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Evidence from Branch Closures

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Abstract

Private firms establish relationships with banks in local markets to obtain adequate financing for their operations through credit and loans. As major banks reduced their branch networks in recent years, many firms have lost access to their local bank. We evaluate the impact of a large number of branch closures on firm operations, wages and employment, and economic output in Brazil from 2011 to 2021. We adopt a difference-in-differences strategy with staggered treatment timing, employing both two-way fixed effects and Callaway-Sant'Anna estimators. Our study finds that bank branch closures result in a reduction in establishments with active operations from 1.2% initially to 8.1% within 4-7 years, a 0.5 decline in weekly hours of formal employment, and a compression in the real wage distribution. Micro firms, trade and service firms, and agricultural firms are found to be the most vulnerable. Our study highlights the importance of physical bank branches that provide financial access and meet the localized financial demand of several types of firms.

JEL classifications: G21, R11, J21

Keywords: Bank branch closures, Employment, Firm activity, Economic impact, Financial access, Brazil

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1 Introduction

The importance of local bank access for private firms cannot be overstated, as local banks provide essential financial services, including credit, loans, and payments. Local access is particularly vital for small and medium-sized enterprises (SMEs) that may not have the same resources as larger corporations to secure financing through alternative channels and face higher costs to switching lenders (Beck et al., 2008; Nguyen, 2019). Through personal interactions, local banks obtain soft information about market conditions and business owners that allows them to better tailor financial products to the specific needs of local firms (Berger et al., 2008). Moreover, the proximity of banks to firms can lead to improved credit availability, as banks are more likely to lend to businesses with which they have established relationships (Cole and Gunther, 1998).

The presence of banks can significantly influence a firm's labor demand and productivity, thereby affecting the labor market equilibrium and local economic output. Banks' presence can have a mixed impact on a firm's financing cost depending on different factors like bank ownership or market power (Ryan et al., 2014; Barth et al., 2013). Furthermore, studies often find credit availability has a positive impact on labor demand and wages by lowering the firm's financial frictions and eventually facilitating job creation and productivity (Popov and Rocholl, 2018; Fonseca and Van Doornik, 2022).

However, the landscape of bank access is changing. Recent World Bank data[2] highlights a decrease in commercial bank branches per capita from its peak in 2016 and identifies a global trend towards digital banking and away from traditional brick-and-mortar. This shift should have implications for firms that rely heavily on local banking relationships for their financial needs. The decline in physical bank branches can lead to reduced access to financial services for firms located in rural or underserved urban areas, potentially hampering their survival, operations, and growth. This leads us to the core questions of our study: What is the impact of closing bank branches on local firm operations, employment, and economic output? And what kinds of firms are most vulnerable to experiencing such shifts?

To study this question, Brazil provides a suitable context. The number of bank branches experienced an increasing trend after the Brazilian government implemented its "Banks for All" program ("Banco para Todos") in 2004. However, this upward trend was disrupted in 2014, and a downward trend has persisted since then. As of the end of 2022, Brazil had lost more than 5,000 bank branches, which is one-fourth of its peak number. Many municipalities lost all of their bank branches in this process. This creates quasi-experimental variation in

[2]See: World Bank, Number of Commercial Bank Branches per 100,000 Adults, at `https://data.worldbank.org/indicator/FB.CBK.BRCH.P5`

local bank access that can be used to study the effects of banking supply on firm activity. Figure 1 presents the evolution of the bank branch landscape in Brazil spanning the last two decades from 2002 to 2022.

Our empirical analysis relies on a primary sample of private sector firms and employees in Brazil spanning the years from 2011 to 2021. We exploit establishment-level cross-sectional data over time in addition to municipality-level panel data on economic and employment conditions across Brazil. We link bank branch-level data with firm-level labor census data and municipality-level data on population and local economic accounts. Considering the geographic variation in bank branch concentration, as well as the heterogeneity arising from different closure patterns, we chose to concentrate on municipalities with only one branch. This subset constitutes the largest group among banked municipalities and exhibits broad geographic variation in Brazil. To identify the effects of bank branch closures on local formal employment, it is imperative to establish both a treatment group and a suitable comparison group. We adopt a staggered treatment timing design by retaining in the sample municipalities where the local branch closure was not reversed during the study period.

We then utilize a difference-in-differences (DiD) framework with variation in treatment timing to identify the effects of bank branch closures on local employment, exploiting the closures of bank branches as a source of plausible exogenous variation. We discuss potential endogeneity challenges in this context, including issues such as reverse causality, omitted variables, anticipation, and spillover effects. To address these issues, several identification assumptions must be made, including the parallel trends assumption and limited anticipation assumption. Our subsequent estimates will be valid provided these assumptions hold, particularly that treatment-related omitted variables do not produce systematic post-treatment effects in one group.

