pandemics that required more intensive use of communication and data processing resources, these prices had a steep increase. Despite being comprised of purely local variables, labor prices (salaries) display the same trends in all regions. Salaries are the highest in the Southeast and the lowest in the North. For salaries, we observe the opposite of what occurs for IT prices: they increase until the end of 2019, plunging during 2020.[47] Infrastructure prices in the Southeast increase during the period and decrease in other regions. This pattern may indicate a geographical reorganization of banks' infrastructure towards the Southeast.

Figure 4f portrays the evolution of region-specific total costs, which is the sum of bank branches' local total costs in the region. The amplitude of total costs differs significantly across regions. Regional total costs fluctuate similarly during the period. Specifically, regional costs decreased slightly for all regions except the Southeast. In the second half of 2020, we see a substantial decrease in the total cost in the Central-West, North, and Northeast, while it remains comparable with pre-pandemic levels in the South and Southeast.

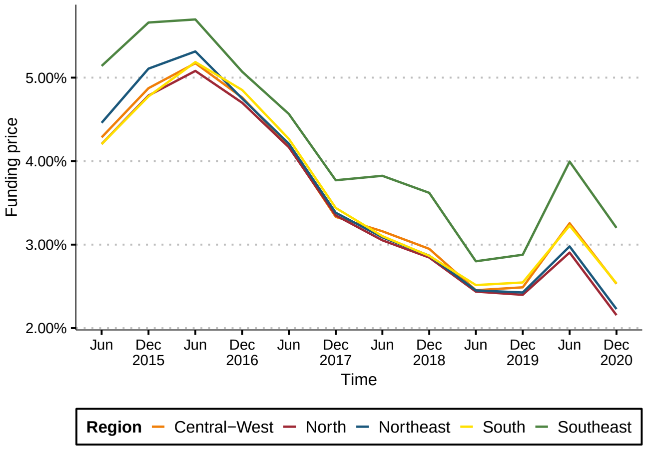
Finally, we look at the variation of local input cost (input price $\times$ input quantity) as a share of the total local cost across Brazilian localities using geographical maps. This information complements our previous analysis of input prices. To better understand the rearrangement of local cost shares due to the COVID-19 outbreak, we focus on December 2019 and December 2020. Figures 5 and 6 display the local cost shares of funding, labor, IT, and tax and other administrative costs.

Figure 5 shows the funding cost share decreased during the COVID-19 pandemic in 2020, and the labor cost share increased in most localities over the country. In general, the sum of these two shares is nearly 70% on both dates. Figure 6 shows the shares of tax and other administrative costs and especially IT increased in 2020.

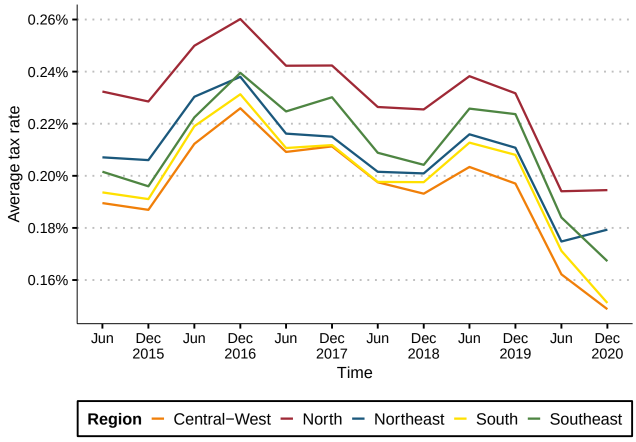
In summary, we have the following picture. After the onset of the COVID-19 pandemic, credit operations have increased while banks' total costs have not increased as much. Funding costs (i.e., operational costs) have migrated to other production factors, especially IT, in more developed regions. This analysis highlights banks are making an effort to adapt, temporarily or not, to a new business model, more IT-intensive, following the COVID-19 outbreak.

[46] For example, the Decree n. 10,305 of April 2020 reduced the rate of the financial transaction tax to 0% from April 3rd to July 3rd, 2020, to relieve financial institutions' costs and foster credit growth.

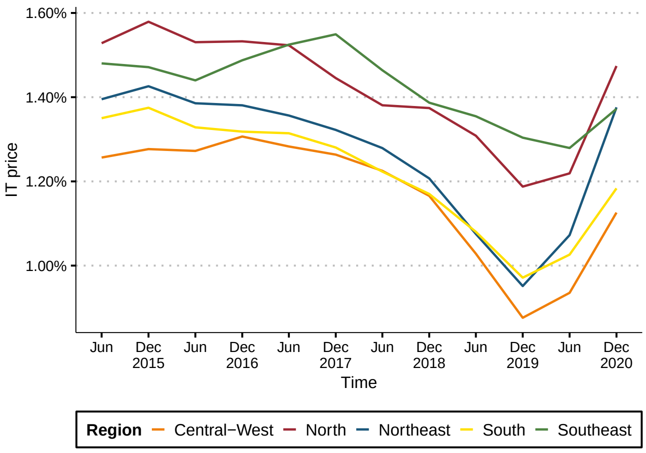
[47] Recall that labor prices do not refer to labor expenses but to semiannual average salaries which had a remarkable fall during the pandemic.



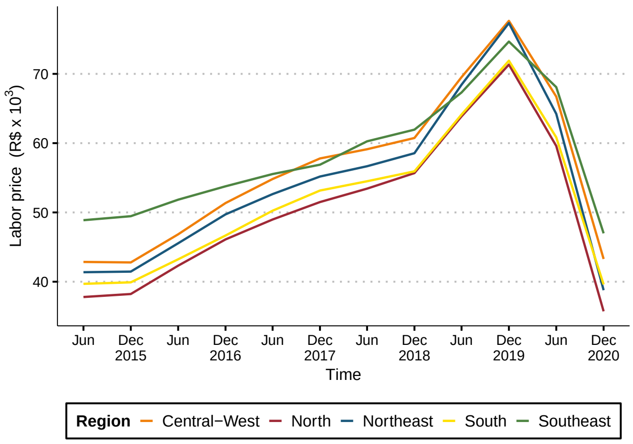
***(a)** Funding Price*



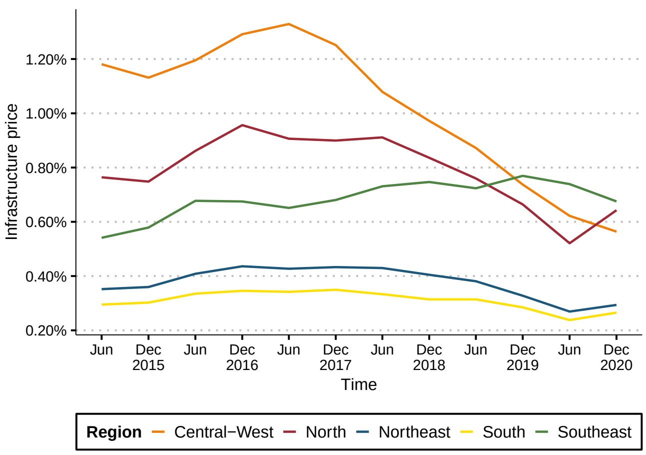
***(b)** Tax Rate*



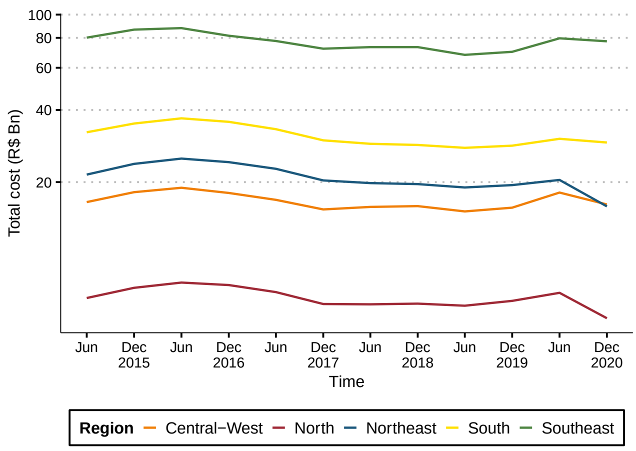
***(c)** IT Price*



***(d)** Labor Price*



***(e)** Infrastructure Price*

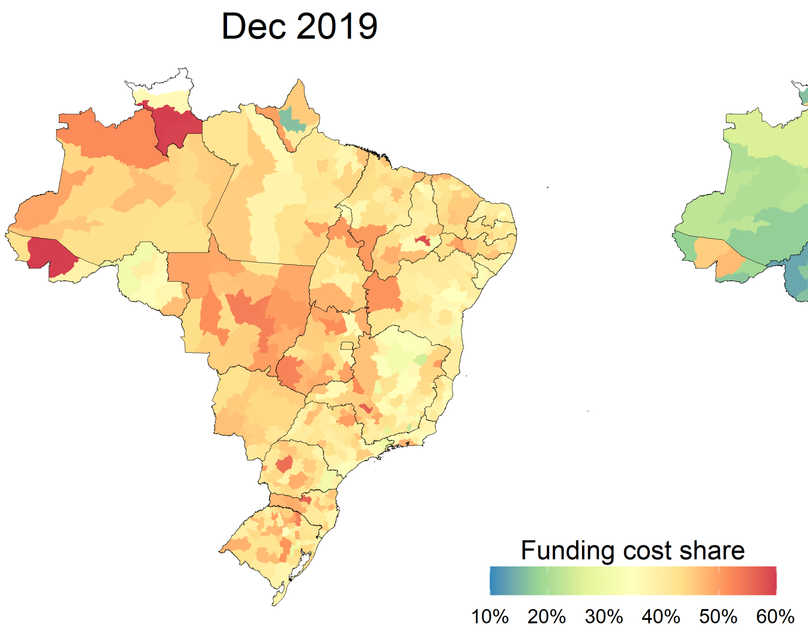


***(f)** Total Costs*

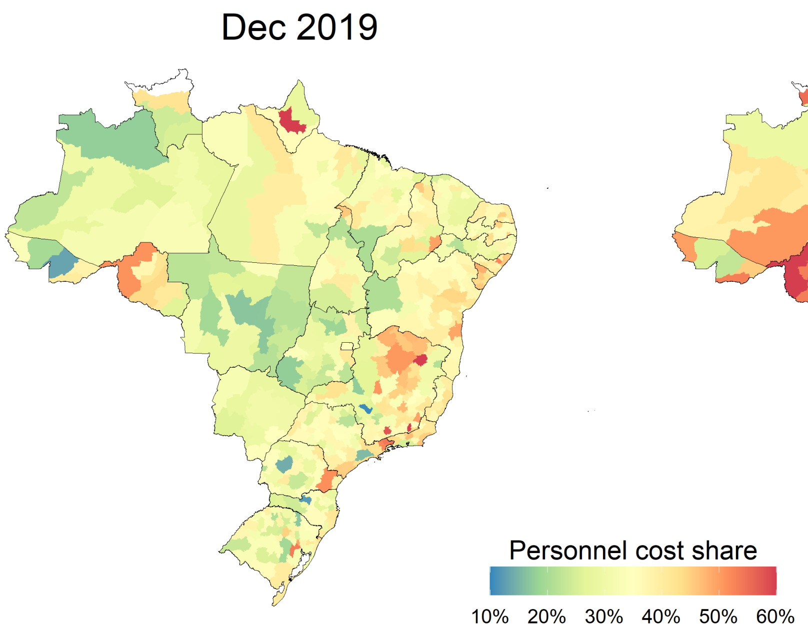
***Figure 4:** Evolution of local input prices and total cost averaged for each Brazilian region. Vertical axis of (f) is in log scale.*

4.2 Evolution of local effective prices, marginal costs, and Lerner indices

This section leverages the results of our methodology in Section 3.1 by providing 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 product in a



(a) *Funding Cost (% total cost)*

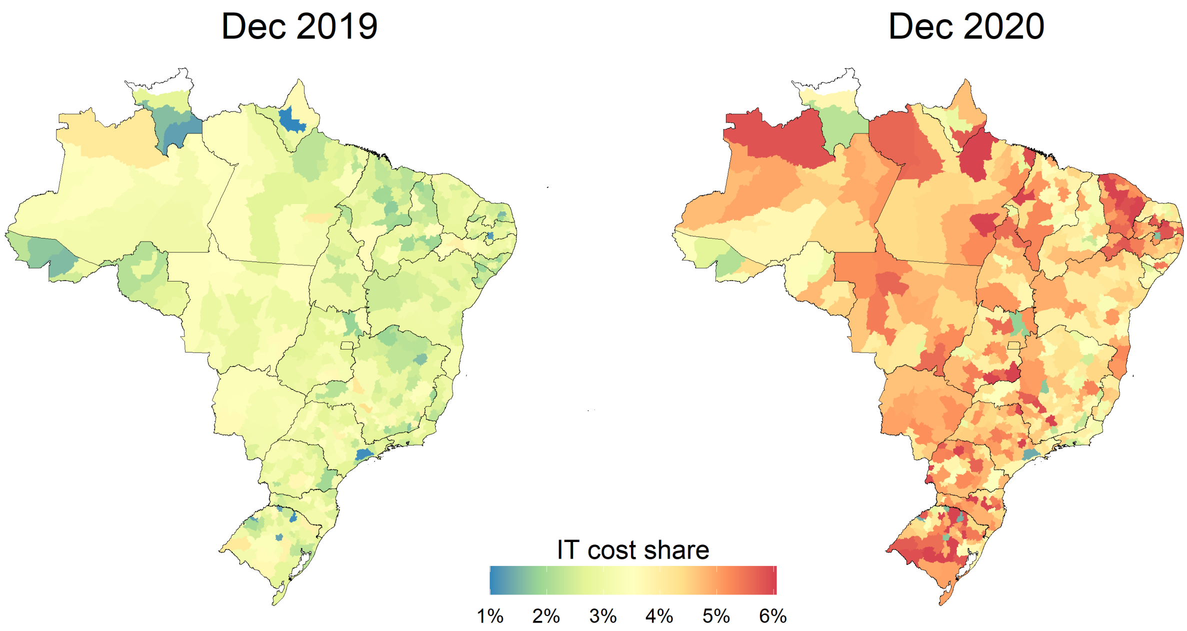


(b) *Labor Cost (% total cost)*

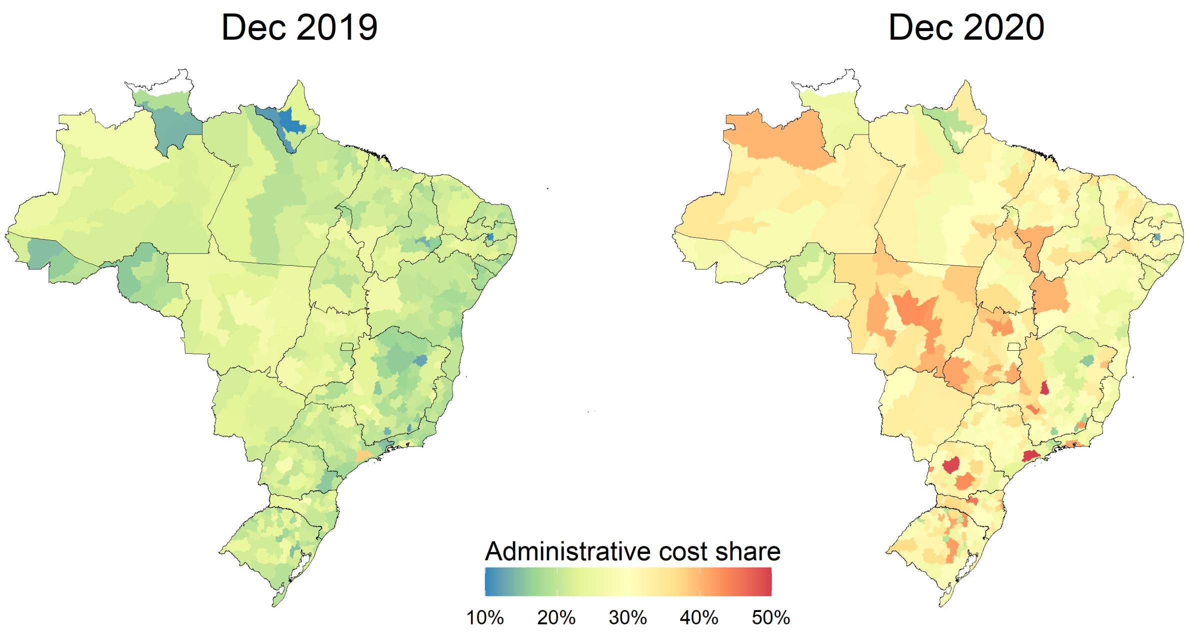
Figure 5: *Evolution of local funding cost and local labor cost as a share of the local total costs from* 2019 *to* 2020 *in Brazilian localities (immediate geographical regions).*

locality during a semiannual period. Our focus is on within-half-year credit products listed in Table 3. We display these variables at different levels of aggregation: localities, regions, and the whole country.[48]

[48] Shaffer and Spierdijk (2020) demonstrate we can aggregate multi-product Lerner indices consistently by using the credit income as a weighting 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.



***(a)** IT Cost (% total cost)*

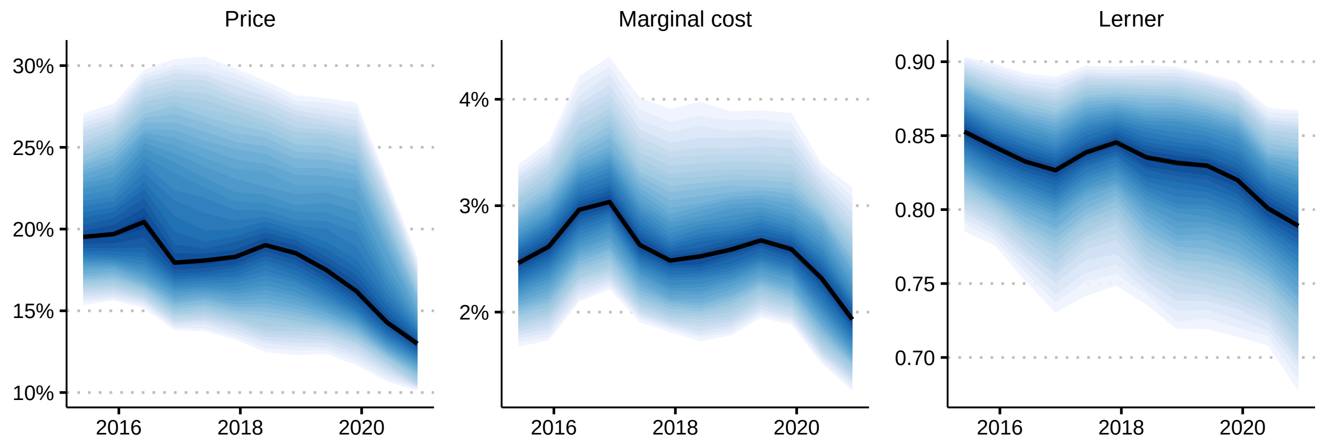


***(b)** Tax + Other Administrative Cost (% total cost)*

***Figure 6:** Evolution of local IT cost and local tax + other administrative cost as a share of the local total costs from* 2019 *to* 2020 *in Brazilian localities (immediate geographical regions).*

Figure 7 shows the distribution of the effective price, marginal cost, and Lerner over time aggregated by locality[49] for the overall credit market in each locality. The black line denotes the median 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

[49]In this case, we aggregate each variable across bank-modality observations within the same locality and time (semiannual period).



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

Figure 7: *Distributions of effective prices, marginal costs and Lerner indices over time at the locality level.*

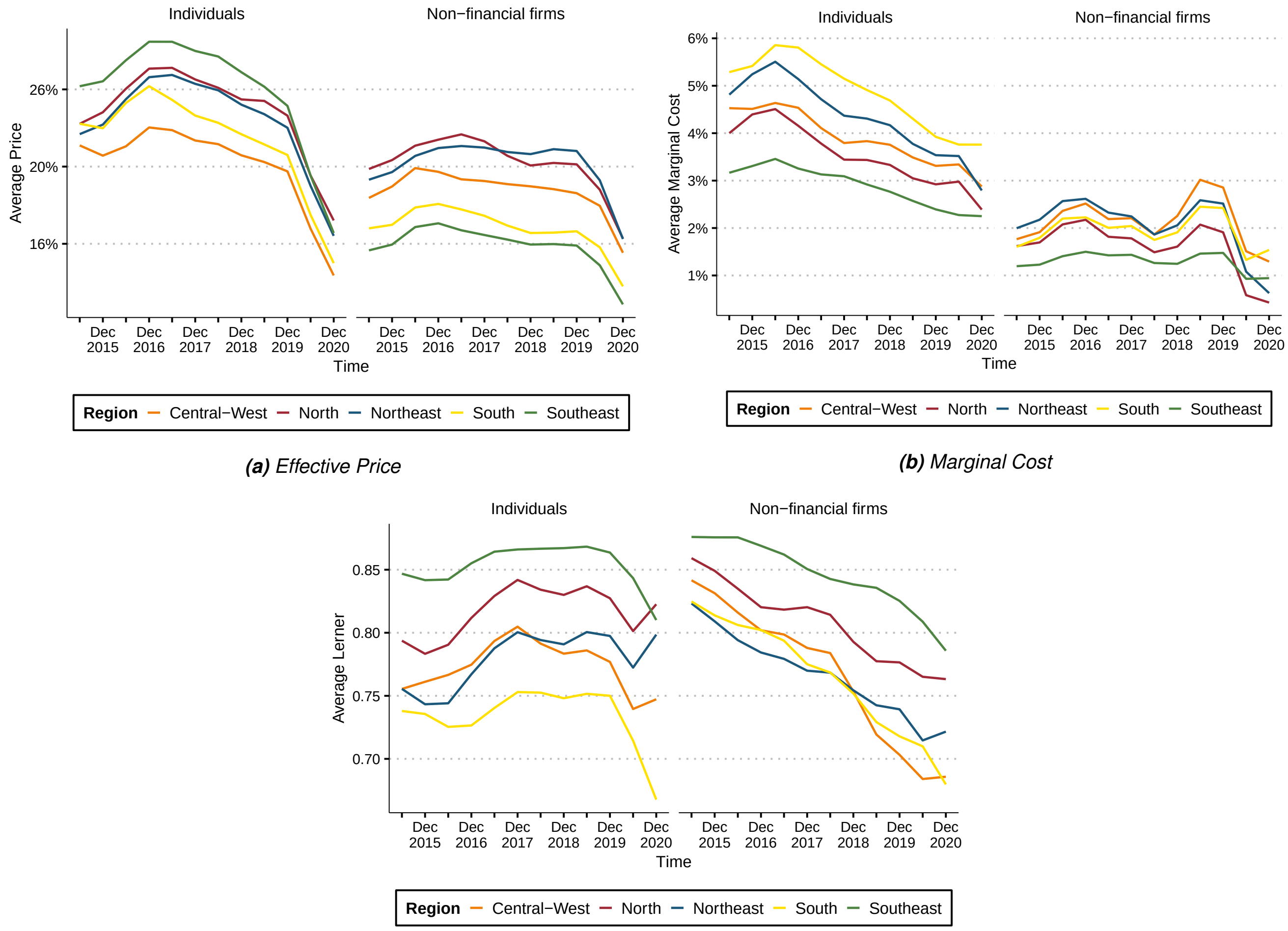
overlook many important aspects of competition across localities, reinforcing the need of developing methods to estimate competition locally. Effective prices decrease over time, with a substantial reduction of its dispersion after the COVID-19 outbreak. Marginal costs have an inverted U-shaped behavior, 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 8a shows the average effective price of operations for individuals was higher than for non-financial firms across Brazilian regions. In 2020, there was a significant drop in the average effective price in both segments, mainly for 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 8b shows the marginal cost of non-financial firms was lower than of individuals across Brazilian regions. Marginal costs for individuals consistently decreased over time. They remain steady for firms until 2018 when marginal costs rise until the end of 2019. After the COVID-19 outbreak, marginal costs for individuals and non-financial firms decreased, notably for non-financial firms and less developed regions (North, Northeast, and Central-West).

Figure 8c exhibits the local Lerner indices for individuals and 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 for individuals suggests that, despite the decrease in effective prices, the reduction in marginal costs was dominant. Conversely, the Lerner index decrease for 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 (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 compositions of



(a) Effective Price

(b) Marginal Cost

(c) Lerner

***Figure 8:** Evolution of effective prices, marginal costs and Lerner indices aggregated by region and segment (individuals and non-financial firms).*

credit modalities. To mitigate this issue, we now further drill down our results and look at the credit modality level across Brazilian regions. Figures 9 and 10 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 7a.[50]

Effective prices of payroll-deducted credit are very similar across regions and are, on average, 10–15 p.p. higher 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 shows increasing dispersion over time, with the lowest effective prices in the Southeast. The “other credit” modality includes overdraft operations. The significant decrease in effective prices of this modality may be a combined effect of the COVID-19 outbreak

[50] The fan charts in Figure 7 are less affected by large banks than the averages we report in Figure 8. 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.

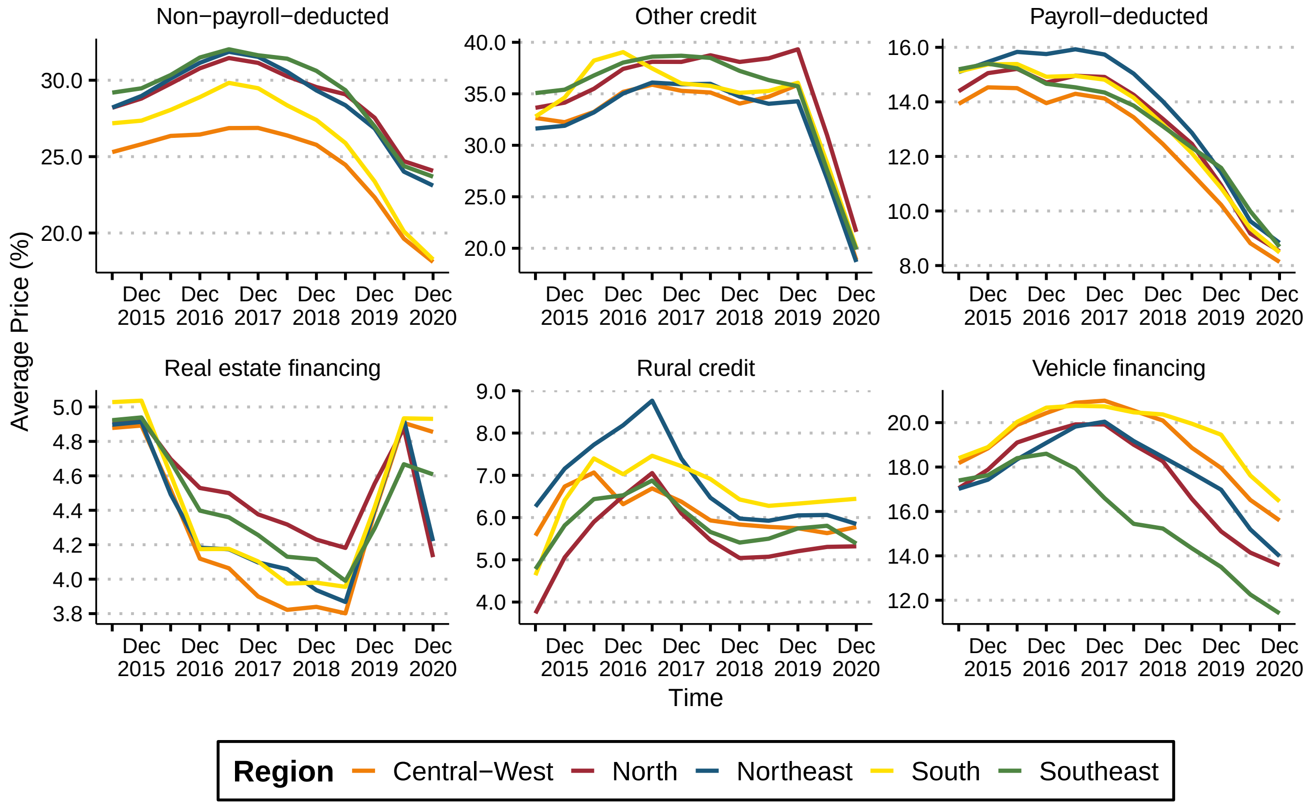


Figure 9: *Evolution of the average effective price of each credit modality for individuals aggregated to the regional level from 2015 to 2020.*

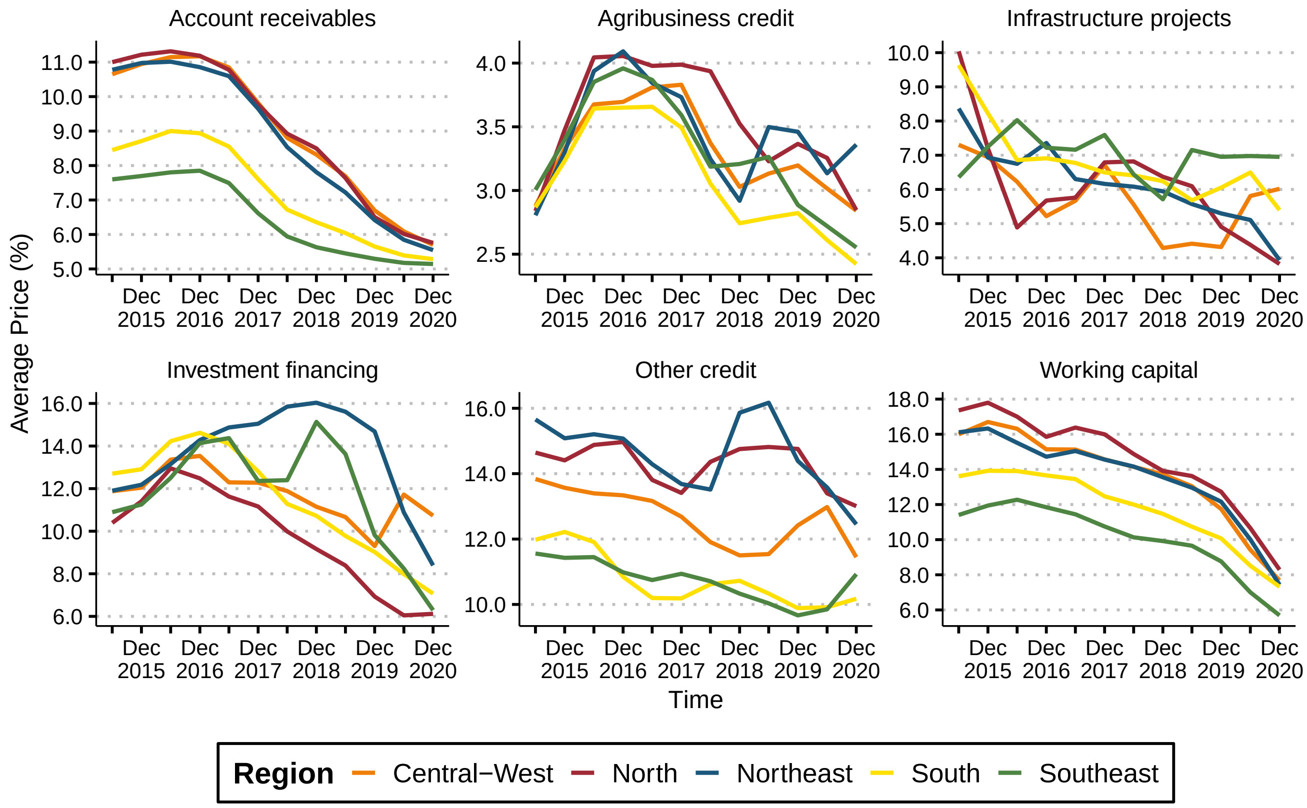


Figure 10: *Evolution of the average effective price of each credit modality for non-financial firms aggregated to the regional level from 2015 to 2020.*

and a new regulation 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 11 and 12 display the marginal cost of each credit modality for individuals and non-financial firms, respectively, across Brazilian regions.[51, 52] 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, they generally increase in the first half-year of 2020 but 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 reminder region is substantial for working capital and account receivables, modalities with the highest within-half-year credit volumes.

Figures 13 and 14 exhibit the Lerner index of each credit modality for individuals and non-financial firms, respectively, across Brazilian regions. Generally, Lerner indices increase for most credit modalities for 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 is more dominant than 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.

There is a mixed pattern in the evolution of the Lerner index of credit modalities for non-financial firms. The Lerner index for working capital and account receivables generally decreases in both pre-pandemic and during the pandemic. An exception is working capital for less developed regions. The decrease in effective prices is the primary driver of decreases in the Lerner index of

[51] 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 is negative in Figure 11 during 2015 and 2020 in the Central-West. Nonetheless, the shares of negative marginal costs and Lerner are not relevant.

[52] A comparison among the marginal cost levels of credit modalities in each segment suggests that they are negatively related to their average tickets. Tables B2 and B3 show a negative and significant association between average local ticket and marginal costs both in comparisons across localities for a given bank / modality / time and in comparisons across different banks for a given locality / modality / time.

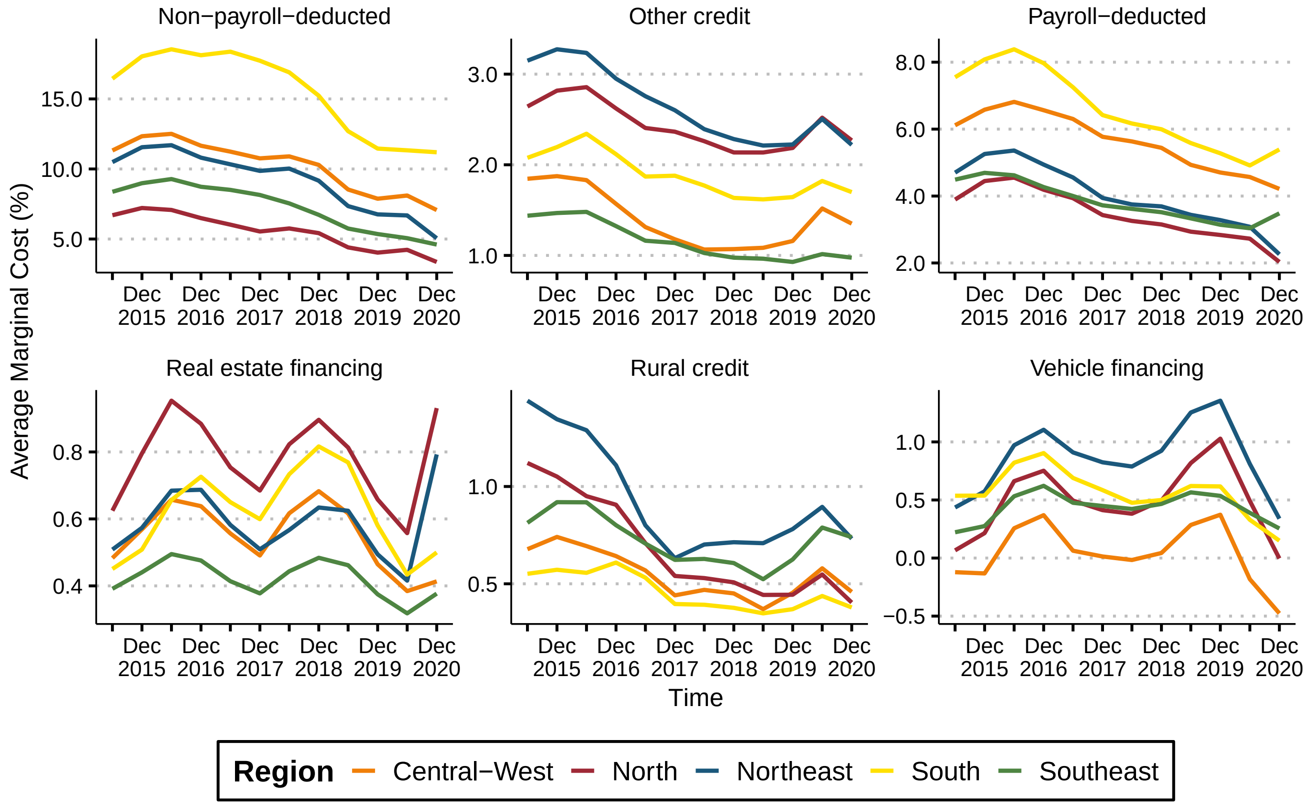


Figure 11: *Evolution of the marginal cost of each credit modality for individuals aggregated to the regional level from 2015 to 2020.*

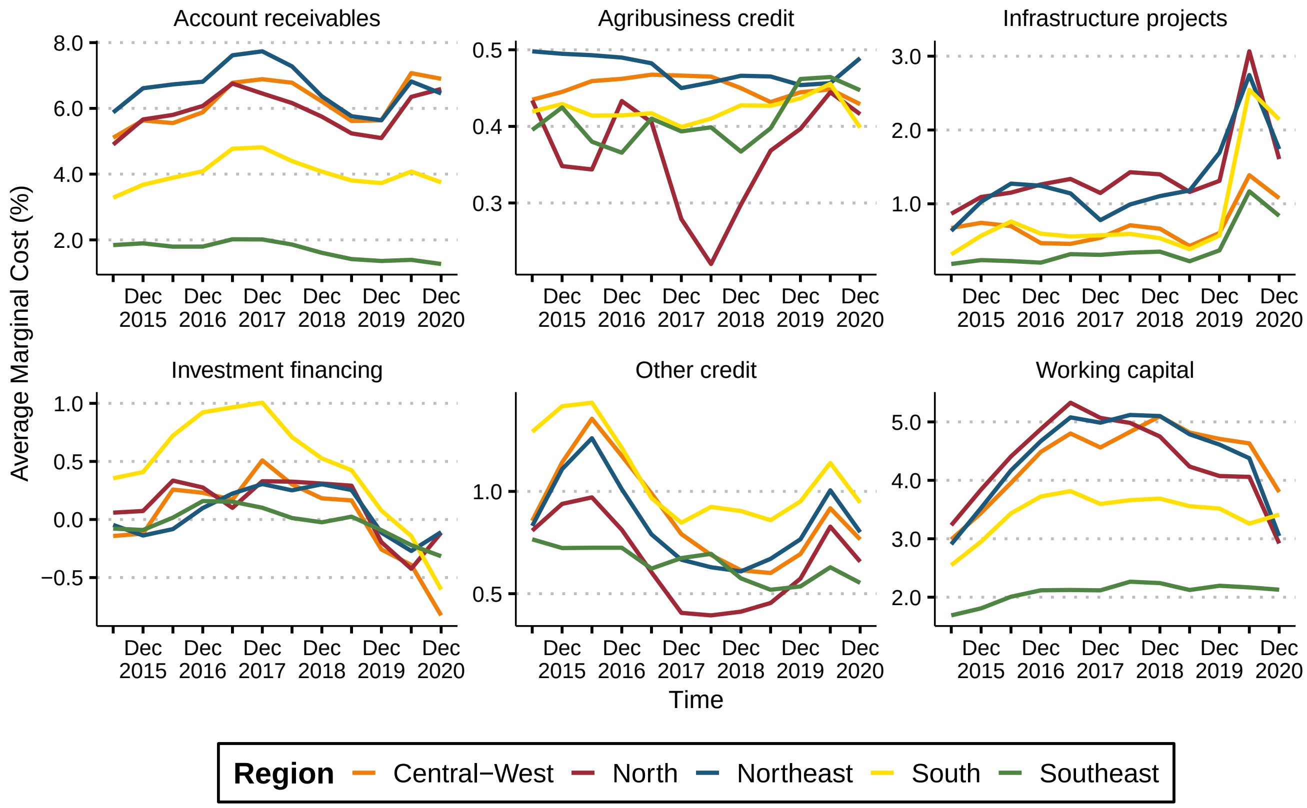


Figure 12: *Evolution of the marginal cost of each credit modality for non-financial firms aggregated to the regional level from 2015 to 2020.*

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.

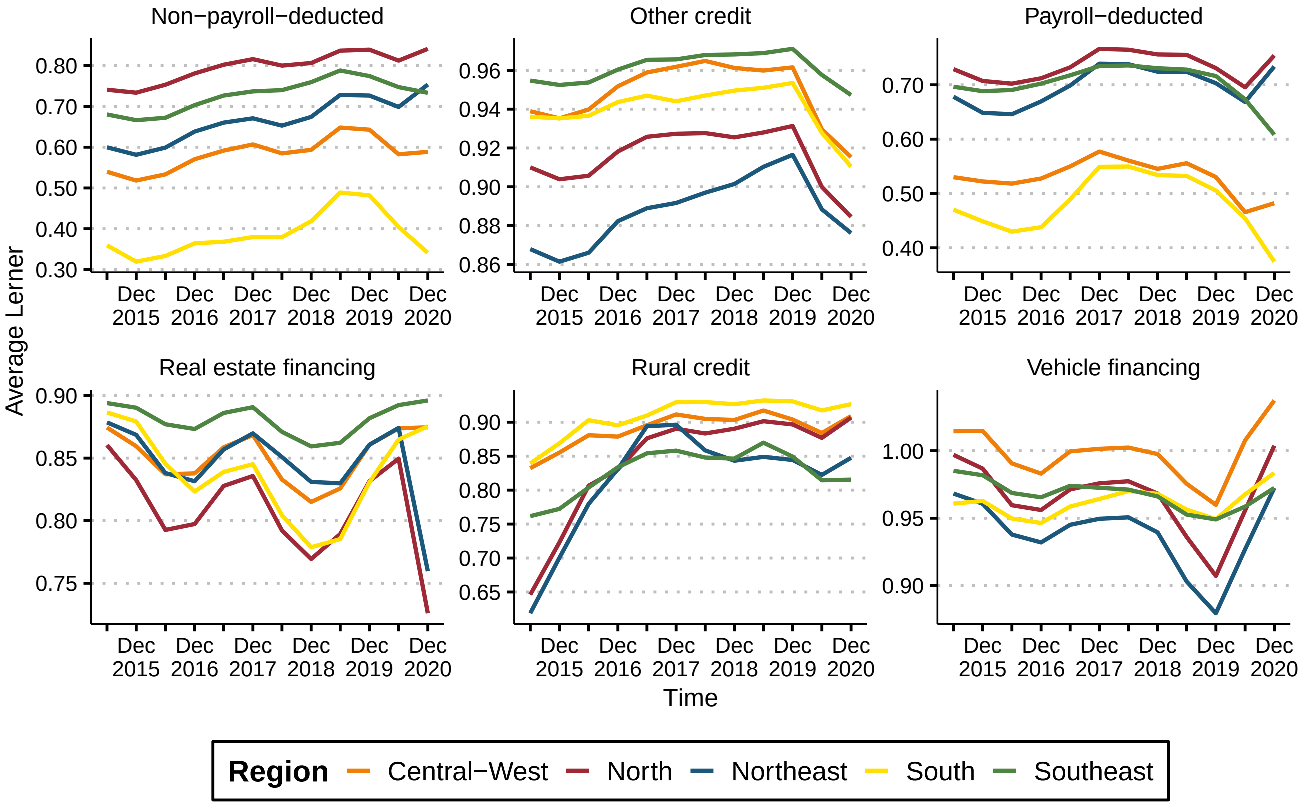


Figure 13: *Evolution of the Lerner index cost of each credit modality for individuals aggregated to the regional level from 2015 to 2020.*

Figure 15 shows the spatial distribution of the average effective prices, marginal costs, and Lerner indices across each of the Brazilian localities. We observe a substantial heterogeneity of these three measures, even within adjacent localities. Figure 16 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 introduction of our methodology attempts to contribute to the literature in this direction.