To provide an overview of the impact of bank branch closures and construct robust estimates, we provide three estimation approaches in our analysis: the two-way fixed effect (TWFE) model, the Callaway-Sant'Anna (CS) estimator with never-treated observations as a control group, and the CS estimator with not-yet-treated observations as a control group. Considering that issues of treatment effect heterogeneity and staggered timing may affect the reliability of the the two-way fixed effect estimator, we compared several newly developed staggered DiD estimators and selected CS estimators; those estimators are discussed in recent literature and can overcome the identification issues associated with TWFE. Moreover, the CS estimator has other benefits that apply in our context: It can accommodate less stable parallel trends (often a concern in long study periods) and it provides transparent control group options (never-treated versus not-yet-treated.) We present CS estimates using both types of control groups to address potential selection concerns.

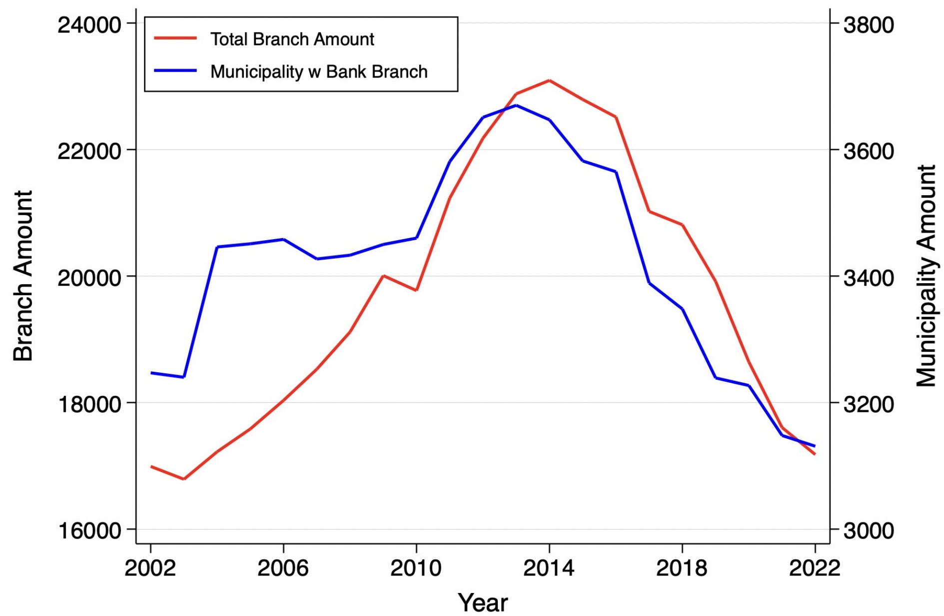


Figure 1: Bank Branch Trends in Brazil, 2002-2022

Notes: This graph presents the number of bank branches and municipalities with bank branches that appeared in Brazil's ESTBAN datasets each December from 2002 to 2022. The red line indicates the trend in the number of bank branches, corresponding to the y-axis on the left side. The blue line indicates the number of municipalities with at least one bank branch, corresponding to the y-axis on the right side. Source: ESTBAN dataset, Banco Central do Brasil.

We conduct several analyses to investigate the impact of local bank branch closures. First, we conduct an establishment-level analysis to see if bank branch closures impact firm operations, including market entry and exit. We find that roughly 1 percent of establishments become inactive between 0 and 3 years after a bank branch closure, and the share of inactive establishments increases from 1.2 percent to 8.4 percent between 4 and 7 years after the closure. However, we find no effect on the overall or specific type of firm entering or exiting. We then evaluate the impact on local formal employment, using a municipality-level panel constructed from worker census data. Our estimates suggest that bank branch closures could have a larger and quicker impact on wages than on employment. While statistically imprecise, our point estimates show bank branch closures decrease the average wage by 1.5 to 1.7 percent in the first three years. For employment, our estimates suggest bank branch closures do not have a significant short-term effect but potentially a long-term negative effect.

Studying wage disparities, we find short-term decreases in the standard deviation of wages, but long-term decreases in the difference between the 90th and 10th percentile wage brackets. This could suggest that branch closures disproportionately affect different wage brackets—in the short run, potentially the middle-income bracket, and in the long run, the lower wage bracket. We conduct a heterogeneity analysis to characterize which types of firms are more vulnerable; we find that micro firms, trade and service firms, and agriculture firms are disproportionately impacted by local bank branch closures. Finally, we analyze economic output accounts and find a decreasing trend in service output due to bank branch closures but not in industrial and agricultural output.

This paper contributes to several strands of literature. First, it adds to the existing literature on the economic effects of banking supply. The effects of bank deregulation have been extensively studied across various periods in different countries. Among the outcomes considered are income inequality, new incorporation growth, real income, output growth, financial inclusion, and household wealth accumulation in the United States (Beck et al., 2010; Black and Strahan, 2002; Jith Jayaratne et al., 1996; Celerier and Matray, 2019); poverty in India (Burgess and Pande, 2005); income levels in Mexico (Bruhn and Love, 2014); and branch occupation, income and employment in Thailand (Ji et al., 2021). In Brazil, studies discuss shocks that could impact bank branch supply and their effects, including bank mergers and acquisitions affecting financial variables, loans, and employment (Joaquim and van Doornik, 2019); national policies for bank branch expansion to rural areas (Fonseca and Matray, 2022); and bank robberies affecting adoption of digital finance tools (Argentieri Mariani et al., 2023). [3]