4.3 Changes in the relevance of production factors during COVID-19

This section investigates the importance of each production input—i.e., funding, tax, labor, IT, and other administrative elements—for the bank branch's total cost function. The translog function in (2) has many interactions, which makes the task of analyzing the marginal contribution of each model's covariate complex and context-dependent. To gain interpretability, we resort to a surrogate model. A surrogate model is a simpler model that mimics the behavior of a more complex model, in

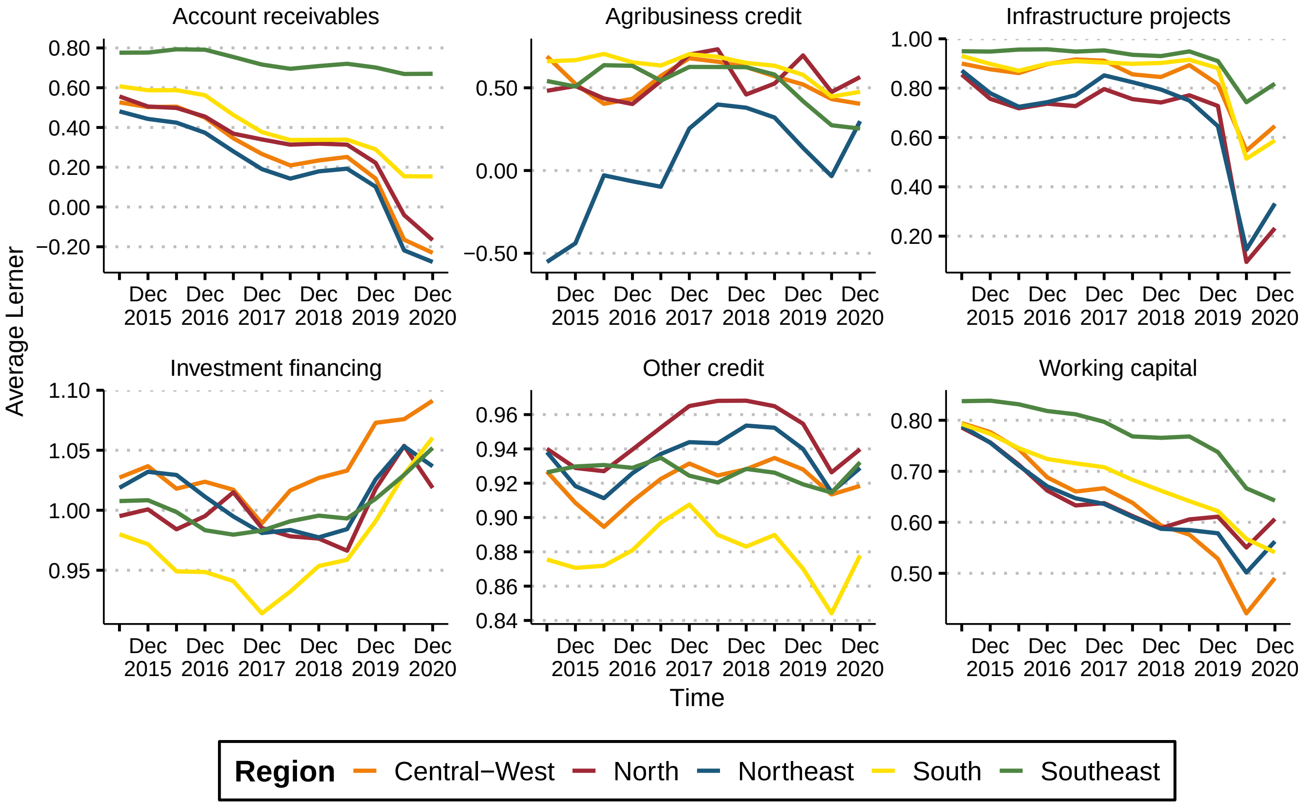
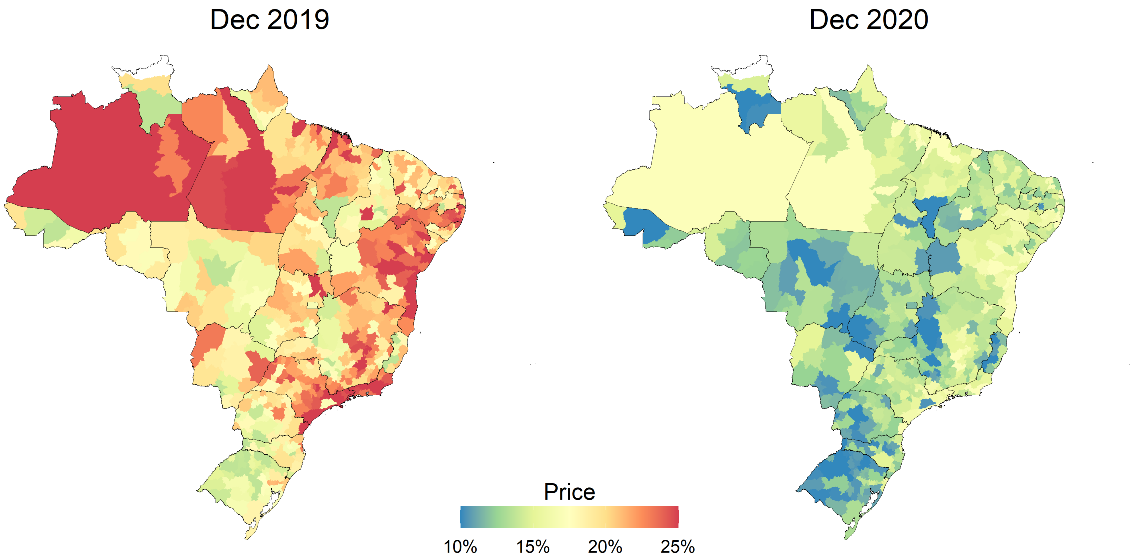


Figure 14: *Evolution of the Lerner index cost of each credit modality for non-financial firms aggregated to the regional level from 2015 to 2020.*

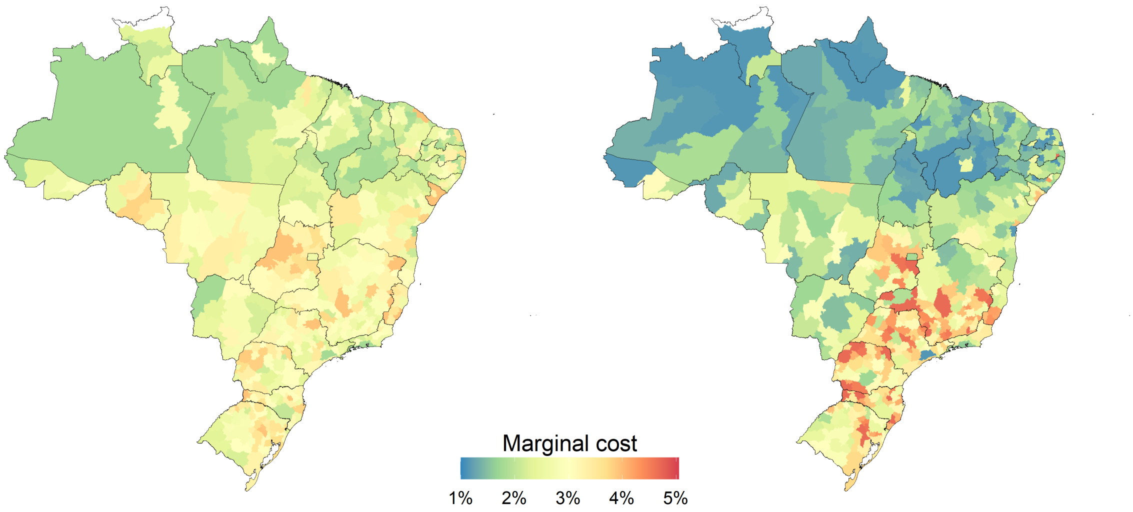
our case, the translog function.[53] We adopt a simple linear regression with the same set of inputs and outputs of the translog function in (2) as covariates, but with no interactions. The surrogate model attempts to follow the fitted dependent variable in (2), $\log(\hat{CT}_{blt})$, and not the original variable. In this model, we do not normalize the inputs and local total cost function by one of the inputs, because we want to understand the link between every input and the local total cost function. If the surrogate model approximates the more complex model well, then the goodness-of-fit measure R^2 should be high, nearing 1. We obtain R^2 values above of 0.989 in all our specifications.

We first investigate the time-varying dependency of the production inputs on the bank branch's total cost function by interacting each input with pulse time dummies. We interpret these coefficients as elasticities: the association of percentual changes in total costs for a 1% increase in a specific cost factor. Figure 17 shows the coefficient estimates of the five production inputs from 2015 to 2020 semiannually. Theoretically, the marginal coefficients should be positive in the translog function. This property may not hold in the surrogate model, as the marginal covariates encode the contributions of both the original translog function's marginal and interaction terms. For instance, the covariate may have a negative coefficient when the interactions in the original translog function have a stronger magnitude with opposite sign relative to the marginal coefficient.

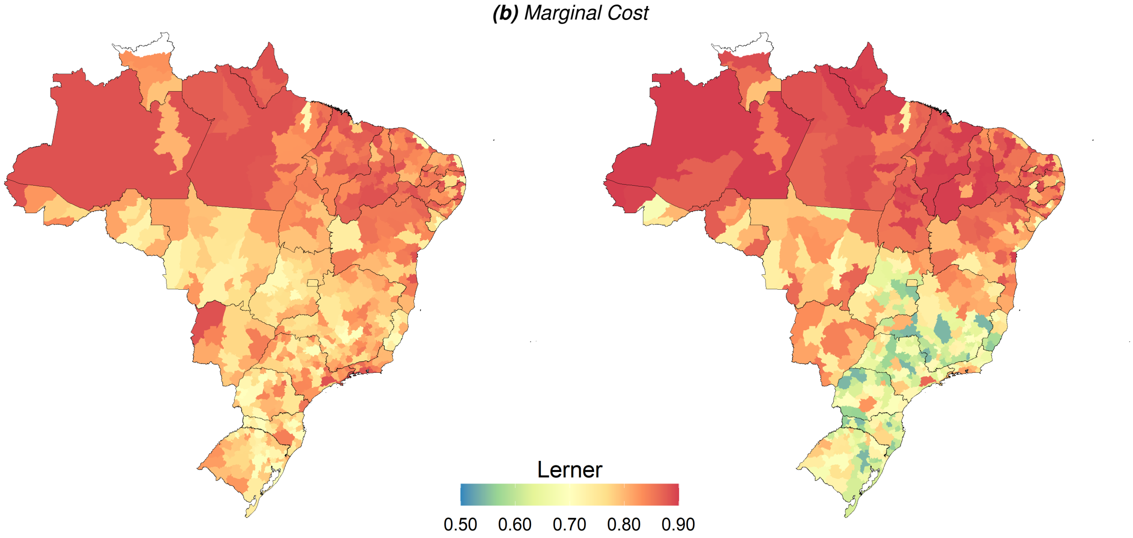
[53]Surrogate modeling is a widely adopted technique in the engineering and computer science areas. Typically, surrogate modeling is employed when (i) the variable of interest cannot be directly measured; (ii) an interpretable model is desired in which sensitivity analysis can be performed; (iii) prototyping new models more quickly (Silva and Zhao, 2016). The widely used linear models in economics and finance can also be conceptualized as a form of surrogate model of an underlying more complex system.



(a) *Effective Price*

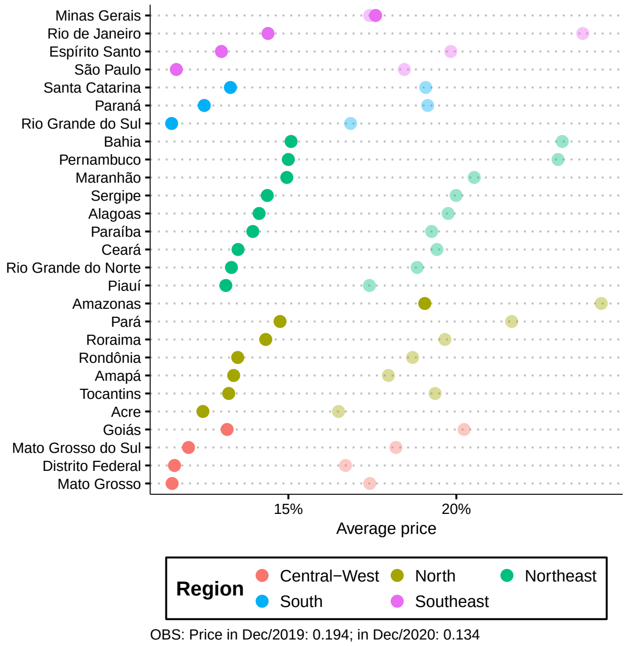


(b) *Marginal Cost*

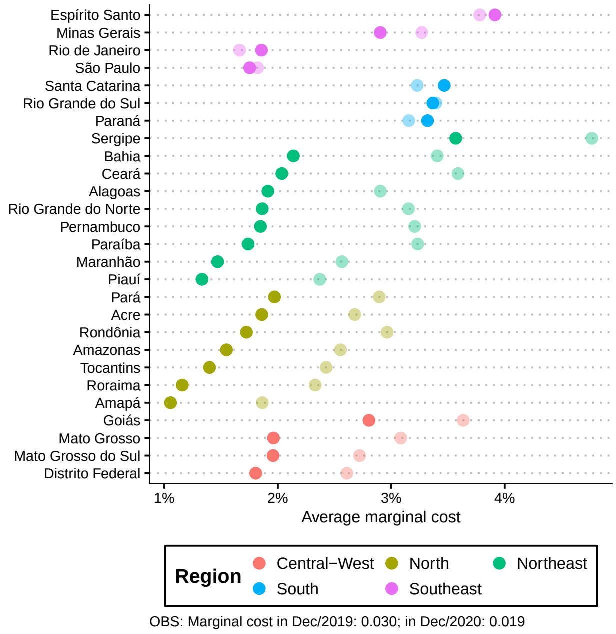


(c) *Lerner*

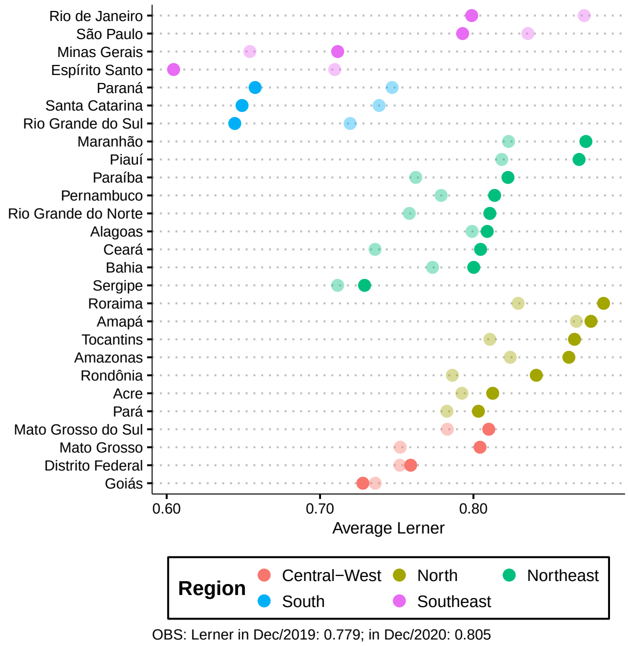
Figure 15: *Spatial distribution of the average effective prices, marginal costs, and Lerner indices across each of the Brazilian localities. We aggregate bank-modality observations within the same locality, including modalities for individuals and non-financial firms. We compare the pre-pandemic (left panel) and pandemic (right panel).*



***(a)** Effective Price*



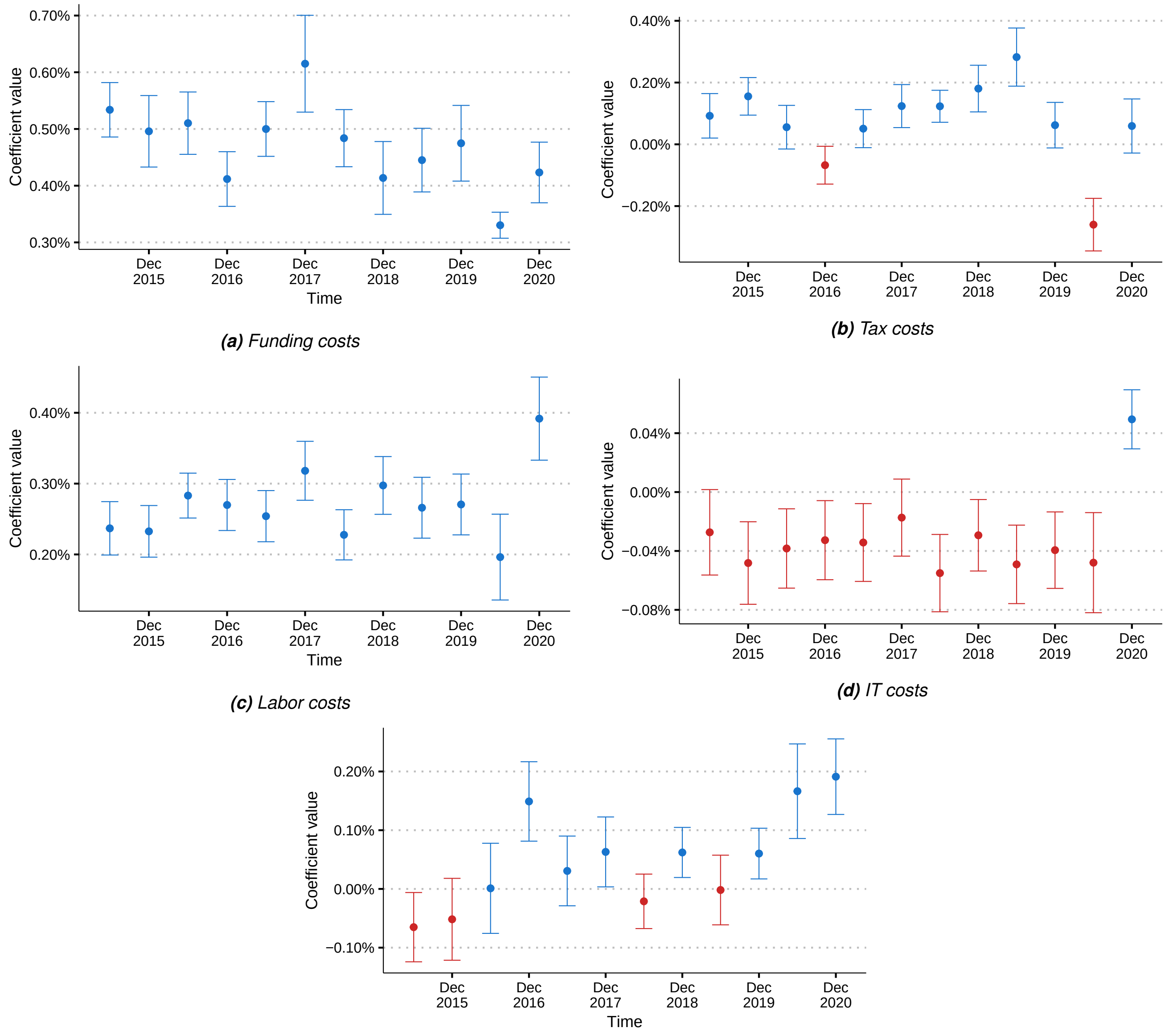
***(b)** Marginal Cost*



***(c)** Lerner*

***Figure 16:** 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.*

The importance of funding costs decreases over time, consistent with the drop in the Selic rate (policy rate in Brazil) during the period. Tax costs increase up to June 2019. There is a substantial reduction of tax costs in the first half of 2020, reflecting the Brazilian government's tax-exemption programs during the COVID-19. Labor costs remain steady until the first half-year of 2020, when their influence on total costs increases significantly. The coefficients for IT costs are mainly negative and constant up to June 2020, when they become positive. The negative coefficients highlight the positive externality of IT infrastructure on bank costs as a whole. The increase in IT costs after the pandemics may relate to social distancing measures that required more investments in



(e) Other administrative costs

Figure 17: *Time-varying dependency of the production inputs on the bank branch's total cost function using a surrogate model (linear regression with only marginal covariates and the same fixed effects) to mimic the translog function in Equation (2). We interact each production input with pulse (semiannual) time dummies. The blue and red colors represent positive and negative coefficients. The opaque circle represents the coefficient estimate at a specific time. The vertical bars display the coefficient's 95% confidence interval. We interpret the coefficient estimates as elasticities. Production inputs: (a) funding costs, (b) tax costs, (c) labor costs, (d) IT costs, and (e) other administrative costs.*

computational infrastructure. Other administrative costs increase after December 2019.

We now focus on how the COVID-19 outbreak changed the relationship between the cost factors and the bank branch's total cost function. Instead of using pulse time dummies, we now interact the production inputs (cost factors) with the step dummy COVID-19, which equals one when the period is after January 2020. Table 5 reports coefficient estimates of the empirical exercise for the entire sample (Spec. I) and sub-samples segmented by bank size (large banks in Spec. II and non-large banks in Spec. III), bank control (private banks in Spec. IV and public banks in Spec. V), socio-economic development (highly-developed regions in Spec. VI and lowly-developed regions in Spec. VII).

Funding costs are the primary and most natural production input that positively correlates with

Table 5: *Surrogate model: how have bank branch's total cost functions changed after the COVID-19 outbreak?*

Dependent Variable:	$\log(\hat{CT}_{blt})$						
Sample:	Full	Large Bank	Non-Large Bank	Private Bank	Public Bank	High Dev.	Low Dev.
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Input Variables							
Funding costs$_{blt}$	0.5181***	0.5809***	0.5307***	0.5190***	0.4471***	0.5109***	0.5532***
	(0.0636)	(0.0357)	(0.1007)	(0.0806)	(0.0177)	(0.0526)	(0.1056)
Tax costs$_{blt}$	0.0650	0.1483***	0.1076	0.1559**	-0.0312	0.0736	0.0418
	(0.0596)	(0.0296)	(0.0880)	(0.0682)	(0.0876)	(0.0595)	(0.0696)
Labor costs$_{blt}$	0.2718***	0.2588***	0.3692***	0.2167***	0.3796***	0.2485***	0.2765***
	(0.0583)	(0.0584)	(0.0802)	(0.0372)	(0.0511)	(0.0663)	(0.0454)
IT costs$_{blt}$	-0.0137	0.0096	0.0077	0.0184	-0.0652	0.0216	-0.0518
	(0.0393)	(0.0450)	(0.0324)	(0.0192)	(0.0437)	(0.0253)	(0.0601)
Other administrative costs$_{blt}$	0.1731**	0.1913**	-0.0570	-0.0660	0.1854*	0.1883*	0.1090
	(0.0847)	(0.0659)	(0.1031)	(0.0640)	(0.0994)	(0.1017)	(0.0729)
COVID-19$_t$							
× Funding costs$_{blt}$	-0.1600***	-0.2436***	-0.1341*	-0.1805***	-0.1183	-0.1404***	-0.1905**
	(0.0513)	(0.0563)	(0.0794)	(0.0558)	(0.0887)	(0.0417)	(0.0836)
× Tax costs$_{blt}$	-0.1581*	-0.1701	0.0775	0.0043	-0.5118	-0.2455***	0.0246
	(0.0885)	(0.0998)	(0.1689)	(0.1026)	(0.4130)	(0.0873)	(0.1346)
× Labor costs$_{blt}$	0.0668	0.2392	0.0408	0.0519	0.3659	0.1748*	-0.0069
	(0.0981)	(0.1680)	(0.1322)	(0.0861)	(0.2298)	(0.1032)	(0.1047)
× IT costs$_{blt}$	0.0558**	0.0591*	0.0283	-0.0195	0.0709***	0.0750***	0.0213
	(0.0234)	(0.0269)	(0.0249)	(0.0201)	(0.0182)	(0.0248)	(0.0251)
× Other administrative costs$_{blt}$	0.2041***	0.3939**	0.0243	0.1402**	0.4108	0.3085***	0.0522
	(0.0586)	(0.1448)	(0.1244)	(0.0691)	(0.3640)	(0.0673)	(0.1134)
Fixed-effects							
Bank · Locality + Time · Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	33,141	25,850	7,291	17,193	15,948	17,672	15,469
R^2	0.9889	0.9913	0.9927	0.9921	0.9903	0.9911	0.9856

Note: This table reports coefficient estimates for the surrogate model (linear regression with only marginal covariates and the same fixed effects) mimicking the translog function in Equation (2) using semiannual data from 2015 to 2020 at the bank-locality-time level. The dependent variable is the fitted local total cost function of the mimicked model. We report results for the entire sample (Spec. I), large banks (Spec. II), non-large banks (Spec. III), private banks (Spec. IV), public banks (Spec. V), highly-developed (Southeast, South) regions (Spec. VI), and lowly-developed (North, Northeast, Central-West) regions (Spec. VII). We use all inputs listed in Table 1 and within- and before the half-year outputs listed in Table 3 (credit products), bonds and securities, and other assets. Only coefficients related to the inputs are reported. A logarithm transformation is applied to all numeric variables (to better approximate the original translog function). We introduce bank-locality and time-locality fixed effects in all regressions. One-way (national bank) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

higher total costs, irrespective of the bank branch's size and control and local socio-economic development. Tax costs are important in shaping the total cost function of large bank branches, which may reflect specific activities that are more common to large banks and with higher tax rates.[54] The importance of labor costs is also pervasive across banks and regions. Other administrative costs are relevant for large banks, public banks and in highly-developed areas. IT costs are not significant for the bank branch's total cost before the pandemic.

After the COVID-19 outbreak, the associations of costs factors to the overall bank branch's total cost significantly changed. The importance of funding costs decreased, reflecting the monetary policy loosening in Brazil at that moment. The relevance of tax costs also reduced during the COVID-19 pandemic, especially in highly-developed areas where bank headquarters concentrate.

[54] The differences may also arise due to the bank branch's locality. Some tax competencies in Brazil are at the municipality level, such as the Services Tax (*Imposto Sobre Serviços* – ISS). ISS is levied on revenues from banking fees and services, an important source of revenue for most of the large Brazilian banks.

Other administrative costs increased for large banks, private banks, and in highly-developed areas. IT costs increased for large banks, public banks, and in highly-developed areas, reflecting the more frequent use of electronic channels and the upscaling of the banks' internal computational systems during the pandemic. The increase in IT costs in highly-developed areas may be explained by the fact that banks center their IT structure in areas with more specialized IT labor force to reduce costs and enjoy gains of scale. The increase in labor costs during the pandemics for highly-developed areas corroborates this view.

5 COVID-19 and local competition

This section explores how the COVID-19 pandemic affected local credit markets and banks. We first define our municipality-level measure of COVID-19 intensity. Then, we show COVID-19 affected economic activity in Brazilian localities. After, we reason about its indirect effects on local market power (as measured by the Lerner index) through the effective price and marginal cost channels. Finally, we examine how COVID-19 affected banks using a bank-specific measure of exposure to the pandemic.

Table 6 reports the summary statistics of the dependent and independent variables used in our differences-in-differences specifications in this section. Apart from the data sets used when computing local market power in the previous section, we use additional data sets in this section. For convenience, we introduce them as we use them.

5.1 Measure for COVID-19 intensity in Brazilian localities

In this paper, we investigate how COVID-19 affected Brazilian localities in many dimensions. We measure to what extent COVID-19 impacts society and the economy locally using the share of the local population with COVID-19.

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.[55] Each Brazilian State Health Department compiles local reports from municipalities inside their geographical circumscription and report to the Federal Ministry of Health for consolidation daily. We end up with 2,238,003 municipality-time epidemiological bulletins.

Figure 18a shows the total number of new COVID-19 cases (incidence) as a share of the local population in capital (27 municipalities) and inland (5,543) regions. 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

[55] 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.

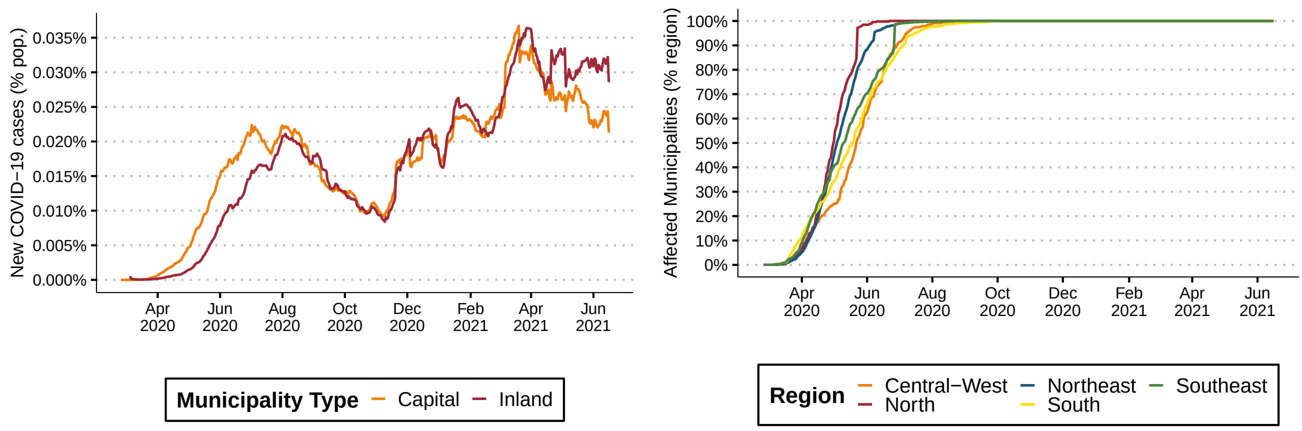
Table 6: *Summary statistics of the dependent and independent variables employed in the econometric exercises in Section 5.*

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
A. Dependent Variables (Variation: Bank-Modality-Locality-Time)								
Effective Price (%, semiannual rate)	92,186	13.510	12.090	0.363	5.466	9.164	17.295	68.241
Marginal Cost (R$)	92,186	0.059	0.316	−1.655	0.013	0.018	0.050	6.813
Lerner	92,186	0.259	2.795	−3.211	0.440	0.821	0.964	6.570
Credit Income (in mill. R$)	91,813	5.143	70.247	0.000	0.152	0.619	2.369	16,058.570
Granted Credit (in mill. R$)	92,186	15.088	163.221	0.00000	0.235	1.287	5.699	17,231.310
B. Dependent Variables (Variation: Bank-Locality-Time)								
Local Total Cost (in bill. R$)	9,342	0.051	0.139	0.001	0.006	0.013	0.034	1.120
% Clients Outside Locality	9,342	18.072	9.215	7.774	11.229	15.293	21.970	40.842
C. 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
D. COVID-19 intensity measurement (Variation: Locality)								
% Local Pop. Affected by COVID-19	509	4.887	3.963	0.514	2.732	4.034	5.932	40.898
E. COVID-19 intensity measurement (Variation: Bank)								
Bank's Exposure to COVID-19 (%)	74	4.751	1.036	2.703	4.089	4.735	5.184	10.234
F. Ex-ante controls (Variation: Bank-Modality-Locality)								
Market Share (%)	23,283	16.196	18.213	0.000	4.257	10.822	20.652	100.000
Provisions / Total Credit (%)	23,172	12.126	14.812	0.000	2.165	5.750	16.755	100.000
Avg. Maturity (in months)	23,159	65.855	77.734	0.000	30.156	45.827	70.754	397.976
Share of Local Pop. as Client (%)	23,172	0.703	1.232	0.00001	0.022	0.089	0.861	15.785
Avg. Local Ticket (in thous. R$)	23,159	1.976	2.332	0.000	0.905	1.375	2.123	11.939
Share Ear. Cred. of Modality (%)	23,172	17.785	34.195	0.000	0.000	0.000	11.111	100.000
Share Ear. Cred. of Other Modalities (%)	23,172	30.193	24.779	0.000	8.062	23.568	49.396	99.621
G. Ex-ante controls (Variation: Bank-Locality)								
Local Cost Factor (% Local Total Cost)								
Funding	2,387	45.787	11.766	0.561	38.760	45.585	53.949	84.701
Tax	2,387	3.488	1.293	0.006	2.637	3.542	4.283	9.938
Labor	2,387	31.606	12.658	1.077	23.608	30.498	37.737	99.380
IT	2,387	2.391	1.036	0.014	1.717	2.324	2.881	12.407
Other Administrative	2,387	16.727	7.774	0.031	11.270	14.253	21.887	56.336
H. Ex-ante controls (Variation: Locality)								
Distance to Capital (in km)	508	402.950	207.590	49.936	251.691	364.315	509.751	1,485.773
Per Capita GDP (in thous. R$)	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
Has Capital	509	0.053	–	–	–	–	–	–
Agriculture as Preponderant Activity	509	0.057	–	–	–	–	–	–
Industry as Preponderant Activity	509	0.067	–	–	–	–	–	–

Note: Panels A and B: data range from January 2019 to December 2020, semiannually. Panel C: data range from January 2019 to June 2021, monthly. Panel D: "Share of Local Pop. Affected by COVID-19" is the average number of local infectious persons per month of 2020 divided by the local population at the end of 2020. Panel E: "Bank's Exposure to COVID-19" is the average locality-specific COVID-19 prevalence (averaged over 2020 monthly) in places where the bank has credit weighted by the bank's outstanding credit in December 2019 in that locality. Panels F and G: data is from December 2019. Panel H: *Per capita* GDP, the dummy variables "Agriculture as Preponderant Activity" and "Industry as Preponderant Activity" refer to 2018 (last available information). The remaining variables are from 2019.

at least one COVID-19 case, as Figure 18b reveals. Before that, inter-municipality contagion was an important triggering factor for inland municipalities, and the COVID-19 dynamic in capitals was the main driver. After that, intra-municipality contagion was the main factor.

Figure 19 displays the spatial COVID-19 prevalence (accumulated cases) in Brazilian municipalities as a share of the local population after three, six, ten months after the first case reported in São Paulo in February 2020. After three months, 4,255 (76.4%) municipalities had already reg-



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

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

Figure 18: *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.*

istered 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.

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 to obtain the share of the population affected by COVID-19 for each month-year.[56] We then take the average of this share over January to December 2020. Since COVID-19 was an exogenous shock, we are able to use the average share of population affected by COVID-19 in 2020 as a continuous treatment variable to measure the local COVID-19 intensity across localities in our regressions.

We also run a cross-section regression to correlate the share of the population affected by COVID-19 with *ex-ante* local determinants (fixed with values in December 2019), such as the distance to the capital, *per capita* GDP, population, and the preponderant activities (agriculture, industry, or services). The local economy's structure may affect COVID-19 contagion as activities related to agriculture have lower population densities than in services and industrial activities. This empirical exercise is important to understand any systematic and underlying observable characteristics across localities correlated with our COVID-19 local intensity measure that could explain our results and be not the COVID-19 shock itself.

Table 7 shows the results of our cross-section estimation when 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[57] (Spec. IV),

[56] 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.

[57] 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 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). The across-locality comparison must be coarser than our unity

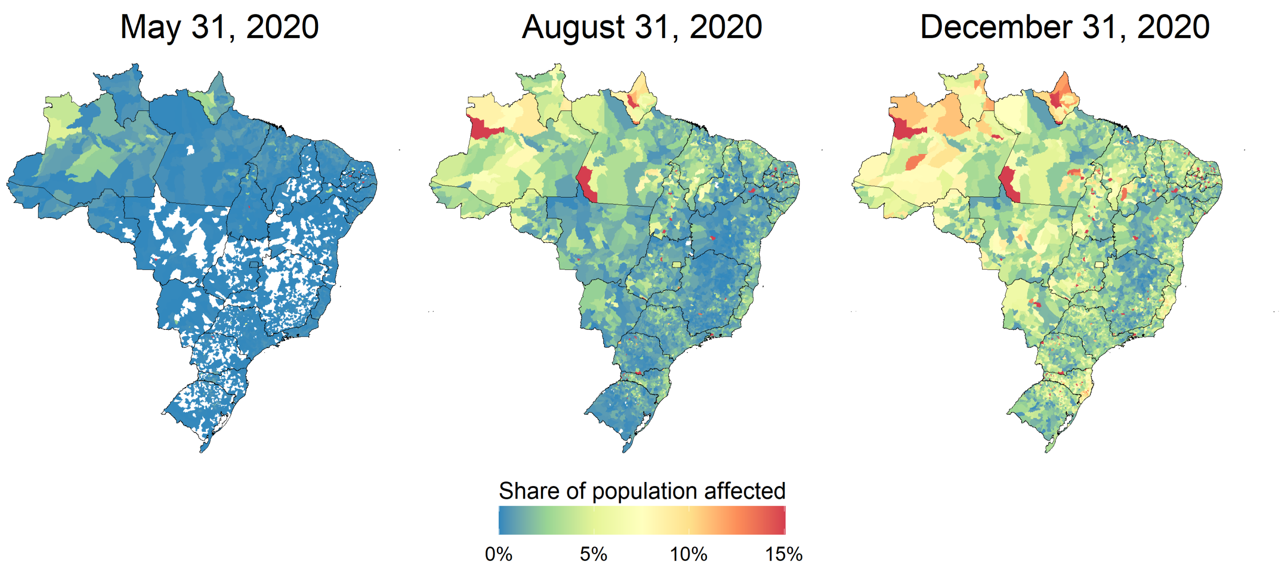


Figure 19: *Spatial COVID-19 prevalence in Brazilian municipalities. Total number of local COVID-19 cases as a share of the local population on May 31, 2020 (left); August 31, 2020 (center); December 31, 2020 (right). Colors from cold to warm represent increasing local COVID-19 prevalence. Blank localities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

and within the same macrolocality *and* localities of similar *per capita* GDP. There is homogeneity in economic activities within a macrolocality, as the dummy coefficients that capture the preponderant activities are insignificant. We use within-macrolocality comparisons of localities with similar *per capita GDP* in the following sections because it does not correlate with the observable determinants tested in the regression in Table 7. 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. We are able to control for the intensity of these programs by comparing localities with similar *per capita* GDP levels.

Figures 20a and 20b depict histograms of the share of local population affected by COVID-19 during 2020 by Brazilian region and *per capita* GDP quantiles (lower and upper median). The heterogeneity observed across regions and local wealth levels corroborates the irregular spreading pattern of COVID-19 across Brazilian municipalities after it hit capitals, as revealed in Figure 19.

of analysis, the immediate geographical region. We have also re-run our empirical specification by cross-comparing localities within the same state and region and with no restrictions. Our results remain qualitatively unchanged.

Table 7: *Locality-specific observable correlates of the measure Share of Population Affected by COVID-19$_l$*

Dependent Variable:	% Pop. Affected by COVID-19$_l$				
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(2)	—	—	—	—	Yes
Fit statistics					
Observations	508	508	508	506	425
R^2	0.0643	0.0983	0.2506	0.3789	0.4613

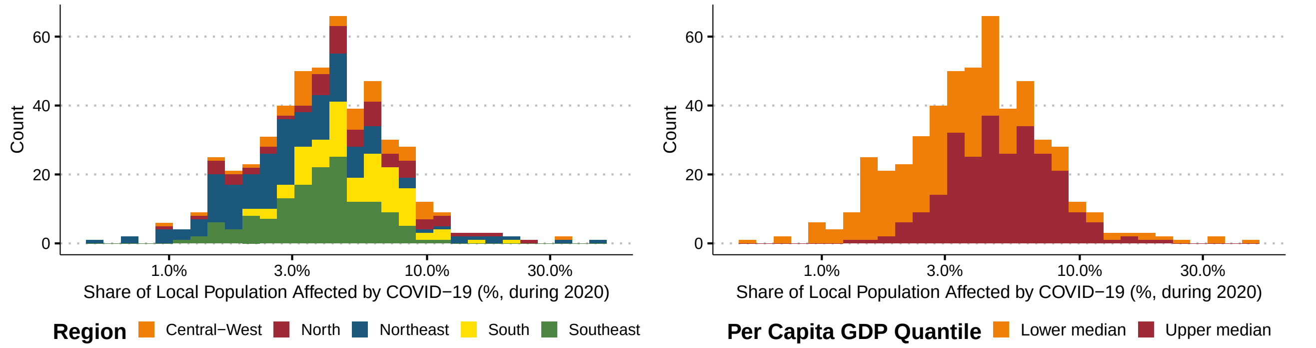
Note: This table reports coefficient estimates of the cross-section regression % Pop. Affected by COVID-19$_l = \alpha_{g(l)} + \beta$Local Covariates$_l + \varepsilon_l$, in which l is the locality. The dependent variable is the monthly average share of affected population by COVID-19 during 2020. We use the following local covariates (fixed with the last available *ex-ante* 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 two quantiles). We standardize numerical variables. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

5.2 COVID-19 and local economic activity

Localities with a higher COVID-19 prevalence are likely to adopt public health measures, such as horizontal social distancing, lockdown, and quarantines to a greater extent. Such measures affect many economic activities, notably those relying on in-site labor force and consumption. This section shows a higher local COVID-19 prevalence caused a decrease in local economic activity. This empirical finding is elaborated further in the next section as one of the channels through which COVID-19 can affect banks' local market power.

A first challenge is data availability 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. These firm-specific inflows serve as a proxy for the firm income. Firms can receive payments in Brazil in several ways. In this empirical exercise, we attempt to encompass many of these income channels using electronic transactions with the following confidential datasets:[58]

[58] We exclude money received from financial institutions and investment funds. We also eliminate transactions within the same firm economic group, which is common in firms with multiple plants for internal liquidity management. Even



(a) *Region*

(b) *Per capita GDP*

Figure 20: *Histograms of the share of local population affected by COVID-19 during 2020 at the locality level. Colors represent Brazilian regions in (a) and lower- and upper-median quantiles of the per capita GDP distribution in (b). Horizontal axis is in log-scale.*

- Transactions from credit and debit cards from open array operations reported by accreditors.[59] Individuals and firms normally settle small-valued transactions in Brazil 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. 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 maintained by the BCB.[60] We collect all economic transactions between non-financial firms. We remove transactions from the financial sector; 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. 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

though we use these data sources as a proxy for the firm income, we should register that there are some potential mismatches between our proxy and the *de facto* firm income. First, our data follows a cash basis flow, while firm income accounting formally follows an accrual basis flow. Second, we do not have transactions settled with cash, checks, direct deposits in accounts, and automatic debit (which is typical for paying water and electricity, telephone, TV, and Internet in Brazil). Third, we do not have information on businesses where the buyer uses the good as part of payment, such as vehicle dealerships and agriculture. Fourth, we do not have registries on operation income from abroad. We do not include PIX operations because they started to run only in November 2020 for the corporate sector.

[59] The data set 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.

[60] 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.

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.[61] 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 channels 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:

$$\text{Income}_{l,t} = \alpha_l + \alpha_{g(l),t} + \beta \text{ Share Affected by COVID-19}_l \cdot \text{COVID-19}_t + \varepsilon_{l,t}, \tag{5}$$

in which l and t index locality and time (January 2019 to June 2021, monthly). We use the locality-level income (of firms) as the dependent variable with different inflow channels: (i) all channels, (ii) credit and debit cards, (iii) invoices, (iv) exports, and (v) wire transfers. The variable Share Affected by COVID-19$_l$ is our locality-specific measure of COVID-19 intensity (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 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 geographically and economically similar localities. The function $g(l)$ ensures we compare localities within the same macrolocality *and* with similar *per capita* GDP (discretized in two quantiles) levels. We follow Abadie et al. (2020) and cluster the errors at the locality level, which coincides with the level of variation of our COVID-19 intensity measure. We apply a standardization procedure (subtract the sample mean and divide by the standard deviation) in all numeric variables.[62] The variable $\varepsilon_{l,t}$ is the usual error term.