Our study relates to existing work investigating the effects of credit supply on employment, consumption, and productivity. Stiglitz and Weiss (1981) and Kochar (1997) discuss the equilibrium in the loan market, specifically credit rationing, household demand for credit, and its role in agricultural development. Credit market shocks have been found to negatively impact employment growth in small businesses in the United States (Greenstone et al., 2020) and result in decreased consumption, earnings, and employment in India (Breza and Kinnan, 2021). Field experiments have yielded similar results, with Karlan and Zinman (2010) demonstrating the positive outcomes of expanding credit supply on employment, income, food consumption, and overall well-being. Banerjee and Duflo (2014) utilize a targeted direct lending program to test credit constraints among Indian firms and suggest severe constraints and high marginal rates of return on capital.

Finally, the finance literature has demonstrated the significance of bank branches in local credit supply. Gilje et al. (2013) demonstrate how bank branch networks help integrate lending markets in the United States, even in the presence of the securitization market. Hasan et al. (2020) study the role of local bank branches and conclude that they serve as irreplaceable lenders for small and medium enterprises. Khwaja and Mian (2008) show that liquidity shocks to banks result in decreased loan amounts to firms and a reduced probability

[3] See also Meslier et al. (2022) and Bragoli et al. (2022).

of loan continuation.

The contributions of this study are threefold. First, this study enhances our understanding of the effect of bank branch network shrinkage in recent decades. Multiple studies show the lending and local financial access are important to local firms; our study provides estimates for the impact of local bank branch closures on local firms, employment, and economic output. Adopting recent estimation strategies, we are able to provide credible estimates that mitigate common endogeneity concerns. Moreover, we examine the medium-term effect of bank branch closures and the dynamic pattern of this effect. Since this study is targeting branch losses that last at least until the end of the study's time span, it gives us room to track the pattern of this effect for up to 7 years. Third, building upon previous studies that explore the economic implications of changes in credit availability, our research contributes further evidence on how bank branch closures influence firm operations, local employment, and overall economic output. By doing so, we not only corroborate earlier findings but also expand understanding of the intricate relationships between financial infrastructure and economic activity.

The paper is organized as follows: Section 2 provides a description of the data sources and presents descriptive statistics. Section 3 outlines the methodology and identification strategy employed, and Section 4 presents the results. Section 5 concludes.

2 Data

We use three primary datasets for this study: a bank branch-level dataset, labor/firm census data, and municipality-level information regarding population and local economic accounts. We use these datasets to construct repeated cross-sectional data at the establishment level and a balanced panel of economic and formal labor market conditions at the municipality level in Brazil. This study focuses on the period from 2011 (three years ahead of the peak in the number of municipalities with bank branches) to 2021 (the last year when all the data are available), a long enough period that we can evaluate the effect of branch closures in Brazil.

Data Sources. The three datasets used in our analysis have the following features:

(i) ESTBAN Dataset—The ESTBAN (Estatística Bancária Mensal por município) dataset is maintained by Banco Central do Brasil, the central bank of Brazil. It includes identification information and balance sheet statistics for each bank branch on a monthly basis, enabling us to track the operational status of every bank branch in each municipality. The available timespan for this dataset is from 1988 to today. The central bank requires mandatory reporting of monthly spreadsheet information from all local branches within 90 days, ensuring accuracy. We use the reporting status of bank branches across time to track their operation status. When a bank branch ceases reporting, it indicates closure.

(ii) RAIS Dataset—The RAIS (Relação Anual de Informações Sociais) dataset is maintained by the Brazilian Ministry of Labor and Employment. It is a comprehensive linked employer-employee dataset generated by a mandatory annual labor census of all formal sector employment in Brazil. The first available year is 1986, and the data have been published annually since then. We rely on the publicly available versions of the RAIS dataset, which separate the restricted data into establishment-level data and worker-level data without the identifiers needed to link workers, establishments, and firms in longitudinal studies. We keep establishment levels as cross-sectional data and aggregate the worker-level raw data at the municipality level to construct a balanced panel. This dataset contains information on wages, economic sector, municipality and year at the worker level, as well as firm size and sector at the establishment level.

(iii) GDP and Population Data—Municipality-level nominal GDP data and population datasets are maintained by the IBGE (Instituto Brasileiro de Geografia e Estatística), Brazil's geographic and statistics agency. The available years for those datasets are, respectively, 1996 to 2021 and 1991 to 2022. The GDP data contain information on output in sectors including services, agriculture, industry, and administration. Municipal populations are estimated from growth rates by IBGE for all years except 2010 and 2022, when Brazil conducted population censuses. The reference date for estimation is July 1 of every year.

Data Structure and Descriptive Statistics. Our rich datasets contain the universe of formal labor contracts in Brazil across decades. However, since local bank branch closures may have heterogeneous impacts on different workers and firms, we carefully investigate possible filters to recover the dynamics of interest: the impact of local bank branch closures on commercial firms and local employment.