Our coefficient of interest is β in (5). We interpret the coefficient as the *relative effect* of a one-standard-deviation increase in the share of the local population affected by COVID-19 on the locality-level income compared to other localities within the same macrolocality and similar *per capita* GDP levels.

Specifications I–V of Table 8 report the coefficient estimates of (5). A one-standard-deviation increase in the share of the local population affected by COVID-19 (4%) causes a reduction of

[61] 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.

[62] Thus, we interpret the results in terms of standard deviations from the sample mean whenever the variable is numeric.

0.0248 standard deviation in the locality's income when we consider all income channels (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 income channels, its effect is statistically significant only for credit and debit cards and invoices, which have widespread use by households and firms. While common in the corporate segment, wire transfers are typically used by households only for relatively large-valued operations. Exports are frequently limited to firms.

Table 8: *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										
% Pop. Affected by COVID-19$_l$	-0.0248***	-0.0092***	-0.0098***	-0.0083	-0.0059	-0.0215***	-0.0161***	-0.0123***	-0.0220	-0.0074
$\times$ COVID-19$_t$	(0.0058)	(0.0034)	(0.0032)	(0.0172)	(0.0038)	(0.0055)	(0.0049)	(0.0045)	(0.0281)	(0.0058)
Fixed-effects & Controls										
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Macrolocality · *Per capita* GDP(2)	Yes	Yes	Yes	Yes	Yes	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 (5) 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 channels: (i) all channels (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 Share of Pop. Affected by COVID-19$_l$ 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 are in terms of standard deviations from the sample mean. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

One of the necessary conditions to pursue causality in our results is that the dynamics of the locality-level income should be similar for less and more treated localities. Only after the COVID-19 outbreak should their dynamic diverge if the event has any economic impact. We can analyze the time-varying effect of COVID-19 over time by changing the step variable COVID-19$_t$ in (5) with monthly pulse dummies. Figure 21 shows 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 introduction 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 they offer 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 do not have information at the firm branch level for some of the income channels, 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 keep

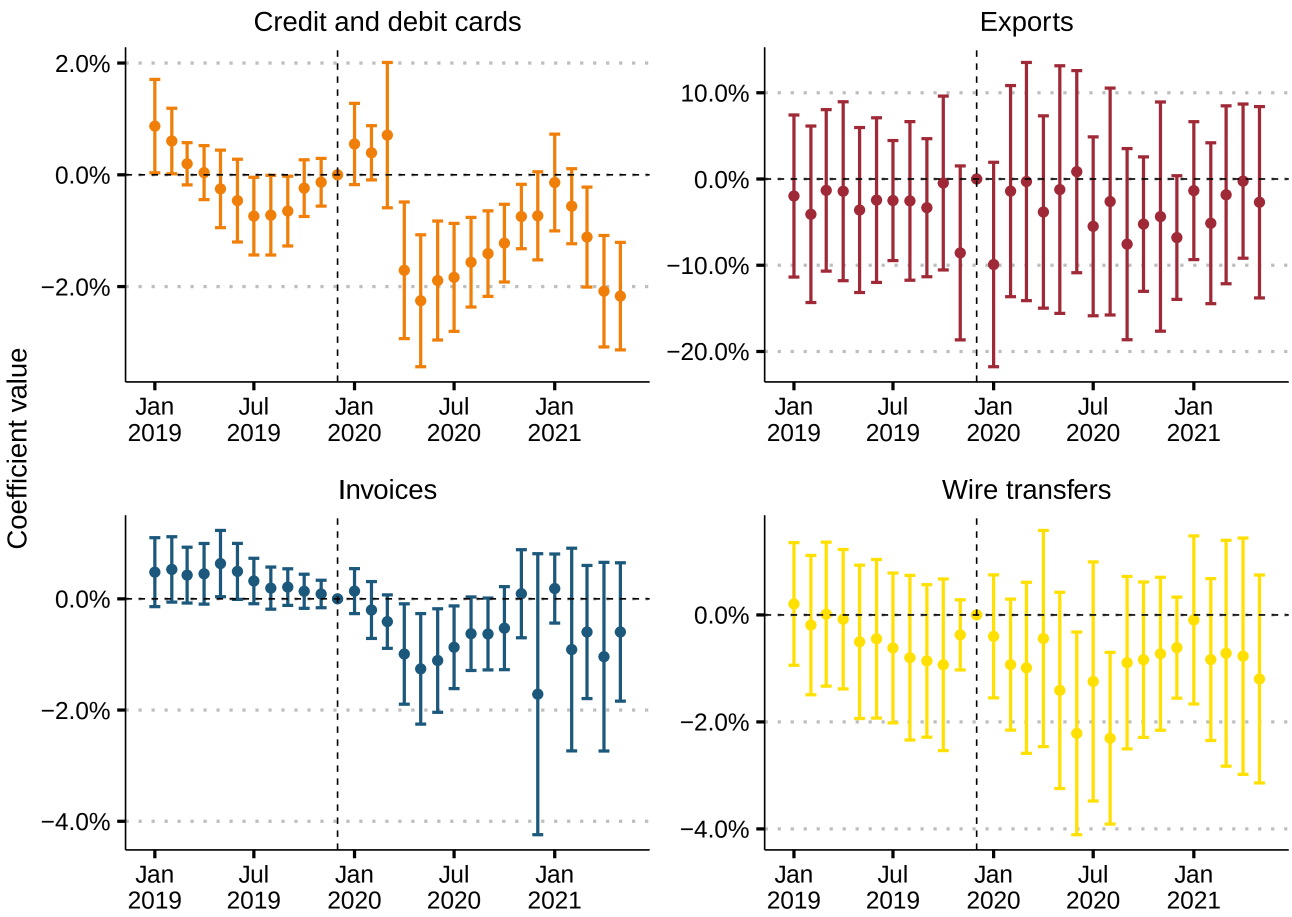


Figure 21: *Time-varying effects of COVID-19 prevalence in Brazilian localities for credit and debit cards (upper left), invoices (bottom left), exports (upper right), and wire transfers (bottom right). We run the specification in (5) but changing the step variable COVID-19$_t$ for monthly pulse dummies. Each point represents the β coefficient for a specific month from January 2019 to May 2021. Vertical bars denote the 95% confidence interval.*

firms without branches before aggregating income at the locality level. Specifications VI–X rerun (5) 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 final consumers who settle their purchases with such payment media.

5.3 COVID-19 and local market power

This section investigates how COVID-19 prevalence affected local market power in the Lerner index sense. We focus on within-half-year credit modalities, as they better convey the current market conditions. There are two channels through which the local market power can be affected: (i) the effective price and (ii) marginal cost channels. Since we want to quantify the effect of COVID-19 on banks' local market power, we need to control for the bank's credit supply while letting locality-specific conditions vary. This locality-specific variation should be only due to COVID-19 prevalence as we desire to attribute our findings to the pandemic. To this end, we use the share of the population affected by COVID-19 as our measurement for local COVID-19 intensity. Empirically, we compare the *same* bank operating in *different* but *similar* localities experiencing *distinct* COVID-

19 intensity levels. With this empirical strategy, we pin down the bank's credit supply and let only locality-specific factors vary. 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.

The previous section shows our local COVID-19 prevalence measure is unrelated to size, preponderant activities, and distance to capital if we look at localities of similar wealth levels within the same macrolocality (intermediate geographical region). We use a similar strategy in this section.[63] In this setup, the variation we capture is how the *relative difference* in the COVID-19 prevalence in these two localities affects local effective price, marginal cost, and Lerner index of that bank-modality.

We employ the following DiD specification with continuous treatment variable:

$$y_{b,m,l,t} = \alpha_{b,m,g(l),t} + \alpha_l + \beta \text{ Share Affected by COVID-19}_l \cdot \text{COVID-19}_t + \gamma^T \cdot \text{Controls}_{b,m,l} + \varepsilon_{b,m,l,t}, \quad (6)$$

in which b, m, l, t index the bank, credit modality (as defined in Table 3), localities (508 immediate geographical regions), and time (semiannually from 2019 to 2020). We look at several dependent variables $y_{b,m,l,t}$: average effective price (credit income / granted credit), marginal cost, Lerner index, credit income, within-half-year granted credit, provisions as a share of the outstanding credit, and contractual prices (interest rate), all of which segregated for each bank b and credit modality m at locality l during half-year t. The vector $\text{Controls}_{b,m,l}$ is a set of *ex-ante* bank-modality-locality controls (fixed with December 2019 values) encompassing: local market share, the share of the local population as clients, provisions as a share of the outstanding credit, average maturity, average ticket, share of earmarked credit of the modality, and share of earmarked credit of other modalities.[64] 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 of similar wealth levels within the same macrolocality—for the *same* credit modality m. We further introduce locality fixed effects α_l to absorb time-invariant locality-specific factors, such as population and number of eligible residents for COVID-19 emergency aid programs, that could contaminate our results. We standardize all numeric variables and cluster errors at the locality level.

Our coefficient of interest is β in (6). It captures the *relative effect* of a one-standard-deviation increase in a locality's share of affected population by COVID-19 on the outcome variable compared

[63] To exemplify, we compare the same bank (e.g., Banco do Brasil) operating in two different but similar localities within the same macrolocality (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).

[64] Joaquim et al. (2019) show changes in credit concentration affect banks' local behavior in credit markets. Therefore, we introduce the variables "local market share" and "share of the local population as clients" to control for any differences in the local concentration in terms of volume and quantity of clients, respectively, for a specific bank-modality across different localities. We also add the controls "provisions as a share of the outstanding credit," "average maturity," and "average ticket" to control for differences in the riskiness profile or locality-specific idiosyncrasies that could differ across localities within the same bank-modality. Ornelas et al. (2021) document a potential cross-selling strategy in which banks increase the price of non-earmarked loans for riskier borrowers that obtain earmarked credit using Brazilian data. We add the controls "share of earmarked credit of the modality" and "share of earmarked credit of other modalities" to account for any changes in earmarked and non-earmarked credit compositions and potential cross-selling behavior of Brazilian banks, respectively.

to similar localities with a share of the population affected by COVID-19 corresponding to the sample mean. Table 9 shows our coefficient estimates for the specification in (6) for our main variables: the average effective price (Spec. I), marginal costs (Spec. II), and Lerner index (Spec. III). We also rerun the same specification but (i) changing the step variable COVID-19$_t$ with semiannual pulse dummies in (6) and (ii) widening the temporal window from the beginning of 2017 to the end of 2020 to verify the parallel trends assumption. Figure 22 shows the estimated β coefficients. The dynamics of the average effective price, marginal cost, and Lerner are statistically the same for localities with different shares of the population affected by the COVID-19 before 2020. Only after the pandemic, the dynamics diverge.

Table 9: *Baseline: 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$_{bmlt}$	$\left(\frac{\text{Provision}_{bmlt}}{\text{Credit}_{bmlt}}\right)$	Contractual Price$_{bmlt}$
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Variables							
% Pop. Affected by COVID-19$_l$ · COVID-19$_t$	-0.0180***	0.0205***	-0.0192***	-0.0139***	-0.0172***	0.0076**	0.0054***
	(0.0042)	(0.0037)	(0.0041)	(0.0049)	(0.0032)	(0.0037)	(0.0016)
Fixed-effects & Controls							
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Modality · · Macrolocality · *Per capita* GDP(2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	75,514	75,514	75,514	75,402	75,514	75,514	75,370
R^2	0.7902	0.7784	0.7450	0.6829	0.8049	0.9024	0.9733

Note: This table reports coefficient estimates for the specification in Equation (6) 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 the following *ex-ante* bank-modality-locality controls (fixed with December 2019 values): local market share, provisions as a share of the outstanding credit, average maturity, the share of the local population as clients, average ticket, share of earmarked credit of the modality, and share of earmarked credit of other modalities. We also introduce locality and time-bank-modality-macrolocality-*per capita* GDP (discretized in two quantiles) fixed effects. Coefficients are in terms of standard deviations from the sample mean. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Effective price channel: A one-standard-deviation increase in the share of the population affected by COVID-19 (4%) reduces the average effective price in 0.0180 standard deviation, which corresponds to a decrease of $0.0180 \cdot 12.090\% = 0.22$ p.p. (semiannual rate) or 1.6% of the sample mean, compared to a similar locality with a share of the population affected by COVID-19 equal to the sample mean. While the direction is consistent with the lower economic activity found in the previous section, the coefficient's magnitude is not as economically relevant as the economic activity reduction.

We now investigate the effective price components to understand further this finding: the credit income (Spec. IV) and granted credit (Spec. V). A one-standard-deviation increase in the local COVID-19 prevalence reduces credit income by 0.0139 standard deviation, corresponding to 0.0139 · R\$ 70.247 = R\$ 0.98 million or 19% of the sample average. The reduction in credit income is economically relevant. Besides the lower economic activity, the introduction of government programs to alleviate the effects of the pandemic, such as repayment postponement of bank debt,

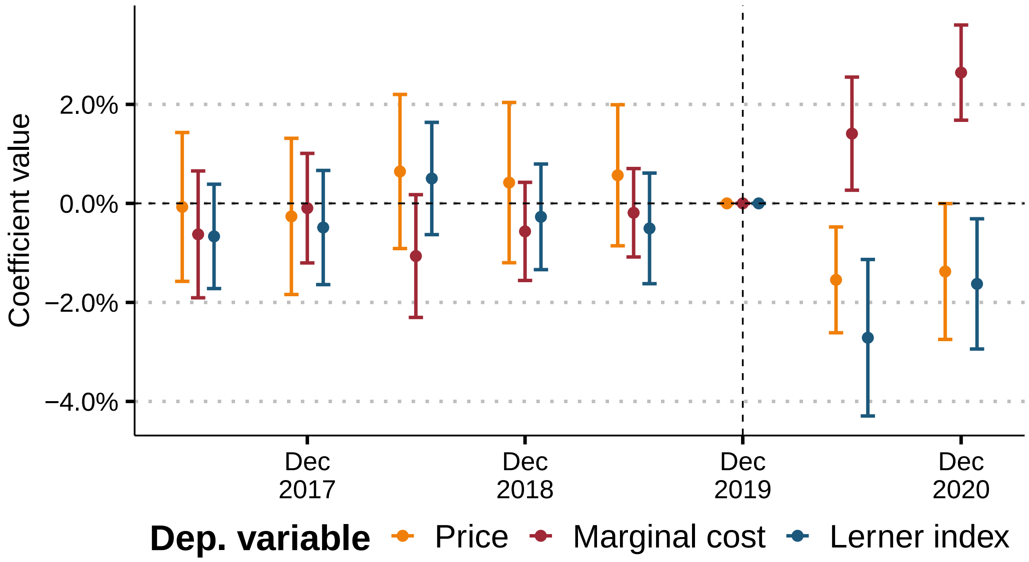


Figure 22: *Parallel trends check. We run specification in (6) but (i) changing the step variable COVID-19$_t$ with semiannual pulse dummies and (ii) widening the temporal window from the beginning of 2017 to the end of 2020. The figure displays the estimated β coefficients for each half-year. Vertical bars denote the 95% confidence interval.*

could partly explain the reduction in credit income. Simultaneously, granted credit decreases by 0.0172 standard deviation, equivalent to $0.0172 \cdot$ R\$ 163.221 = R\$ 2.81 million or 18.6% of the sample average. While the bank-time fixed effects capture the bank balance-sheet channel, we cannot cleanly identify the borrower balance-sheet channel (credit demand), because our data is at the bank-modality-locality level (and not at the borrower level). For instance, higher COVID-19 prevalence increased borrowers' aggregate riskiness: the share of provisions over credit (Spec. VI) and contractual prices or interest rates increase (Spec. VII). Therefore, the substantial decrease in credit income was offset by a similar decrease in local credit granting, resulting in a roughly similar effective price in localities with more COVID-19 prevalence. We conclude 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 0.0205-standard-deviation increase in banks' marginal costs, corresponding to a $0.0205 \cdot 0.316 \approx 1$ cent more expensive marginal cost, or 11% of the sample mean. If banks could adjust their total costs based on their output volumes frictionlessly, we would not expect changes in their marginal costs. We have seen that granted credit decreases in localities with more COVID-19 prevalence (Spec. V, Table 9). The increase in marginal costs suggests banks are unable to reduce their total costs mostly because cost factors are sticky due to economic, legal, and financial frictions.

To verify this hypothesis empirically, we analyze whether bank branches' total cost $CT_{b,l,t}$—which is the sum the cost components listed in Table 2—reduces in localities more affected by COVID-19. We run the following econometric specification:

$$CT_{b,l,t} = \alpha_{b,g(l),t} + \alpha_l + \beta \text{ Share Affected by COVID-19}_l \cdot \text{COVID-19}_t + \varepsilon_{b,l,t}, \tag{7}$$

in which b, l, and t index bank, locality, and time, respectively. The fixed effects $\alpha_{b,g(l),t}$ enable us to interpret the results in terms of the *same* bank operating in *different* but *similar* localities $g(l)$

(macrolocality and similar *per capita* GDP levels) over time. Our coefficient of interest is β in (7). It captures the effect of a one-standard-deviation increase in a locality's share of affected population by COVID-19 on the bank branch's total cost *vis-à-vis* another branch of the same bank in a locality with a sample mean's share of population affected by COVID-19. The remainder setup is equal to specification (6) but at the bank-locality-time instead of bank-modality-locality-time. Specification I of Table 10 shows the coefficients estimates of (7). We confirm our hypothesis that bank branches in localities more affected by COVID-19 are unable to adjust their local total costs, despite the reduction in credit grants. This result confirms that bank branch's cost factors are sticky and cannot be adjusted frictionlessly in the short term.

Table 10: *How does COVID-19 affect bank branches' total costs and geographical lending behavior?*

Dependent Variables:	Local Total Cost$_{blt}$						% Clients Outside Locality$_{blt}$	
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Variables								
% Pop. Affected by COVID-19$_l$								
$\times$ COVID-19$_t$	0.0068	0.0077	0.0062	0.0076	0.0077	0.0051	-0.0411*	-0.0415**
	(0.0171)	(0.0170)	(0.0174)	(0.0161)	(0.0175)	(0.0183)	(0.0168)	(0.0170)
$\times$ % Local Funding Cost$_{bl}$		-0.0137						
		(0.0093)						
$\times$ % Local Tax Cost$_{bl}$			-0.0065					
			(0.0087)					
$\times$ % Local Labor Cost$_{bl}$				-0.0072				
				(0.0069)				
$\times$ % Local IT Cost$_{bl}$					0.0286**			0.0177
					(0.0119)			(0.0214)
$\times$ % Local Other Administrative Cost$_{bl}$						0.0379***		
						(0.0146)		
% Pop. Affected by COVID-19$_l$								
$\times$ COVID-19$_t$								
$\times$ % Local Funding Cost$_{bl}$		-0.0031						
		(0.0027)						
$\times$ % Local Tax Cost$_{bl}$			-0.0035					
			(0.0036)					
$\times$ % Local Labor Cost$_{bl}$				0.0111				
				(0.0082)				
$\times$ % Local IT Cost$_{bl}$					-0.0119***			0.0271***
					(0.0018)			(0.0052)
$\times$ % Local Other Administrative Cost$_{bl}$						-0.0094		
						(0.0146)		
Fixed-effects & Controls								
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Macrolocality · *Per capita* GDP(2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	9,342	9,342	9,342	9,342	9,342	9,342	9,342	9,342
R^2	0.9378	0.9382	0.9380	0.9379	0.9383	0.9382	0.8003	0.8006

Note: This table reports coefficient estimates for the specifications in Equations (7) (Spec. I and VII) and (8) (Specs. II–VI and VIII) using semiannual data from 2019 to 2020 at the bank-locality-time level. To save space, we only report coefficients that interact with the Share of Population Affected by COVID-19$_l$. The dependent variable in Specs. I–VI is the bank branch's total cost, which is the sum of the cost components in Table 2. We make triple interactions of our COVID-19 local intensity measure, the step variable COVID-19, and the bank branch's cost components (as a share of the total cost) fixed with December 2019 values one at a time. We use the following cost components: funding (Spec. II), tax (Spec. III), labor (Spec. IV), IT (Spec. V), and other administrative costs (Spec. VI). The dependent variable in Specs. VII and VIII is the bank branch's share of clients outside the locality. We triple interact our COVID-19 local intensity measure, the step variable COVID-19, and the share of local IT costs (with values of December 2019) in Spec. VIII. We add locality and time-bank-macrolocality-*per capita* GDP (discretized in two quantiles) fixed effects. Coefficients are in terms of standard deviations from the sample mean. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

We now investigate whether banks more reliant on a specific cost factor can better adjust their total cost compared to the previous baseline result. In this analysis, we seek to investigate whether there is stickiness in all cost factors. For each specification, we triple interact our measure of local COVID-19 intensity, the step variable COVID-19, and a specific cost factor as a share of the bank branch's local total cost (fixed with December 2019 values) as follows:

$$\begin{aligned} CT_{b,l,t} = \alpha_{b,g(l),t} + \alpha_l + \beta \text{ Affected}_l \cdot \text{COVID-19}_t + \tau^{(c)}\text{Cost Factor}_{bl}^{(c)} + \gamma^{(c)}\text{Affected}_l \cdot \text{Cost Factor}_{bl}^{(c)} + \\ + \rho^{(c)}\text{Cost Factor}_{bl}^{(c)} \cdot \text{COVID-19}_t + \lambda^{(c)} \text{ Affected}_l \cdot \text{COVID-19}_t \cdot \text{Cost Factor}_{bl}^{(c)} + \varepsilon_{b,l,t}, \end{aligned} \tag{8}$$

in which c is one of the following bank branch's specific cost factors: funding, tax, labor, IT, and other administrative costs. For convenience, the variable Affected$_l$ is a shorthand for Share of Population Affected by COVID-19$_l$. Our coefficient of interest is $\lambda^{(c)}$ in (8). If banks can quickly adjust a specific cost factor following the COVID-19 outbreak, this should be loaded in this coefficient. Specifications II–VI of Table 10 shows the coefficient estimates of (8) for each cost factor, one at a time. The local pattern of spending on funding, tax, labor, and other administrative costs *ex-ante* 2020 is unrelated to the bank branch's ability to adjust the total local cost during the pandemic, suggesting a strong stickiness of these factors.

In contrast, banks with a one-standard-deviation higher share of IT local cost (1%) *ex-ante* the COVID-19 outbreak reduce total local costs by 0.0119 standard deviation, or $0.0119 \cdot$ R\$ 0.139 bi $\approx$ R\$ 1.7 million (3.2% of the sample average) for the bank branch. This finding highlights the importance of IT spending and the flexibility it gives in times of distress. IT development enables credit transactions electronically over the Internet or cellphones 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.

We elaborate further on this finding by bringing another empirical evidence. Suppose IT spending enables credit-granting regardless of the borrower's location through electronic medium. In that case, we should expect that banks with more developed IT systems can more easily replace borrowers in localities more affected by COVID-19 with other remote borrowers. That is, COVID-19 would affect banks with relatively high IT costs to a lesser extent. We then should observe a change in their borrower's locality concentration: the share of borrowers outside (inside) the locality should increase (decrease) after the bank branch's locality is affected by COVID-19. To check this hypothesis, we run through loan-level data in the SCR, inspecting the bank branch's and borrower's locations of each credit operation. SCR directly contains the bank branch's CEP (or ZIP code). We can extract the borrower's location by matching its tax identifier with the *Receita Federal do Brasil* dataset. We then compute the share of borrowers that live outside the bank branch's locality by aggregating the data at the bank-locality-time level.

To have a baseline irrespective of IT spending, we first rerun specification in (7) but changing the dependent variable with the bank branch's share of clients outside the locality. Specification VII in Table 10 shows the coefficient estimate. Bank branches in localities more affected by COVID-19 lend more to borrowers within the affected locality than other remote borrowers compared to another branch of the same bank in a locality with the sample mean's COVID-19 prevalence. Specification VIII in Table 10 shows the coefficient estimates when we use the bank branch's share of clients outside the locality as the dependent variable and the share of local IT costs *ex-ante* the COVID-19 pandemic as the cost factor. Banks with more local IT costs increase the share of clients outside the locality, suggesting local IT spending facilitates the replacement (or the complement) of local borrowers with remote borrowers, perhaps through online banking. This feature permits bank branches to be less sensitive to local borrower's conditions.

Our previous results suggest the marginal costs of bank branches with more local IT costs should be relatively less affected during the pandemic as they can adjust more easily their borrowers' portfolios. To verify this hypothesis empirically, we build upon specification in (6) but adding a triple interaction of the share of affected population by COVID-19, the step variable COVID-19, and the share of local IT costs. We run the following empirical specification at the bank-modality-locality-time level:

$$\begin{aligned} y_{b,m,l,t} = \alpha_{b,m,g(l),t} + \alpha_l + \beta \text{ Affected}_l \cdot \text{COVID-19}_t + \tau^{(c)}\text{Cost Factor}_{bl}^{(c)} + \gamma^{(c)}\text{Affected}_l \cdot \text{Cost Factor}_{bl}^{(c)} + \\ + \rho^{(c)}\text{Cost Factor}_{bl}^{(c)} \cdot \text{COVID-19}_t + \lambda^{(c)} \text{ Affected}_l \cdot \text{COVID-19}_t \cdot \text{Cost Factor}_{bl}^{(c)} + \\ + \gamma^T \cdot \text{Controls}_{b,m,l} + \varepsilon_{b,m,l,t}. \end{aligned} \tag{9}$$

Table 11 reports the coefficient estimates of (9) using the following dependent variables: average effective price (Spec. I), marginal cost (Spec. II), and Lerner (Spec. III). For the same credit modality, a higher share of local IT costs before the COVID-19 outbreak associates with a lower marginal cost for bank branches in localities more affected by COVID-19 than another less affected locality. Since banks with a higher share of local IT costs are likely to have more developed computational systems, they can replace the decrease in credit granting in localities more affected by COVID-19 with remote borrowers, potentially in less affected areas. In this way, they can maintain or comparatively reduce less their credit levels. Thus, there is less need to adjust their total local costs. In this scenario, they do not experience the frictions of adjusting total local costs in the short term, and marginal costs do not change substantially. The *ex-ante* share of local IT costs is unrelated to effective prices, perhaps because it is a component that associates more with the borrower's conditions.

We now investigate the relationship between the *ex-ante* share of local IT costs and marginal costs after the COVID-19 pandemic for different types of credit modality. We rerun the specification in (9) with the marginal cost as the dependent variable but splitting the sample into credit modalities that pertain to the corporate (Spec. IV) and households (Spec. V) segments. Higher *ex-ante* shares of local IT costs associate with decreases in marginal costs after the COVID-19 outbreak, especially for the corporate sector. The corporate sector, on average, has large potential borrowers, which often run all their finance and employee payroll within the bank, reducing information asymmetries and enabling remote transactions at better contractual conditions. Firms are also more likely to pursue better contracts outside their physical localities. In contrast, a significant share of households receives and runs their finances outside the financial system, increasing information asymmetry.

We again rerun the specification in (9) but splitting the sample into modalities that usually mature in the short (Spec. VI) and long term (Spec. VII). While higher shares of local IT costs associate

***Table 11:** What is the role of local IT spending during the COVID-19 pandemic?*

Dependent Variables:	Price_{bmlt}	$\text{Marginal Cost}_{bmlt}$	Lerner_{bmlt}	$\text{Marginal Cost}_{bmlt}$			
Sample:	Full	Full	Full	Firms	Individuals	Short-Term	Long-Term
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Variables							
% Pop. Affected by COVID-19_l							
× COVID-19_t	-0.0185***	0.0175***	-0.0185***	0.0221***	0.0132**	0.0174**	0.0181***
	(0.0046)	(0.0045)	(0.0043)	(0.0075)	(0.0050)	(0.0066)	(0.0058)
×% Local IT Cost_{bl}	0.0104	0.0124	-0.0127**	0.0157	0.0093	0.0118	0.0144**
	(0.0064)	(0.0078)	(0.0059)	(0.0197)	(0.0072)	(0.0102)	(0.0061)
× COVID-19_t · % Local IT Cost_{bl}	-0.0077	-0.0223***	0.0201***	-0.0355**	-0.0120	-0.0268***	-0.0117*
	(0.0078)	(0.0079)	(0.0068)	(0.0151)	(0.0076)	(0.0100)	(0.0071)
Fixed-effects							
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Modality ·	Yes	Yes	Yes	Yes	Yes	Yes	Yes
· Macrolocality · *Per capita* GDP(2)							
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	75,514	75,514	75,514	37,134	38,380	43,351	32,163
R^2	0.7908	0.7482	0.7363	0.7345	0.7885	0.7256	0.7958

Note: This table reports coefficient estimates for the specification in Equation (9) 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 (Specs. II, IV–VII), and Lerner (Spec. III). To save space, we only report coefficients that interact with the Share of Population Affected by COVID-19_l. We use the full sample in Specs. I–III and the following sub-samples: credit modalities for non-financial firms and individuals as listed in Table 3 in Specs. IV and V and credit modalities that usually mature in the short and long term in Specs. VI and VII. All specifications have the following *ex-ante* bank-modality-locality controls (fixed with December 2019 values): local market share, provisions as a share of the outstanding credit, average maturity, the share of the local population as clients, average ticket, share of earmarked credit of the modality, and share of earmarked credit of other modalities. We also introduce locality and time-bank-modality-macrolocality-*per capita* GDP (discretized in two quantiles) fixed effects. Coefficients are in terms of standard deviations from the sample mean. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

with lower marginal costs after the COVID-19 pandemic in both cases, the result is stronger for short-term credit. This finding may be driven by the fact that short-term credit contracts are more likely to be available remotely as they require less human and even collateral analysis.

Local market power: We find that effective prices decrease, but the impact is not economically significant. Marginal costs increase substantially due to a combination of (i) reduced credit granting in localities more affected by COVID-19 and (ii) stickiness of cost factors that bank branches are unable to adjust quickly following the reduction in credit due to economic, legal, and financial frictions. Therefore, the COVID-19 pandemic reduced the local market power of Brazilian banks through the marginal cost channel during 2020. Local IT spending attenuated the reduction in the local market power by reducing the frictions that banks experience in adjusting total local costs (Spec. III in Table (9)). We find evidence that banks with more IT infrastructure can more easily replace their credit portfolio with borrowers outside the locality, potentially less affected by the pandemic, corroborating the finding.

Further tests with subsets of credit modalities: We rerun our baseline specification in (7) using subsets of credit modalities. Table 12 reruns our baseline specification by splitting the sample into credit modalities for non-financial firms (Specs. I-IV) and individuals (Specs. V–VIII). The decrease in effective prices in localities more affected by the COVID-19 is limited to the corporate sector. Credit granting reduces for both segments, which partly explains the increase in marginal costs for non-financial firms and individuals. Again, the marginal cost channel is stronger than the effective price channel, yielding lower Lerner indices in localities more affected by COVID-19.

Table 12: *How does COVID-19 affect credit for non-financial firms and individuals across localities?*

Sample:	Non-Financial Firms				Individuals			
Dependent Variables:	Effective Price$_{bmlt}$	Marginal Cost$_{bmlt}$	Lerner$_{bmlt}$	Granted Credit$_{bmlt}$	Effective Price$_{bmlt}$	Marginal Cost$_{bmlt}$	Lerner$_{bmlt}$	Granted Credit$_{bmlt}$
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Variables								
% Pop. Affected by COVID-19$_l$ × COVID-19$_t$	-0.0349*** (0.0100)	0.0239*** (0.0077)	-0.0241** (0.0107)	-0.0203*** (0.0051)	-0.0037 (0.0043)	0.0170*** (0.0059)	-0.0149*** (0.0048)	-0.0158*** (0.0046)
Fixed-effects								
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Modality · · Macrolocality · *Per capita* GDP(2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	37,134	37,134	37,134	37,134	38,380	38,380	38,380	38,380
R^2	0.7084	0.7568	0.7316	0.7737	0.8820	0.8202	0.7589	0.8317

Note: This table reports coefficient estimates for the specification in Equation (6) using semiannual data from 2019 to 2020 at the bank-modality-locality-time level. We use the following dependent variables: effective price (Specs. I, IV), marginal cost (Specs. II, VI), Lerner (Spec. III, VII), and within-half-year granted credit (Specs. IV and VIII). We split the sample into credit modalities for non-financial firms (Specs. I–IV) and for individuals (Specs. V–VIII), as classified in Table 3. All specifications have the following *ex-ante* bank-modality-locality controls (fixed with December 2019 values): local market share, provisions as a share of the outstanding credit, average maturity, the share of the local population as clients, average ticket, share of earmarked credit of the modality, and share of earmarked credit of other modalities. We also introduce locality and time-bank-modality-macrolocality-*per capita* GDP (discretized in two quantiles) fixed effects. Coefficients are in terms of standard deviations from the sample mean. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Table 13 further revisits our baseline specification in (7) by splitting the sample into credit modalities that usually mature in the short (Specs. I-IV) and long term (Specs. V–VIII). Our conclusions discussed in the baseline specification hold for both subsets of credit modalities.

5.4 COVID-19 and banks

The previous section investigated how COVID-19 local prevalence affected localities using a within-bank and across-locality analysis. This empirical setup does not allow us to understand how COVID-19 prevalence affected *different* banks. This section complements these results and investigates how COVID-19 influenced effective prices, marginal costs, and Lerner indices across different banks operating in the *same* location. The empirical strategy of comparing different banks in the same locality enables us to control for any locality-specific factor that could drive our results, such as the COVID-19 local prevalence. Therefore, this section employs a within-locality and across-bank analysis.

We need a bank-specific measure of COVID-19 exposure for this empirical exercise. We combine information about the locality-level measure of COVID-19 prevalence employed in the previous sections and bank-specific outstanding credit across different Brazilian localities in 2019. We first identify the locality-specific outstanding credit in December 2019 of each bank using data on credit operations from the SCR and the borrowers' location from the *Receita Federal do Brasil*. We aggregate these credit operations to the bank-borrower's locality level. Finally, we define the measure

Table 13: How does COVID-19 affect short and long term credit across localities?

Sample:	Short-Term Credit				Long-Term Credit			
Dependent Variables:	Effective Price$_{bmlt}$	Marginal Cost$_{bmlt}$	Lerner$_{bmlt}$	Granted Credit$_{bmlt}$	Effective Price$_{bmlt}$	Marginal Cost$_{bmlt}$	Lerner$_{bmlt}$	Granted Credit$_{bmlt}$
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Variables								
% Pop. Affected by COVID-19$_l$	-0.0161***	0.0205***	-0.0164**	-0.0199***	-0.0201*	0.0192***	-0.0222**	-0.0166***
$\times$ COVID-19$_t$	(0.0058)	(0.0067)	(0.0064)	(0.0055)	(0.0102)	(0.0063)	(0.0087)	(0.0051)
Fixed-effects								
Locality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Bank · Modality ·	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
· Macrolocality · *Per capita* GDP(2)								
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	43,351	43,351	43,351	43,351	32,163	32,163	32,163	32,163
R^2	0.8390	0.7603	0.7023	0.8373	0.7381	0.8124	0.7868	0.7920

Note: This table reports coefficient estimates for the specification in Equation (6) using semiannual data from 2019 to 2020 at the bank-modality-locality-time level. We use the following dependent variables: effective price (Specs. I, IV), marginal cost (Specs. II, VI), Lerner (Spec. III, VII), and within-half-year granted credit (Specs. IV and VIII). We split the sample into credit modalities that usually mature in the short (Specs. I–IV) and in the long term (Specs. V–VIII). All specifications have the following *ex-ante* bank-modality-locality controls (fixed with December 2019 values): local market share, provisions as a share of the outstanding credit, average maturity, the share of the local population as clients, average ticket, share of earmarked credit of the modality, and share of earmarked credit of other modalities. We also introduce locality and time-bank-modality-macrolocality-*per capita* GDP (discretized in two quantiles) fixed effects. Coefficients are in terms of standard deviations from the sample mean. One-way (locality) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Bank's Exposure to COVID-19$_b$ as average locality-specific COVID-19 prevalence in places where the bank has credit weighted by the bank's outstanding credit in that locality. Mathematically:

$$\text{Bank Exposure to COVID-19}_b = \frac{\sum_{l \in \mathscr{L}} \text{Credit}_{bl} \cdot \text{Share of Population Affected by COVID-19}_l}{\sum_{l \in \mathscr{L}} \text{Credit}_{bl}}, \qquad (10)$$

in which b and l index the bank and locality, respectively. We denote the set of localities (immediate geographical region) as $\mathscr{L}$. The term Credit$_{bl}$ is the bank b's end-of-month outstanding credit in December 2019 at locality l. Table 14 shows observable bank-specific correlates with the measure Bank's Exposure to COVID-19$_b$. Liquidity, solvency, bank size and control are unrelated even without the introduction of fixed effects (Spec. I). However, the Brazilian government introduced many programs to incentive credit to combat the effects of the pandemic, which large banks mainly operationalized. In this way, we opt to compare banks of the same size in the regressions in this section. This strategy also enables us to control for any size-specific changes in regulation among banks.The measure Bank's Exposure to COVID-19$_b$ maintains unrelated to observable bank-specific characteristics when we make within-comparisons of similar-sized banks (Spec. II).

We employ the following empirical specification:

$$y_{b,m,l,t} = \alpha_{g(b),m,l,t} + \alpha_b + \beta \text{ Bank's Exposure to COVID-19}_b \cdot \text{COVID-19}_t + \gamma^T \text{Controls}_{b,m,l} + \varepsilon_{b,m,l,t}, \qquad (11)$$

in which b, m, l, and t index bank, credit modality, locality, and time, respectively. We use the same set of dependent variables as in our within-bank across-locality baseline analysis in (6). The

Table 14: *Bank-specific observable correlates of the measure Bank Exposure to COVID-19$_b$.*

Dependent Variable:	Bank's Exposure to COVID-19$_b$	
Model:	(I)	(II)
Variables		
Liquidity Index$_b$	-0.0005	-0.0005
	(0.0006)	(0.0006)
Solvency Index$_b$	0.0002	0.0004
	(0.0004)	(0.0004)
Total Assets$_b$	-0.0005	-0.0004
	(0.0006)	(0.0015)
Public Bank$_b$ (dummy)	0.0066	0.0064
	(0.0052)	(0.0055)
(Intercept)	0.0031***	
	(0.0002)	
Fixed-effects		
Bank Size(4)	—	Yes
Fit statistics		
Observations	74	74
R^2	0.1485	0.1682

Note: This table reports coefficient estimates of the cross-section regression Bank's Exposure to COVID-19$_b = \alpha_{g(b)} + \beta$Bank Covariates$_b + \varepsilon_b$, in which b is the bank. The dependent variable is the bank's exposure to COVID-19 as defined in (10). We use the following bank-specific covariates (fixed with values in December 2019): liquidity index (LCR), solvency index (capitalization level), total assets, and a dummy variable that equals one if the bank is public. The term $\alpha_{g(b)}$ represents bank size (large, medium, small, and micro) fixed effects that permits us to perform comparisons within banks of the same size. One-way (bank) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

fixed effects $\alpha_{g(b),m,l,t}$ enables us to compare *different* banks operating in the *same* credit modality *within* the same locality over time. The function $g(b)$ further compares banks of similar size (large, medium, small, micro). We also add bank fixed effects to capture any bank-specific time-invariant factors. We also use the same set of bank-modality-locality controls fixed with December 2019 values. The term $\varepsilon_{b,m,l,t}$ is the usual error term. We standardize all numeric variables. We cluster errors at the bank level, the same variation of the measure Bank's Exposure to COVID-19$_b$.

Our coefficient of interest is β in (11). It captures the *relative effect* of a one-standard-deviation increase in the bank's exposure to COVID-19 on the outcome variable compared to another bank of similar size with a sample mean's exposure to COVID-19 within the same locality and same credit modality. Table 15 shows our coefficient estimates for the specification in (11) for our main variables: the average effective price (Spec. I), marginal costs (Spec. II), and Lerner index (Spec. III). Likewise the previous section, we also perform parallel trends check of these variables. Figure 23 shows the estimated β coefficients over time.

Effective price channel: A one-standard-deviation increase in the bank's exposure to COVID-19 (1%) raises the effective price in 0.0933 standard deviation compared to another bank of similar size operating in the same market (credit modality) at the same location (Spec. I). This coefficient corresponds to $0.0933 \cdot 12.09 = 1.13$ p.p. higher effective prices, which is economically relevant (8.3% of the sample average). If we look at the components of the effective price, credit income is linearly unrelated to the bank's exposure to COVID-19 (Spec. IV), which reinforces the view that local conditions strongly drive the bank's credit income. Since we perform within-locality comparisons, such feature ends up being controlled for, and we do not observe statistically significant changes in the credit income (Spec. IV). In contrast, a one-standard-deviation increase in bank's exposure

Table 15: *Baseline: how does the bank's exposure to COVID-19 affect market power components and lending behavior?*

Dependent Variables:	Effective Price_{bmlt}	Marginal Cost_{bmlt}	Lerner_{bmlt}	Credit Income_{bmlt}	Granted Credit_{bmlt}	$\left(\frac{\text{Provision}_{bmlt}}{\text{Credit}_{bmlt}}\right)$	Contractual Price_{bmlt}
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Variables							
Bank's Exposure to COVID-19_b	0.0933***	-0.0193	0.0413**	0.0242	-0.0172***	-0.0483**	0.0252*
× COVID-19_t	(0.0306)	(0.0229)	(0.0182)	(0.0209)	(0.0065)	(0.0229)	(0.0146)
Fixed-effects & Controls							
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Modality · Locality · Bank Size(4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	89,390	89,390	89,390	89,227	89,390	89,390	89,181
R^2	0.7915	0.3074	0.4725	0.7469	0.7360	0.8194	0.8786

Note: This table reports coefficient estimates for the specification in Equation (11) 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 the following *ex-ante* bank-modality-locality controls (fixed with December 2019 values): local market share, provisions as a share of the outstanding credit, average maturity, the share of the local population as clients, average ticket, share of earmarked credit of the modality, and share of earmarked credit of other modalities. We also introduce bank and time-bank size-modality-locality fixed effects. Coefficients are in terms of standard deviations from the sample mean. One-way (bank) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

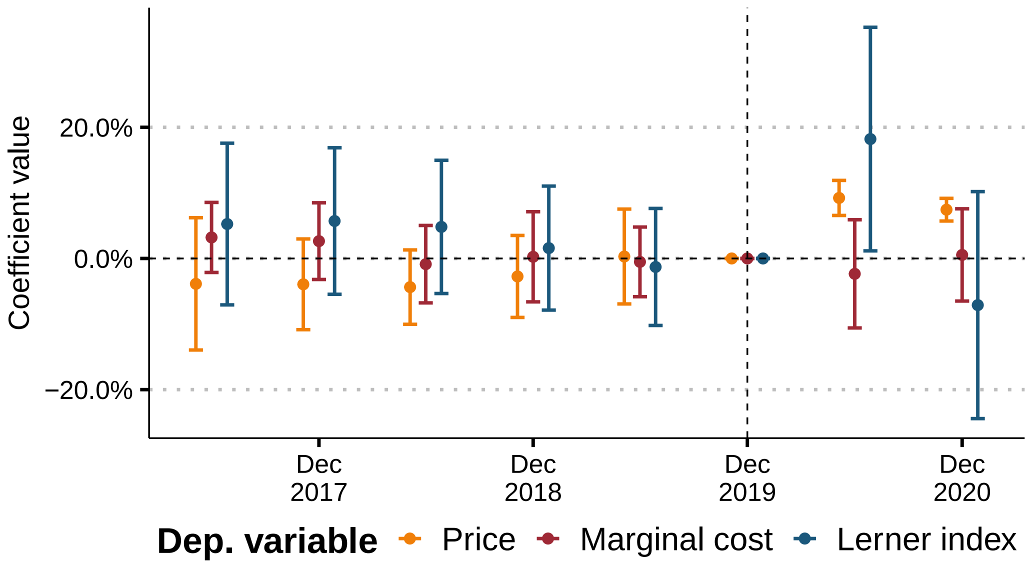


Figure 23: *Parallel trends check. We run specification in (11) but (i) changing the step variable COVID-19_t with semiannual pulse dummies and (ii) widening the temporal window from the beginning of 2017 to the end of 2020. The figure displays the estimated β coefficients for each half-year. Vertical bars denote the 95% confidence interval.*

(1%) reduces granted credit by 0.0172 standard deviation (Spec. V), or $0.0172 \cdot$ R\$ 163.221 million = R\$ 2.81 million (18.6% of the sample average). Combining this finding with the observed (despite marginally significant) increase in contractual prices or interest rates (Spec. VII) suggests COVID-19 caused a negative credit supply shock in more exposed banks. Banks more exposed to the COVID-19 also reduced their credit portfolio riskiness (Spec. VI). This deleveraging indicates banks searched for better borrowers following the negative credit supply shock.