In establishment-level data processing, we introduce the following filters: (i) We exclude public administrations and international and extraterritorial institutions, which mainly comprise government agencies, international organizations and multilateral alliances. Public and foreign firms do not belong to these categories. The reason behind this filter is that these agencies and organizations may have banking needs and financing channels that are distinct from those of firms, so a local bank branch's closure would not affect them as much. (ii) We also chose to exclude financial institutions from our subsample. A bank branch closure implies an establishment (branch) ceasing operations and laying off its workers, which are the outcomes of interest among firms affected by branch closures. To insulate our estimates from operational and staffing changes in bank branches themselves, we eliminate the financial sector from our sample.

We apply similar filters to the worker-level raw data before aggregating it into the municipality-level panel, excluding employees of public administrations and international, extraterritorial, and financial institutions. We further limit the sample using worker characteristics: (i) We chose to report estimates without year-round unpaid workers, aiming to capture the wage effect among those who are being paid. However, since this can create sample selection issues for working individuals, we report estimates with unpaid workers in Appendix C to assess robustness. (ii) We restrict our subsamples to the same working-age population so that our sample is comparable across years, even though Brazil raised its retirement age in 2019. We restrict the age range from 16 to 60 for men and 16 to 55 for women. We also adjust workers' nominal wages to real wages according to the annual consumer price index. Finally, worker-level statistics, along with some establishment-level statistics, are aggregated into the municipality panel using either totals, means, standard deviations, or ratios to recover a fuller picture of labor market dynamics.

Descriptive statistics for aggregated variables across municipalities and employees are presented in Table 5. Table 8 illustrates the patterns of bank branch closures in the dataset, indicating the varying timing of closures. Most bank branches closed between 2017 and 2019, when Brazil's economy began to recover from the 2014 economic crisis and returned to growth.

Banking Market and Sample Selection. Similar to Joaquim and van Doornik (2019), we use municipalities as the benchmark of the local banking market in Brazil, described by Sanches et al. (2018) and Coelho et al. (2013). Joaquim and van Doornik (2019) survey the literature on widely accepted ways to measure the distance to a bank in the United States—e.g., Metropolitan Statistical Area (MSA) or non-MSA county (Black and Strahan, 2002), 24km radius (Garmaise and Moskowitz, 2006), 10km radius (Granja et al., 2022)—and argue that using municipalities allows computation of outcomes at a finer level. Using municipalities as a benchmark for access to local banks is an approximate measure, considering that the firm could be at any point within a municipality and may not always choose a bank branch in its municipality, not least because municipalities can have highly variable physical sizes. However, confining the sample to one-branch municipalities from 2011 to 2013 would focus on economically less developed and rural areas, making getting financial services at the only bank branch within the municipality a reasonable option for most firms, thus making the municipality a good proxy for the banking market.

We are interested in measuring the effect of a large wave of bank branch closures in

Brazil starting in 2014, which followed a long period of expansion in the previous decade (see Figure 1). Some municipalities that experienced bank branch closures soon after 2014 had seen these branches open only a few years prior. So, we chose a benchmark sample of municipalities that had open bank branches during the three years between 2011 and 2013. Figure 8 in the Appendix shows the number of bank branches per municipality in Brazil. Very few municipalities have a large number of bank branches, while the vast majority of municipalities have 1-3 branches. Considering that single-branch municipalities are the most common case among Brazilian municipalities in the past decade, we chose to focus on municipalities with a single branch during as of 2011-2013 to estimate the economic impact of becoming an unbanked municipality.

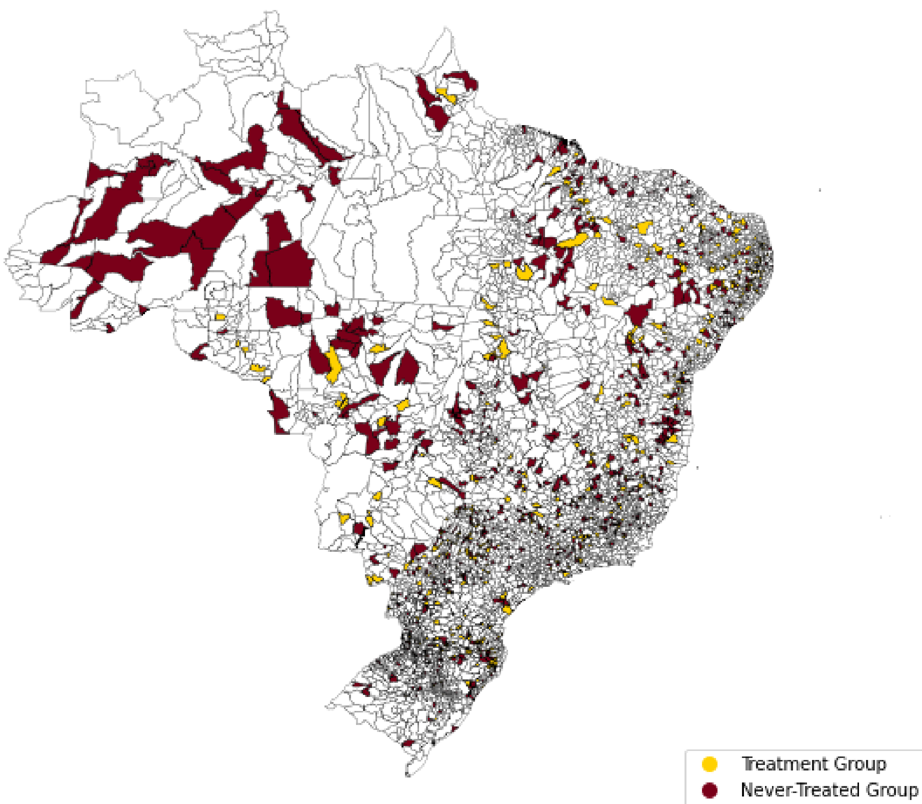


Figure 2: Brazil Municipalities, Treated and Never-Treated Groups

Note: This graph represents the treated and never-treated municipalities in our sample. We use maroon to represent the never-treated group and gold for the treatment group. The treatment and control group are geographically evenly distributed in all areas in Brazil.
Map Source: Instituto Brasileiro de Geografia e Estatística (IBGE)

This filter also provides a straightforward non-arbitrary solution to handling the different patterns of branch closures. During this large wave of bank branch closures in Brazil, there are a few cases where municipalities experienced a large decrease in banking supply without the number of branches going down to zero. There are also municipalities that went from several bank branches to zero. This difference in patterns could lead to difficulties in defining a uniform treatment. Focusing on one-branch municipalities simplifies comparisons and eliminates heterogeneity from different closure patterns.

Furthermore, in each local banking market, the number of bank branches does not always fall into the absorbing stage during the study period. For example, a municipality that experiences a branch loss could have this branch reopen in a year, or other banks could open new branches after several years. In other cases, one-branch municipalities may have bank branch openings without first losing their only branch. We rule out these cases when defining treated and comparison groups so that treatment (branch closure) follows a staggered pattern over time.

The final sample of local banking markets consists of 1,109 municipalities, with 433 in the treated group and 676 in the comparison never-treated group. This represents 19.9% of all municipalities in Brazil. Similarly, establishments/firms are considered treated or never-treated if they are located in the corresponding groups of municipalities. Figure 2 shows the geographic locations of treated and never-treated municipalities. The map indicates that the two groups are in general evenly distributed and not clustered in any one area of Brazil.

3 Empirical Framework

Our main goal is to study the economic effects of local bank branch closures on firm operations and municipality-level employment and economic outcomes. In the Rubin Causal Model, the average treatment effect on the treated can be expressed as follows:

$$ATT = \mathbb{E}[Y(1) - Y(0)|D = 1] \tag{1}$$

In this equation, D indicates whether a firm or municipality is treated, $Y(1)$ is a firm operation status or a municipality outcome, and $Y(0)$ is the outcome for the same firm or municipality if not treated. The ATT can differ across time, which can be represented with a group-time average treatment effect. First, the ATT from being treated for T periods can be written as:

$$ATT(T) = \mathbb{E}[Y_{it}(1)|D_{it} = 1, S_{it}(T) = 1] - E[Y_{it}(0)|D_{it} = 0, S_{it}(T) = 1] \tag{2}$$

where Y_{it} represents the status of firm i (or municipality m)'s outcome at time t, D_{it} represents the treatment status of i at time t, and $S_{it}(T)$ is a binary variable equaling 1 if i is in its Tth period since treatment. Then:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0)|G_g = 1] \tag{3}$$

where G_g represents a binary variable to capture the effect for the group of firms or municipalities that were first treated at time g. The group-time average effect measures at time t the branch closure effect on firms (municipalities) that experienced branch closures at time g. $Y_t(0)$ represents their potential outcomes at time t had they not lost a branch.

We construct a dynamic difference-in-differences model with two-way fixed effects to calculate $ATT(T)$. The structural relationships can be expressed by:

$$y_{imt} = \alpha_m + \theta_t + \sum_e \beta_e D^e_{mt} + \varepsilon_{imt} \tag{4}$$

In equation (5), y_{imt} stands for firm i's operational status in year t and municipality m, and y_{mt} would represent the municipality's outcomes. α_m and θ_t are the municipality and year fixed effect terms. While $D^e_{m,t}$ is a binary variable equal to 1 if time t is e periods away from g, i.e., $D^e_{mt} = \mathbb{I}[t - G_m] = e$, β_e measures the treatment effect of leads and lags of bank branch closure on treatment group municipalities m at time t between 2011 and 2021. ε_{imt} stands for the error term. Estimating this equation in our sample assumes α_m absorbs the differences in firm operations caused by internal differences across municipalities, and θ_t absorbs all the year-relevant shocks, letting $\beta_{t,m}$ only explain variation due to bank branch closures.

To perform unbiased estimation, two assumptions need to hold: (i) The ε_{imt} has zero correlation with the year and municipality fixed effects and treatment status, and (ii) branch closures have a homogeneous effect on firms and establishments. We also present average TWFE estimates based on the following equation:

$$y_{imt} = \alpha_m + \theta_t + \beta D_{mt} + \varepsilon_{imt} \tag{5}$$

In this equation, $D_{m,t}$ is defined as a binary variable indicating whether municipality m lost a branch in year t.