Marginal cost channel: We do not find evidence of bank's exposure to COVID-19 affecting local marginal costs when we compare banks of the same size operating in the same locality and modality

(Spec. II). We expect this result since locality-specific conditions, such as COVID-19 prevalence and economic activities, are similar for banks in the same locality.

Local market power: We find effective prices increase and marginal costs stay the same in the within-locality and across-bank analysis. The net effect is an increase in the local market power of banks more affected by COVID-19 through the effective price channel (Spec. III). The increase in the effective price operates through a negative supply shock and not through increased credit income.

Bank-specific determinants: In this part, we look at bank-specific determinants that change the relationship between the bank's exposure to COVID-19 and average prices, marginal costs, and Lerner indices. We build upon specification in (11) and add a triple interaction corresponding to the bank's exposure to COVID-19, COVID-19, and the bank-specific factor as follows:

$$\begin{aligned} y_{b,m,l,t} = \alpha_{g(b),m,l,t} + \alpha_b + \beta \text{ Exposure}_b \cdot \text{COVID-19}_t + \tau \text{ Factor}_{bl} + \gamma \text{ Exposure}_b \cdot \text{Factor}_{bl} + \\ + \rho \text{ Factor}_{bl} \cdot \text{COVID-19}_t + \lambda \text{ Exposure}_b \cdot \text{COVID-19}_t \cdot \text{Factor}_{b,l} + \gamma^T \text{Controls}_{b,m,l} + \varepsilon_{b,m,l,t}. \end{aligned} \tag{12}$$

in which Factor_{bl} is one of the following bank-specific factors (fixed with December 2019 values): share of local IT costs (bank-locality variation), local market share (bank-modality-locality), and liquidity index (bank).[65] We use Exposure_b as a shorthand for Bank's Exposure to COVID-19_b. All the remaining empirical setup follows the specification in (11). The coefficient of interest is λ in (12).

Table 16 shows the coefficient estimates of (12) when we use the following dependent variables: effective price (Specs. I–III), marginal cost (Specs. IV–VI), and Lerner (VII–IX). We run one specification for each bank-specific factor. Even though the bank's exposure to COVID-19 does not relate to marginal costs, we find a different picture for banks that spent relatively more on IT before the pandemic. After 2020, banks with higher shares of local IT costs *ex-ante* the COVID-19 outbreak have lower marginal costs than banks of similar size operating in the same locality and credit modality that have not spent as much on IT (Spec. IV). Such finding corroborates the related within-bank empirical result from the previous section but from the across-bank perspective: higher IT spending also associates with decreased *relative* marginal costs across banks. Banks with higher shares of local IT spending before the pandemic enjoy higher market power after the COVID-19 upsurge. The cost of providing one additional credit is cheaper, while effective prices are the same as other banks of similar size in the same locality and modality that have not spent as much on IT before the COVID-19 outbreak.

Banks with higher local market shares charge higher effective prices but have comparable marginal costs than similar banks in the same locality and credit modality, suggesting that local concentration could drive higher local market power through the effective price channel. Finally, banks more liquid charge less effective prices, suggesting financial constraints played a role in the effective price after the COVID-19 outbreak.

[65]When we use the liquidity index (bank-level variation), the coefficients τ and γ in (12) become collinear with the bank fixed effects α_b.

Table 16: *Bank-specific determinants: how do they affect the relationship of the bank's exposure to COVID-19 and its market power components?*

Dependent Variables:	Price$_{bmlt}$			Marginal Cost$_{bmlt}$			Lerner$_{bmlt}$		
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Variables									
Bank's Exposure to COVID-19$_b$									
× COVID-19$_t$	0.0941***	0.0957***	0.1127***	-0.0217	-0.0199	-0.0251*	0.0448***	0.0385***	0.0432***
	(0.0162)	(0.0154)	(0.0111)	(0.0135)	(0.0146)	(0.0139)	(0.0092)	(0.0098)	(0.0108)
× % Local IT Cost$_{bl}$	-0.0024			0.0031			0.0004		
	(0.0017)			(0.0059)			(0.0045)		
× Market Share$_{bml}$		-0.0118			-0.0061			0.1069***	
		(0.0207)			(0.0151)			(0.0243)	
Bank's Exposure to COVID-19$_b$									
× COVID-19$_t$									
× % Local IT Cost$_{bl}$	0.0012			-0.0161***			0.0152***		
	(0.0013)			(0.0052)			(0.0050)		
× Market Share$_{bml}$		0.0467***			-0.0243			0.0093	
		(0.0149)			(0.0150)			(0.0198)	
× Liquidity Index$_b$			-0.0283***			0.0015			0.0011
			(0.0068)			(0.0065)			(0.0052)
Fixed-effects									
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time · Modality · Locality · Bank Size(4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	89,390	89,390	89,390	89,390	89,390	89,390	89,390	89,390	89,390
R^2	0.7917	0.7920	0.7920	0.3082	0.3077	0.3074	0.4741	0.4772	0.4725

Note: This table reports coefficient estimates for the specification in Equation (12) using semiannual data from 2019 to 2020 at the bank-modality-locality-time level. For convenience, we only report in the table coefficients related to the Bank's Exposure to COVID-19$_b$ (marginal and associated interactions). We use the following dependent variables: effective price (Specs. I–III), marginal cost (Specs. IV–VI), and Lerner (Spec. VII–IX). We use as Factor$_{bl}$: the bank-locality share of IT costs (Specs. I, IV, VII), the bank-modality-locality market share (Specs. II, V, VIII), and the bank liquidity index (Specs. III, VI, IX). We use the Liquidity Coverage Ratio as the liquidity index from the Cosif dataset. All specifications have the following *ex-ante* bank-modality-locality controls (fixed with December 2019 values): local market share, provisions as a share of the outstanding credit, average maturity, the share of the local population as clients, average ticket, share of earmarked credit of the modality, and share of earmarked credit of other modalities. We also introduce bank and time-bank size-modality-locality fixed effects. Coefficients are in terms of standard deviations from the sample mean. One-way (bank) standard errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

6 Conclusions

This paper investigates how the COVID-19 pandemic affected the bank market power in Brazil using a multi-product Lerner index. We adapt the index to enable estimations of banking competition at the local level and for each credit modality. Studies on banking competition typically take the bank at the national level as the unit of analysis. Such limitation arises from the absence of microdata needed to estimate banks' local production functions. This research attempts to overcome this limitation by using microdata from various proprietary and public sources and resource allocation heuristics to estimate inputs, outputs, and costs for each bank in each locality and credit modality.

The estimation of competition at more fine-grained levels has several advantages. First, it permits us to understand possible competitive interrelationships among credit modalities (earmarked vs. non-earmarked; collateralized vs. non-collateralized; short-term vs. long-term) within the same or across different financial institutions. Second, it enables to identify apparently similar localities but with substantially different levels of local competition. Understanding these relationships can support policies that encourage competition in regional credit markets.

We apply this methodology to the Brazilian banking system using many matched and detailed datasets, including loan-level bank credit information, physical locations of borrowers and bank branches, bank financial and income statements, localities' socioeconomic conditions, formal employer-employee relationships, and borrower-specific information. To gain insight into regional differences and the effects of the COVID-19 pandemic, we first carried out an exploratory analysis, looking at the evolution of the local Lerner and its components: effective price and marginal cost before and after 2020. In the aggregate, credit granted increased during the COVID-19 period without a similar increase in banks' total costs. Using a more detailed analysis at the locality level, effective prices and marginal costs decreased after the COVID-19 outbreak but not homogeneously across locations. The net effects of these two components on the Lerner index vary from location to location. As a result, we document significant heterogeneity in local market power in Brazilian credit markets that aggregate analyses are likely to overlook. By analyzing the cost factors that comprise a bank branch's total costs, there was a shift in relevance between factors in 2020: local IT expenses increased substantially, probably due to the public health measures to combat COVID-19. These results were confirmed at the bank branch level using a surrogate model.

We then pursued a causal link between the pandemic effects and local market power through the effective price and marginal cost channels. 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 to investigate local market power from two perspectives: (i) how is the local market power of a bank operating in two different locations affected by COVID-19?; and (ii) what is the effect of a bank's exposure to COVID-19 on the local market power when compared to similar banks operating in the same location? In both cases, we employed DiD models.

To answer the first question, we use the share of the affected population to measure local COVID-19 intensity. To mitigate concerns about omitted-variable biases, we compare similar localities, defined as localities of similar wealth and within the same macrolocality (adjacent localities). In this way, we can compare the same bank operating in different but similar locations affected by COVID-19 with different intensities. In this within-bank analysis, the local market power of banks reduces in localities more affected by the COVID-19 through increases in the marginal cost channel. Bank branches with higher IT costs manage to minimize this loss of market power: they can lend to remote borrowers more, possibly in less affected localities. Marginal costs increase due to the simultaneously reduced volume of granted credit and the maintenance of the bank branches' total cost: they cannot adjust costs in the short term due to economic rigidities and legal and financial frictions. Effective prices also decrease, but the reduction is not economically relevant: banks offset the reduction in income with a correspondingly similar reduction of granted credit.

The second question complements the first, allowing for a comparison of the market power across different banks. To answer it, we construct a proxy for the bank's exposure to COVID-19 by taking the average locality-COVID-19 intensity across localities where the bank has outstanding credit weighted by the bank's outstanding credit in each location before the COVID-19 upsurge. We then compare similar banks operating in the same locality and credit modality. In this within-locality analysis, the local market power of the banks most exposed to the COVID-19 increases through the effective price channel. Banks most affected by the pandemic raise their effective prices through a negative credit supply shock, while the marginal cost does not change. Banks with higher shares of local IT spending before the crisis increase even further their local market power.

Our methodology allows us to identify the non-trivial effects of banks' market power in the face of the COVID-19 outbreak. The results show the relevance of analyzing market power granularly. With social distancing, banks had to intensify their use of new technologies. More technological banks could sustain higher local market power levels following the pandemic. Our findings highlight the heterogeneous effects of the pandemic at the bank level using an important emerging market country: banks better prepared to deal with sudden changes in the market were less impacted by the pandemic. These banks, generally innovation leaders, have distanced even further from follower banks.

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Appendix A Local Lerner estimation: summary statistics

Table A1 shows summary statistics of variables used in the estimation of local Lerner indices.

Table A1: *Summary statistics of variables used in the estimation of local Lerner indices. Semiannual data, from 2015 to 2020. Total local 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. Total local cost in a half-year (in log R$)								
Local cost	32,975	16.453	1.446	13.795	15.422	16.284	17.293	20.517
B. Input prices (in log R$)								
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
IT	32,975	−5.229	0.989	−7.514	−5.956	−5.180	−4.455	−3.161
Labor	32,975	10.618	0.385	9.718	10.399	10.611	10.880	11.485
Administrative (other)	32,975	−4.346	0.454	−5.454	−4.592	−4.330	−4.157	−3.124
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

Appendix B Local correlates of competition

This appendix complements the temporal and spatial information analysis on the average price, marginal cost, and Lerner indices of local credit markets in Section 4. Here instead we explore how local financial, geographic, and socioeconomic factors correlate with those three variables. Even though we saturate our model to mitigate concerns with potential omitted-variable biases, we still cannot input causal meaning to our estimates. We pursue causal interpretation in the main text, Section 5.

We collect and match information from many data sources to perform the analysis. For convenience, we provide a description of each financial, geographic, and socioeconomic covariates employed in this section of the paper, along with the level of variation and respective data source in Table B1.

B.1 Association of local features and competitive measures across different locations

This section investigates local financial, geographic, and socioeconomic factors that correlate with average effective prices, marginal costs, and Lerner indices of banks at the locality level (immediate geographical region). As such measures depend on unobservable characteristics of both the borrower and the creditor bank, we compare the same bank (within-bank) operating in different similar locations (across localities) for the same credit modality. This approach allows us to control for unobservable characteristics of the same bank, such as credit supply for each credit modality. The variation we capture in our empirical estimates comes from across-locality heterogeneities where the bank operates for the same type of credit modality. We compare different localities *within* the same intermediate geographical region that the same bank operates in a specific credit modality to reduce omitted variable problems.

We employ the following empirical specification in a panel-data format:

$$y_{bmlct} = \alpha_{bmct} + \beta^T \cdot Factor_{bmlt} + \varepsilon_{bmlct}, \tag{13}$$

in which b, m, l, c, t index the bank, credit modality (as defined in Table 3), localities (508 immediate geographical regions), cluster of different localities to perform the across-localities comparison (133 intermediate geographical regions), and time (semiannually from 2015 to 2020). We look at three dependent variables y_{bmlct}: average effective price, marginal cost, and Lerner index of bank b for credit modality m in location l belonging to a specific cluster of localities c in the semiannual period t. The introduction of the fixed effect of time-bank-modality-cluster $\alpha_{b,m,c,t}$ allows us to interpret the results in terms of the *same* bank and *same* credit modality but at *different* locations *within* the same cluster of localities. The term ε_{bmlct} is the stochastic error. Due to the interdependence of credit operations of the same bank at different locations, we cluster errors at the national bank level. Since most of the observations are from large banks whose presence is roughly pervasive across

Table B1: *List of financial, geographic, and socioeconomic covariates used in the empirical exercises to understand their relationship with average price, marginal cost, and Lerner index of banks.*

Variable	**Source**	**Employed in Spec.**	**Description**
		Variation Level: Bank-Modality-Locality-Time	
Market Share	SCR	(13) and (14)	Ratio between a bank's credit volume in a specific modality and the total credit of that modality in the locality.
Provisions / Total Credit	SCR	(13) and (14)	Ratio between a bank's credit provision in a specific modality and its associated credit volume in a locality.
Avg. Maturity	SCR	(13) and (14)	Average maturity of each credit modality weighted by the operations' income flows in a locality.
Share of Local Pop. as Client	SCR + IBGE	(13) and (14)	Number of customers with credit in a specific modality and locality / local population.
Avg. Local Ticket	SCR	(13) and (14)	Volume of credit operations / number of customers with credit, all with respect to a same credit modality and locality.
Share of Earmarked Credit of the Modality	SCR	(14)	Share of earmarked credit in a specific modality with respect to the total credit in that modality in a locality.
Share of Earmarked Credit of Other Modalities	SCR	(14)	Share of earmarked credit in all modalities except the current one with respect to the total (earmarked + nonearmarked) credit in those modalities in a locality.
		Variation Level: Locality-Time	
Credit Union Market Share	SCR	(13)	Credit volume of all credit unions / total credit volume in the locality.
Earmarked Credit Share	SCR	(13)	Total earmarked credit / total (earmarked + nonearmarked) credit volume in the locality.
Per Capita GDP	IBGE	(13)	Local GDP / local population.
Number of Financial Institutions	SCR	(13)	Number of financial institutions (banks and non-banks, such as credit unions) in the locality with at least one active credit operation.
Share of Public Banks	SCR + Unicad	(13)	Public banks with at least one active credit operation as a share of the total number of banks in the locality.
Agricultural Region	IBGE	(13)	Dummy that equals 1 if the locality has its local GDP composed predominantly of agricultural activities, and 0 otherwise.
Industrial Region	IBGE	(13)	Dummy that equals 1 if the locality has its local GDP composed predominantly of industrial activities, and 0 otherwise.
Has capital?	IBGE	(13)	Dummy that equals 1 if the locality contains the state's capital, and 0 otherwise.
		Variation Level: Bank-Time	
Public Bank	Unicad	(14)	Dummy that equals 1 if the bank is state-owned, and 0 otherwise.
Capitalization Level	Cosif	(14)	Ratio between the (national) bank's net worth and total assets.
Liquidity Index	Cosif	(14)	Bank's Liquidity Coverage Ratio (LCR).
Total Assets	Cosif	(14)	Bank's total assets.

Brazilian localities, this error clustering technique is very conservative.

The vector $Factors_{bmlt}$ in Equation (13) contains the financial, geographic, and socioeconomic covariates listed in Table B1. We apply a standardization procedure in all numerical dependent and independent variables (mean subtraction followed by division by the sample standard deviation). Thus, we interpret the results in terms of standard deviations from the sample mean whenever the variable is numeric.

Table B2 shows the coefficient estimates for Equation (13) for average effective prices (Specs. I and IV), marginal costs (Specs. II and V), and Lerner indices (Specs. III and VI). As most localities in Brazil comprise small municipalities, we provide unweighted estimates (Specs. I–III) and population-weighted (average population) estimates (Specs. IV–VI). In this way, we can analyze the effect of the covariates in the dependent variables for large and relevant localities (weighted regressions) *vis-à-vis* the average locality (unweighted regressions).

Table B2: *Evidence at the bank-modality-locality-time level (within-bank, across nearby localities): how do local features associate with average effective prices, marginal costs, and Lerner indices across different locations?*

Regression Type:	Unweighted			Weighted by Avg. Population		
Dependent Variables:	Effective Price_{bmlct}	Marginal Cost_{bmlct}	Lerner_{bmlct}	Effective Price_{bmlct}	Marginal Cost_{bmlct}	Lerner_{bmlct}
Specification Number:	(I)	(II)	(III)	(IV)	(V)	(VI)
Variables at the Bank-Modality-Locality Level						
Market Share_{bmlt}	-0.0474***	-0.1034***	0.1399***	-0.0810*	-0.1297***	0.1411*
	(0.0102)	(0.0276)	(0.0382)	(0.0463)	(0.0340)	(0.0828)
Provisions / Total Credit_{bmlt}	-0.0038	0.0143**	-0.0048	0.0043	0.0039	0.0011
	(0.0152)	(0.0062)	(0.0064)	(0.0293)	(0.0082)	(0.0307)
Avg. Maturity_{bmlt}	0.0034	-0.0570	0.1109	-0.0331	-0.2059**	0.1004
	(0.0136)	(0.0370)	(0.0844)	(0.0412)	(0.0940)	(0.2652)
Share of Local Pop. as Client_{bmlt}	0.0261**	-0.0513***	0.0309**	0.0629	-0.0568***	0.0386
	(0.0112)	(0.0055)	(0.0131)	(0.1033)	(0.0184)	(0.0394)
Avg. Local Ticket_{bmlt}	-0.0077**	-0.0314*	0.0518	-0.0447	-0.0472*	0.0305
	(0.0036)	(0.0173)	(0.0368)	(0.0282)	(0.0266)	(0.3442)
Variables at the Locality Level						
Credit Union Market Share_{lt}	-0.0074***	-0.0033	0.0215**	-0.0021	0.0099	0.0105
	(0.0026)	(0.0114)	(0.0090)	(0.0201)	(0.0199)	(0.0373)
Earmarked Credit Share_{lt}	-0.0591***	0.1071*	-0.2306***	-0.1632	0.4362***	-0.2329
	(0.0088)	(0.0576)	(0.0542)	(0.2250)	(0.0860)	(0.2886)
Per Capita GDP_{lt}	-0.0045**	0.0220	-0.0157	0.0026	0.0196	-0.0076
	(0.0022)	(0.0142)	(0.0115)	(0.0133)	(0.0204)	(0.0586)
Population_{lt}	0.0179*	-0.1117**	0.0856***	0.0038	-0.1377***	0.0859
	(0.0093)	(0.0498)	(0.0303)	(0.4651)	(0.0484)	(0.9513)
Number of Financial Institutions_{lt}	-0.0764***	0.0696	-0.0416	-0.1197	0.0832	-0.0773
	(0.0121)	(0.0653)	(0.0451)	(0.1077)	(0.0588)	(0.3865)
Share of Public Banks_{lt}	-0.0017*	-0.0085**	0.0065	-0.0067	-0.0131**	0.0006
	(0.0009)	(0.0041)	(0.0040)	(0.0074)	(0.0055)	(0.0312)
Agricultural Region_{l} (dummy)	0.0211**	0.0305	-0.0479***	0.0245	0.0583	-0.0495
	(0.0096)	(0.0207)	(0.0158)	(0.0328)	(0.0498)	(0.1387)
Industrial Region_{l} (dummy)	0.0109*	-0.0265	0.0118	0.0132	-0.0346	0.0516
	(0.0065)	(0.0246)	(0.0293)	(0.0137)	(0.0273)	(0.1103)
Has capital_{l} (dummy)	-0.0365*	0.1070	-0.0694	-0.0346	0.0508	-0.0279
	(0.0198)	(0.0766)	(0.0618)	(0.2865)	(0.0597)	(0.5802)
Fixed-effects						
Time× Bank × Modality × Macrolocality	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	270,630	279,742	270,630	270,630	279,742	270,630
R^2	0.9485	0.7955	0.7997	0.8613	0.9435	0.8844

Note: This table reports coefficient estimates for Equation (13) using semiannual data from 2015 to 2020 at the bank-modality-locality-time level. Our sample encompasses commercial and universal banks in Brazil. Credit modalities follow the categories listed in Table 3. An immediate geographic region delimits the locality. We employ three dependent variables: average effective price (Specs. I and IV), marginal cost (Specs. II and V), and the Lerner index (Specs. III and VI). We present unweighted (Specs. I–III) and population-weighted (Specs. IV-VI). The same set of independent variables is used in the six specifications, as listed in Table B1. A standardization procedure is applied to all numeric variables. We introduce fixed effects at the time-bank-modality-macrolocality dimension in all specifications. The macrolocality is composed of localities within the same intermediate geographic region (set of nearby and contiguous localities). These fixed effects enable us to interpret each coefficient in terms of the same bank operating in the same credit modality market but at different locations in the same intermediate geographic region (cluster) in a given half-year. One-way (national bank) standard-errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

The increase in a bank's local market share in a specific credit modality is associated with lower average effective prices compared to the prices that the same bank charges in other nearby locations for the same credit modality market (Spec. I). This relationship is also statistically relevant when we give more importance to large localities (Spec. IV). In contrast, banks that hold a larger share of the local population as clients charge higher effective prices than the price they practice in nearby localities in which it has a smaller share of local clients (Spec. I). This finding suggests the customer's portfolio size is relevant to local credit pricing, especially in small localities (Spec. IV). The average maturity does not have a statistically significant relationship with the local effective price (Specs. I and IV), perhaps because we are looking *within* the same credit modality across different municipalities when we pin down the same bank in the analysis.