To address concerns about negative weights when using TWFE with heterogeneous effects of staggered-timing treatments, multiple heterogeneous-staggered robust estimators were developed under the generalized difference-in-differences framework in recent years, including the Imputation estimator (Borusyak et al., 2023), CS estimator (Callaway and Sant'Anna, 2021), SA estimator (Sun and Abraham, 2021), DD estimator (De Chaisemartin and D'Haultfœuille, 2020), stacked regression estimator (Cengiz et al., 2019), and LP-DiD estimator (Dube et al., 2023).

In our study, since different municipalities have bank branch closures in different years, we adopt the CS estimator as an alternative robust estimator as it can provide flexibility in choosing control groups and robust confidence intervals via bootstrapping, according to Baker et al. (2022) and Roth et al. (2023). The CS estimator calculates the treatment effect by choosing different control groups and assigning them weights different from those of the TWFE model. Their estimated parameter can be expressed as follows:

$$ATT^{nev}(g,t;\omega) = \mathbb{E}[Y_t - Y_{g-\omega-1} \mid G_g = 1] - \mathbb{E}[Y_t - Y_{g-\omega-1} \mid C = 1] \tag{6}$$

$$ATT^{ny}(g,t;\omega) = \mathbb{E}[Y_t - Y_{g-\omega-1} \mid G_g = 1] - \mathbb{E}[Y_t - Y_{g-\omega-1} \mid D_{t+\omega} = 1] \tag{7}$$

In equations (7) and (8), ATT^{nev} measures the group-time treatment effect with the limited treatment anticipation assumption imposed. It compares the difference between the outcome at time t and the outcome at time $g-\omega-1$ in the treatment group for group G_g and the same difference in the never-treated group, i.e., those municipalities with a single branch open during the study period. ATT^{ny} calculates the group-time average effect using the difference within the same group G_g minus the difference in the not-yet-treated samples, i.e., samples that enter the treatment group after period $t+\omega$. Choosing different control groups can have different benefits in the context of our study: the never-treated group can provide a stable comparison regarding the time effects, while the not-yet-treated group helps mitigate selection concerns by comparing groups that all eventually get treated. Furthermore, the CS estimator aggregates $ATT(g,t)$ to $ATT(T)$ using the following equation:

$$ATT(e) = \sum_{g \in G} \mathbb{I}\{g + e \leq \tau\} \mathbb{P}\{G = g \mid G + e \leq \tau\} ATT(g, g+e) \tag{8}$$

where e stands for the time since the treatment and τ stands for the end of the study period, 2021. It multiplies the treated share of the sample by the group average treatment effect to recover $ATT(e)$.

The CS estimator requires the following key assumptions for identification: (i) limited treatment anticipation—the treated firms or municipalities should have limited anticipation for $\omega \geq 0$ terms ahead; and (ii) conditional parallel trends based on the "not-yet-treated" or "never-treated" groups—had they not been treated, the treatment group firms or municipalities would have maintained a parallel trend compared with their control group peers.

The empirical challenge in estimating the impact of a local bank branch closure is that the strict exogeneity of the treatment can be questioned in two dimensions: reverse causality and omitted variable bias. Reverse causality occurs when the closure of local bank branches follows worsening economic conditions; omitted variable bias represents the existence of ex-ante unobserved factors that affect the treatment groups. For example, this can happen when banks base their closure decisions on predictions of future branch performance. If banks can observe ex ante local factors and use them to form predictions, while we cannot, these factors become omitted variables, biasing our estimates.

We base our identification on the parallel trends (PT) assumption. The first part of PT requires that the treatment and control groups maintain a parallel trend. If banks close branches in response to deteriorating local economic conditions, the outcomes for municipalities with closed branches would likely display a downward pre-closure trend, diverging from the control group. For the post-treatment period, PT assumes no omitted variables change the current trend except for the treatment. PT cannot be strictly tested, as we cannot observe an untreated counterpart for each treated firm and municipality. However, we do provide pre-trend analysis to argue PT does hold and note that our estimates will remain unbiased only if PT is satisfied.

We also consider issues of anticipation and spillovers in our study and are able to conclude the concerns are minimal. Anticipation refers to the possibility that local businesses may anticipate the closure of local bank branches and adjust their employment patterns in advance. Local bank branch closures are due to bank strategic decisions, and it is reasonable to assume most firms will not have access to inside information about an upcoming branch closure in a specific location. So, we assume no anticipation and set $\omega = 0$. Spillover effects occur when firms that lost access to the local bank branch seek credit in a neighboring municipality, which can potentially affect that municipality's firms' performance. Figure 1 shows that treated and comparison groups are geographically separated; it is thus likely that spillovers will be relevant in this context. However, nationwide bank branch closures can still have an impact on both groups, leading to potential underestimates of the impact.

4 Empirical Results

We first report results regarding firm operations, using both establishment-level and municipality-level data. Then we look at employment variables. Finally, we conduct a heterogeneity analysis by firm type and economic sector.