Localities in Brazil show substantial heterogeneity in their demographic, socioeconomic, and financial dimensions. For instance, while the overall credit share held by credit unions is small, these financial institutions have a relevant role in specific localities, such as in the South and some areas of the Central-West (mostly agricultural localities). Our results are consistent with this view: banks charge lower effective prices in localities with a more substantial presence of credit unions, especially in inland municipalities (Specs. I and IV). Earmarked credit also plays a vital role in the Brazilian credit market.[66] Banks charge a lower effective price in localities with a higher overall share of earmarked credit compared to neighboring locations with lower shares of earmarked credit. The effective price is lower in localities that are more wealthy, have more active financial institutions, have more public banks, and in capitals (Spec. I). Localities with a larger population and with preponderant agricultural or industrial activities have comparatively higher prices (Spec. I). We do not find a statistically significant correlation between wealth, population, and the number nor the ownership of financial institutions in large centers (Spec. IV).

For a specific credit modality, banks that (i) hold a larger market share, (ii) have a higher share of the local population as a client, (iii) have a higher average local ticket in a locality have lower marginal costs compared to the marginal cost they experience in nearby localities where they have lower market share and local customers as a share of the local population (Spec. II). These findings are in line with potential local gains of scale. Consistent with this view, banks also have a lower marginal cost in more populated regions. Although negative, maturity does not correlate with marginal cost in a statistically significant way.

The relationships between the covariates and the local Lerner index can be understood as a combined effect of the average price and the marginal cost. For example, even though banks charge lower effective prices and experience lower marginal costs in localities with comparatively higher market shares, the Lerner indices in these localities are higher (Spec. III). An opposite picture happens for the city-level earmarked credit share (Spec. III). Effective price and marginal costs can also move together, amplifying their effect on the Lerner index. For instance, banks charge higher effective prices and experience lower marginal costs in localities with (i) a comparatively higher share of local customers and (ii) larger local populations. Both components contribute to a higher Lerner index. These results highlight the importance of analyzing the price and the marginal

[66] Earmarked loans comprise a relevant share of the Brazilian credit market and are directed to specific sectors or activities through resources regulated by law. For instance, we highlight mandatory lending to specific sectors, such as small rural producers or low-income families financing their first houses.

components alone before looking at the overall Lerner index: an increase in the Lerner index does not necessarily indicate higher local effective prices.

B.2 Association of local bank features and competitive measures in the same location

The previous section analyzed how local financial, geographic, and socioeconomic factors associate with average effective prices, marginal costs, and Lerner indices for the same bank operating in different locations concerning the same credit modality. This section complements these results and investigates how these three quantities are associated with bank-specific observable features in the *same* location. We can control for unobservable locality-specific factors such as demand for local credit when we make within-location comparisons. The BCB introduced in 2016 the concept of prudential segmentation, which establishes an increasing set of rules proportional to the size of the bank, integration with international markets, and importance to the domestic economy. During the COVID-19 crisis, the Brazilian government also introduced many programs to incentive credit to combat the effects of the pandemics, which large banks mainly operationalized. Considering these aspects, we opt to compare banks of the same size. In this way, we can control for regulatory asymmetries among banks and credit government programs and better capture how different banks correlate with local average effective price, marginal cost, and Lerner index. Thus, the variation in the model occurs *across* banks with the *same* size operating in the *same* location for the *same* credit modality market.

We use the following econometric specification in a panel-data format:

$$y_{bsmlt} = \alpha_{smlt} + \beta^T \cdot Factor_{bmlt} + \varepsilon_{bmlt}, \tag{14}$$

in which b, s, m, l, and t index the bank, the bank's size (large, medium, small, micro), credit modality (as defined in Table 3), localities (508 immediate geographical regions), and time (semiannually from 2015 to 2020). We use the same three dependent variables from the previous section. The introduction of the bank size-modality-location-time fixed effect α_{smlt} allows us to interpret the results for the same local credit modality market m in the same location l for different banks of the same size s. The term ε_{bsmlt} is the stochastic error. We cluster errors at the (national) bank level. We standardize all numeric variables. The vector $Factors_{bmlt}$ contains the covariates listed in Table B1 for Equation (14).

Table B3 reports the coefficient estimates for Equation (14) using average effective prices (Specs. I and IV), marginal costs (Specs. II and V), and Lerner indicators (Specs. III and VI) as dependent variables. Similar to the previous section, we report unweighted (Specs. I–III) and population-weighted (Specs. IV–VI) regressions.

Banks with higher average tickets and earmarked credit shares have lower average effective prices than other banks of the same size that operate in the same locality and credit modality (Spec. I). Public banks have lower prices than private banks of the same size in the same locality

Table B3: *Evidence at the bank-modality-locality-time level (within-locality, across banks of same size): how do local bank branch features associate with average effective prices, marginal costs, and Lerner indices in the same location?*

Regression Type:	Unweighted			Weighted by Avg. Population		
Dependent Variables:	Effective Price$_{bmlct}$	Marginal Cost$_{bmlct}$	Lerner$_{bmlct}$	Effective Price$_{bmlct}$	Marginal Cost$_{bmlct}$	Lerner$_{bmlct}$
Specification Number:	(I)	(II)	(III)	(IV)	(V)	(VI)
Variables at the Bank-Modality-Locality Level						
Market Share$_{bmlt}$	0.0222	-0.2496***	0.3253***	0.0269	-0.3844***	0.3260**
	(0.0480)	(0.0443)	(0.0346)	(0.1358)	(0.0701)	(0.1470)
Provisions / Total Credit$_{bmlt}$	-0.1254***	-0.0449	0.0431	-0.1299	-0.0367	0.0434
	(0.0248)	(0.0407)	(0.0293)	(0.0871)	(0.0281)	(0.1183)
Avg. Maturity$_{bmlt}$	0.0122	-0.0932*	0.1649*	0.0212	-0.2657**	0.1744
	(0.0476)	(0.0537)	(0.0917)	(0.2395)	(0.1108)	(0.3249)
Share of Local Pop. as Client$_{bmlt}$	0.0828	0.0086	-0.0556	0.0775	0.0610**	-0.0503
	(0.0518)	(0.0270)	(0.0398)	(0.0876)	(0.0267)	(0.1431)
Avg. Local Ticket$_{bmlt}$	-0.0129**	-0.0159***	0.0160***	-0.0129	-0.0125***	0.0134
	(0.0063)	(0.0048)	(0.0044)	(0.2702)	(0.0047)	(0.2193)
Share of Earmarked Credit	-0.3888***	-0.1942**	0.1674	-0.4113	-0.3759**	0.1651
of the Modality$_{bmlt}$	(0.1289)	(0.0973)	(0.1178)	(0.3478)	(0.1616)	(0.3670)
Share of Earmarked Credit	0.0031	0.0675**	-0.0766*	0.0011	0.1746**	-0.0812
of Other Modalities$_{bmlt}$	(0.0486)	(0.0306)	(0.0420)	(0.3626)	(0.0766)	(0.3246)
Variables at the Locality Level						
Public Bank$_b$ (dummy)	-0.5404***	-0.1783	0.0978	-0.5524	0.1492	0.1008
	(0.1657)	(0.1699)	(0.1079)	(0.9759)	(0.2493)	(0.8818)
Capitalization Level$_{bt}$	-0.1073**	-0.1567***	0.0938***	-0.1048	-0.0154	0.0963
	(0.0463)	(0.0353)	(0.0251)	(0.4903)	(0.0341)	(0.6001)
Liquidity Index$_{bt}$	0.0687	0.1753**	-0.1064***	0.0898	0.0709	-0.1113
	(0.0817)	(0.0724)	(0.0266)	(1.148)	(0.0539)	(1.786)
Total Assets$_{bt}$	-0.0920	0.1987***	-0.1750***	-0.0896	0.1332***	-0.1701
	(0.0763)	(0.0317)	(0.0441)	(0.2322)	(0.0433)	(0.2136)
Fixed-effects						
Time· Modality · Locality · Bank Size(4)	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	270,603	279,714	270,603	270,603	279,714	270,603
R^2	0.8241	0.6493	0.6787	0.6495	0.5428	0.4640

Note: This table reports coefficient estimates for Equation (14) using semiannual data from 2015 to 2020 at the bank-modality-locality-time level. Our sample encompasses commercial and universal banks in Brazil. Credit modalities follow the categories listed in Table 3. An immediate geographic region delimits the locality. We employ three dependent variables: average effective price (Specs. I and IV), marginal cost (Specs. II and V), and the Lerner index (Specs. III and VI). We present unweighted (Specs. I–III) and population-weighted (Specs. IV-VI) estimates. The same set of independent variables is used in the six specifications, as listed in Table B1. A standardization procedure is applied to all numeric variables. We introduce fixed effects at the time-modality-locality-bank size dimension in all specifications. We follow the BCB's bank size classification of large, medium, small, and micro (four levels). These fixed effects enable us to interpret each coefficient in terms of different banks with the same size operating in the same locality and the same credit modality market in a given half-year. One-way (national bank) standard-errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

and credit modality (Spec. I). The correlation between local market share and the average price is not statistically significant when we cross-compare banks of the same size within the same location in the same credit market (Spec. I). When we emphasize large localities, neither the average local ticket size, the share of earmarked credit, nor bank ownership of different banks of similar size operating in the same locality and credit modality correlates with average local prices in a statistically significant way (Spec. IV).

In contrast, banks with higher local market shares have lower marginal costs than other banks of the same size that operate in the same locality and credit modality market (Spec. II). This finding further corroborates our within-bank, across-locality analysis performed in the previous section that showed potential local scale gains. This statistical relationship becomes even stronger in more populated localities (Spec. V). Banks with a high share of earmarked credit in a specific modality have lower marginal costs than similar banks operating in the same locality and credit modality, consistent with the subsidized nature of such a credit. However, banks with a higher share of earmarked credit in other modalities (except the credit modality under analysis) have comparatively higher marginal costs. These two relationships also hold in large localities (Spec. V). Banks with higher liquidity also face higher marginal costs. Similar to the previous section, we can better understand the Lerner index dynamics regarding variations in the price and marginal costs in isolation (Specs. III and VI).

Competition in different regions: Brazil has five vast regions with unique socioeconomic and demographic characteristics that could correlate with the local average effective price, marginal cost, and Lerner index. Table B4 reruns the previous econometric exercise using Equation (14) but separating the sample in terms of Brazilian regions: Central-West (Specs. I, VI, XI), Northeast (Specs. II, VII, XII), North (Specs. III, VIII, XIII), Southeast (Specs. IV, IX, XIV), and South (Specs. V, X, XV).

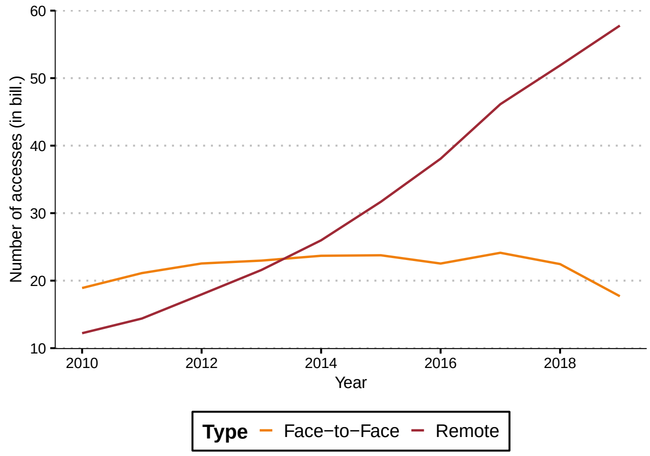
Banks with higher local market shares have comparatively lower marginal costs in all five regions. The magnitude of this association does not seem to relate to the locality's wealth. Local market shares do not correlate with effective prices. Consequently, higher local market shares correlate positively with Lerner indices, mainly through the marginal cost channel. The share of the local population as clients correlates negatively with effective prices and marginal costs for more developed regions, especially the Southeast. Public banks charge prices differently across Brazilian regions when compared to other banks of the same size in the same locality and credit modality. They charge significantly lower prices in the Central-West, North, and Northeast. Public banks also have comparatively lower marginal costs in less developed regions (Northeast and North regions) and similar marginal costs in more developed regions (Southeast and South regions).

Table B4: *Evidence at the bank-modality-locality-time level (within-locality, across banks of same size) for Brazilian regions: do local bank branch features associate with average effective prices, marginal costs, and Lerner indices in the same location?*

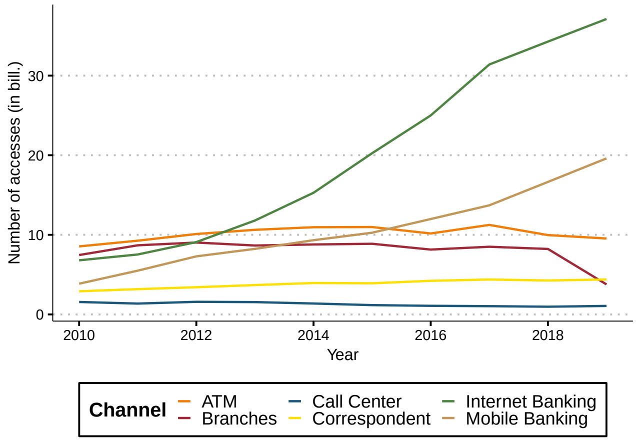
Dependent Variables:	Effective Price$_{bsmlt}$					Marginal Cost$_{bsmlt}$					Lerner$_{bsmlt}$				
Region:	Central-West	Northeast	North	Southeast	South	Central-West	Northeast	North	Southeast	South	Central-West	Northeast	North	Southeast	South
Model:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)	(XIII)	(XIV)	(XV)
Variables															
Market Share$_{bmlt}$	0.0382	-0.0028	0.0188	0.0346	0.0735	-0.0881**	-0.1239***	-0.0853***	-0.1138***	-0.0906***	0.2836***	0.3160***	0.2933***	0.3349***	0.3255***
	(0.0515)	(0.0320)	(0.0437)	(0.0517)	(0.0514)	(0.0334)	(0.0306)	(0.0191)	(0.0390)	(0.0232)	(0.0449)	(0.0295)	(0.0248)	(0.0581)	(0.0437)
Provisions / Credit$_{bmlt}$	-0.0987***	-0.1443***	-0.1235***	-0.1338***	-0.1224***	-0.0004	-0.0183	-0.0207	-0.0004	-0.0041	0.0306	0.0695**	0.0491	0.0446	0.0178
	(0.0277)	(0.0143)	(0.0195)	(0.0318)	(0.0283)	(0.0142)	(0.0153)	(0.0167)	(0.0125)	(0.0125)	(0.0420)	(0.0271)	(0.0275)	(0.0348)	(0.0320)
Avg. Maturity$_{bmlt}$	0.0632	0.0522	0.0251	-0.0338	0.0533	-0.0315	0.0006	-0.0412*	-0.0546	-0.0318	0.2550*	0.1767	0.2183*	0.1473	0.0869**
	(0.0736)	(0.0654)	(0.0646)	(0.0518)	(0.0480)	(0.0243)	(0.0181)	(0.0188)	(0.0414)	(0.0250)	(0.1265)	(0.1478)	(0.1215)	(0.0997)	(0.0388)
Share of Pop. as Client$_{bmlt}$	0.0027	0.1574	0.1158	0.0660**	-0.0306	-0.0159	0.0450	0.0208*	0.0210	-0.0097**	0.0299	-0.1248***	-0.1202***	-0.0393	0.0481
	(0.0550)	(0.0945)	(0.1001)	(0.0278)	(0.0300)	(0.0208)	(0.0291)	(0.0114)	(0.0201)	(0.0039)	(0.0457)	(0.0379)	(0.0266)	(0.0425)	(0.0349)
Avg. Local Ticket$_{bmlt}$	-0.0590	-0.2668**	-0.1108	-0.0126*	-0.0095	-0.0078	-0.0158	-0.0596	-0.0068**	-0.0087*	-0.0271	-0.1044	0.1760*	0.0150***	0.0268*
	(0.0382)	(0.0949)	(0.1096)	(0.0066)	(0.0059)	(0.0074)	(0.0827)	(0.0517)	(0.0030)	(0.0049)	(0.0501)	(0.1855)	(0.0951)	(0.0041)	(0.0156)
Share of Ear. Credit	-0.2643**	-0.4834*	-0.4722***	-0.3026*	-0.3844**	-0.0087	-0.1633***	-0.0867***	-0.0621	-0.0656	0.1059	0.2735***	-0.0016	0.1448	0.1544
of the Modality$_{bmlt}$	(0.1199)	(0.2423)	(0.1374)	(0.1525)	(0.1454)	(0.0364)	(0.0566)	(0.0278)	(0.0609)	(0.0509)	(0.1059)	(0.0481)	(0.0854)	(0.1708)	(0.1764)
Share of Ear. Credit	-0.0882	0.0578	-0.0032	-0.0215	-0.0069	-0.0498	0.0049	0.0218	0.0430	0.0070	0.0015	-0.1099***	-0.0689	-0.1282**	-0.0069
of Other Modalities$_{bmlt}$	(0.0516)	(0.0496)	(0.0668)	(0.0565)	(0.0400)	(0.0373)	(0.0219)	(0.0356)	(0.0324)	(0.0148)	(0.0466)	(0.0206)	(0.0521)	(0.0566)	(0.0237)
Public Bank$_{b}$	-0.3736	-0.7514***	-0.6709***	-0.4362***	-0.5085***	0.1081	-0.1505**	-0.1912***	-0.0644	-0.0480	-0.2880***	0.2233**	0.0773	0.2065	0.0124
	(0.2248)	(0.0943)	(0.1516)	(0.1478)	(0.1630)	(0.0701)	(0.0650)	(0.0611)	(0.1275)	(0.0600)	(0.0866)	(0.1061)	(0.0981)	(0.1796)	(0.0686)
Capitalization Level$_{bt}$	-0.0987*	-0.1320***	-0.1918***	-0.1006**	-0.1019*	-0.0229*	-0.0551*	-0.0764***	-0.0600**	-0.0624***	0.0212	0.0858**	0.0289	0.1186***	0.1389***
	(0.0527)	(0.0423)	(0.0497)	(0.0396)	(0.0558)	(0.0129)	(0.0310)	(0.0156)	(0.0271)	(0.0224)	(0.0442)	(0.0370)	(0.0339)	(0.0344)	(0.0368)
Liquidity Index$_{bt}$	0.1201	0.1655**	-0.1193**	0.1099	0.2314*	0.0918**	0.1937***	0.0242**	0.1420**	0.1776**	-0.0929**	-0.0791	-0.0898***	-0.1333**	-0.1893**
	(0.0991)	(0.0773)	(0.0464)	(0.0664)	(0.1230)	(0.0321)	(0.0514)	(0.0092)	(0.0698)	(0.0697)	(0.0354)	(0.0746)	(0.0138)	(0.0631)	(0.0820)
Total Assets$_{bt}$	-0.0687	-0.1000	-0.0161	-0.1517**	-0.1152	0.0623***	0.1049***	0.1420***	0.0511**	0.0478*	-0.1575***	-0.1654***	-0.2007***	-0.1874***	-0.1730***
	(0.0684)	(0.0644)	(0.0572)	(0.0671)	(0.0914)	(0.0111)	(0.0266)	(0.0423)	(0.0224)	(0.0250)	(0.0512)	(0.0251)	(0.0629)	(0.0556)	(0.0590)
Fixed-effects															
Time· Modality · Locality · Bank Size(4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics															
Observations	26,978	67,116	24,615	91,717	60,177	27,776	69,326	25,508	94,808	62,296	26,978	67,116	24,615	91,717	60,177
R^2	0.8213	0.8433	0.8295	0.8283	0.8166	0.4282	0.6946	0.7447	0.4270	0.4690	0.5504	0.8050	0.7836	0.5903	0.5958

Note: This table reports coefficient estimates for Equation (14) using semiannual data from 2015 to 2020 at the bank-modality-locality-time level for each Brazilian region (Central-West, Northeast, North, Southeast, and South). The setup in this empirical exercise follows the description in Table B3. Dependent variables: average effective price (Specs. I–V), marginal costs (Specs. VI–X), and Lerner index (Specs. XI–XV). The same set of independent variables is used in all specifications, as listed in Table B1. One-way (national bank) standard-errors in parentheses. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Appendix C Face-to-face and remote transactions in Brazil



(a) *Face-to-face vs. remote transactions*



(b) *Transactions by access channels*

Figure C1: *Number of transactions in Brazil from 2010 to 2019. (a) Face-to-face 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)].*