4.1 Firm Operations

To evaluate the impact of losing access to bank branches for firm operations and number of firms, we employ the labor census data that covers the universe of formal firms. The publicly available version of the RAIS dataset contains an "active establishment" variable—an indicator for firms/establishments conducting any economic activity during the year—and the number of employees. [4] We adopt the "active establishment" as our primary outcome measure for firm operations. Additionally, since the RAIS dataset itself comes from the annual labor census in Brazil and requires all registered firms to report, we can track the numbers of firms registered in the dataset or proportions of certain types of firms to measure whether firms are entering or leaving the market.

Henceforth, we report either the overall effect or the event study effects for the variables of interest, but we sometimes choose to focus on one kind of effect for different variables under discussion. In the main text we display the CS estimates using the never-treated group for event studies and report the event study plots with all three estimators in Appendix B. The estimates are generally very similar, suggesting selection issues are minor, and the PT assumption holds well across different control groups.

Figure 3 shows the event study results, namely dynamic regression coefficients for firm operations via the binary variable "active establishment." The revealed pattern suggests that bank branch closures make roughly 1 percent of establishments become inactive in the following 3 years, with the effect increasing from 1.1 to 1.4 percent between the first and second years after a closure. Our estimates suggest that bank closures could have a severe impact in the long run: The share of inactive establishments increases from 1.2 percent to 8.1 percent between the 4th and 7th years after a closure.

Roth (2024) indicates the default way to calculate the pre-treatment effect with the CS estimator is to use short gaps and display violations of PT as kinks in pre-treatment estimates. We follow this approach and calculate the pre-treatment effect using long gaps instead, thus making the pre-treatment estimates comparable with the dynamic TWFE model and visual checks for pre-treatment effects possible. We find no evidence of an existing pre-trend.

While some firms may respond to shrinking credit supply by scaling back operations, others may close down. At the same time, lack of local bank access can create a barrier to entry for new firms. In the absence of data on firm exit and entry, we report estimates using the number of firms within the municipality by aggregating establishment-level data to the municipality level. Furthermore, we calculate the proportions of SMEs, agricultural firms, and non-zero-employee firms.

We report an overall ATT effect in Table 1. In general, in these data we do not find evidence that a bank branch closure leads to a change in the total number of local firms or

[4] Over 60 percent of establishments report zero active employees at the end of the year in our subsample. For this reason, firm-level employee numbers are not a reliable measure of firm activities.

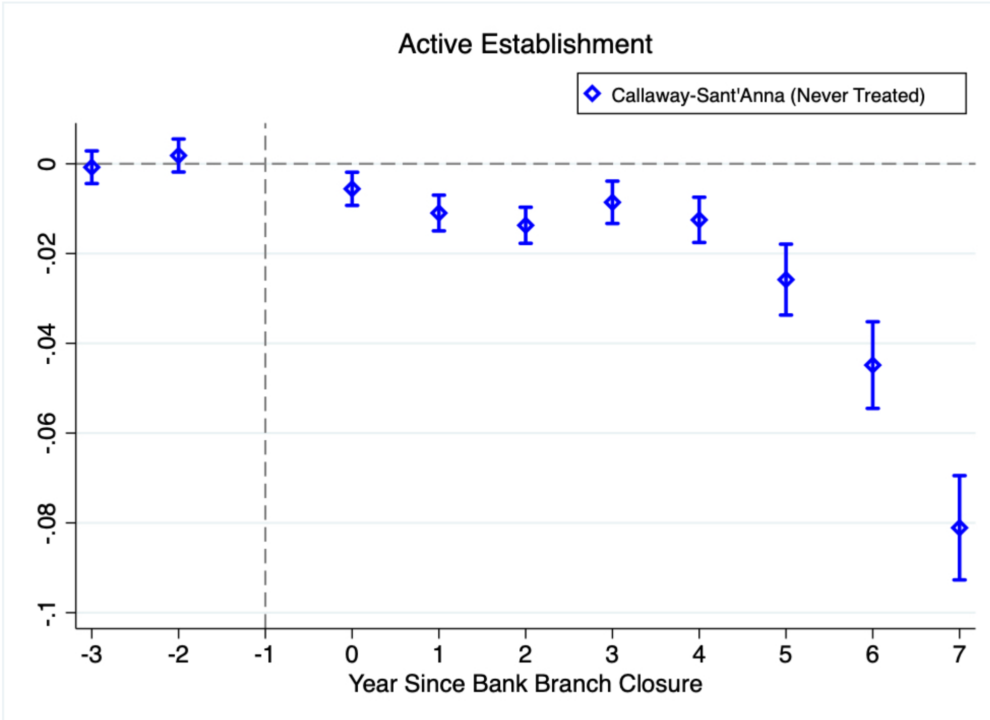


Figure 3: Effect of Exposure to Bank Branch Closure on Firm Operations at the Local Level
Note: This figure shows estimates from equation (7) regarding the binary "active establishment" variable, using CS estimators with never-treated municipalities as the control group. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors are computed by wild bootstrap. We use the "long2" option under "csdid" in Stata according to Roth's (2014) suggestion, making the pre-treatment estimates comparable with the dynamic TWFE model and visual checks for pre-treatment effects possible. We use establishment-level data to conduct this analysis.
Source: RAIS, authors' calculations.

a compositional change in the types of firms. In column (1), the static TWFE estimates indicate a slightly positive or small effect on the number of firms and shares of firms. However, by investigating with the more robust CS estimators and analyzing dynamic patterns (not reported), we observe a lack of consistent evidence of significant impact.

4.2 Employment

Through firms, bank branch closures could have an impact on local employment. In this section, we evaluate the impact of bank branch closures on formal sector employment.

In conducting our analysis, we find that some municipalities have very few paid formal workers registered. To avoid boundary effects, we reframe the employment analysis around those municipalities where paid private sector employees totaled more than one percent of the municipal population during our study period. It appears that municipalities with low shares of paid workers are randomly distributed and not affected by the treatment. This exclusion rules out similar numbers of observations across groups: 43 (6.3%) of control group municipalities and 36 (8.3%) of treatment group municipalities.

Table 1: Estimates of the Impact of Bank Branch Closure on Firms

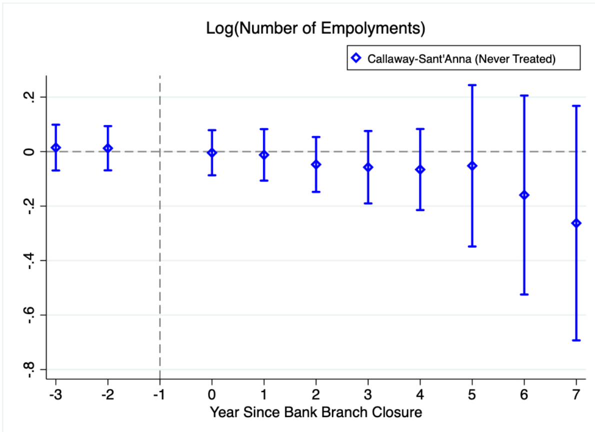
	N (Firms) (1)	P(SME) (2)	P(Ag Firms) (3)	P(Nonzero Firms) (4)
Panel A. TWFE				
δ_{twfe}	5.057*	-0.000	0.002	0.000
	(2.390)	(0.000)	(0.002)	(0.003)
Panel B. CS-Never				
δ_{csnev}	2.411	-0.000	0.001	0.001
	(7.927)	(0.000)	(0.011)	(0.007)
Panel C. CS-Notyet				
δ_{csny}	1.883	0.000	0.001	0.001
	(7.971)	(0.000)	(0.011)	(0.008)
Baseline Mean	281.285	0.996	0.176	0.357
Observations	12,199	12,199	12,199	12,199

Note: This table shows overall ATT estimates for the treatment effects on numbers and shares of firms from equations (6) and (9). The standard errors are reported in parentheses. The standard errors for static TWFE estimates are clustered at both the municipality and year levels. The standard errors for the CS estimates are computed by wild bootstrap. The significance level in this table is represented by: *** p<0.01, ** p<0.05, * p<0.10. The baseline mean represents the mean of the outcome variables for all observations in the sample during 2011-2013. We use a municipality-level panel constructed from establishment-level data to conduct this analysis.
Source: Authors' calculations

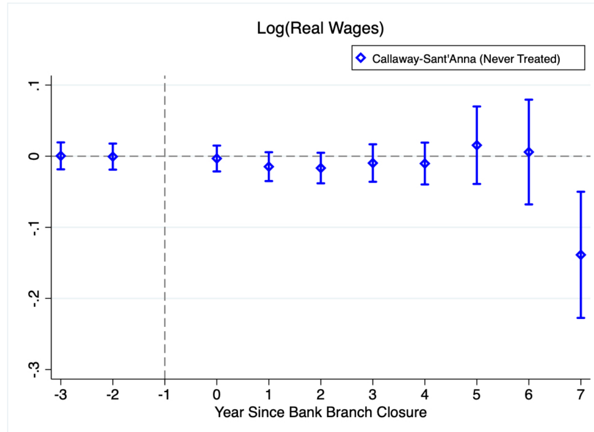
Two key dimensions for understanding the equilibrium effects of bank branch closures on employment are quantity and price. We calculated the natural log of numbers of employed workers and the natural log of worker real wages. We find that employment and wages display significant variation—they react to a broad range factors regarding workers and their working environment—so adjusting for covariates can improve estimation precision. We thus include workers' demographic profiles within municipalities as covariates, along with job and establishment information. We include the following variables: female share of workers, average education level (11 levels, adapting the scale from the RAIS dataset), average weekly hired hours, average establishment size in groups, time in employment, and whites as a share of workers.

Figure 4 Panel A shows the results from this analysis. The point estimates are relatively robust to the inclusion of covariates, which narrow the confidence intervals (see Figure 12 for comparison). However, the confidence intervals do not reach statistical significance at the 95% level. The impact of bank branch closure on employment can be read as either a null or

Panel A. Local Level of Employment and Real Wage

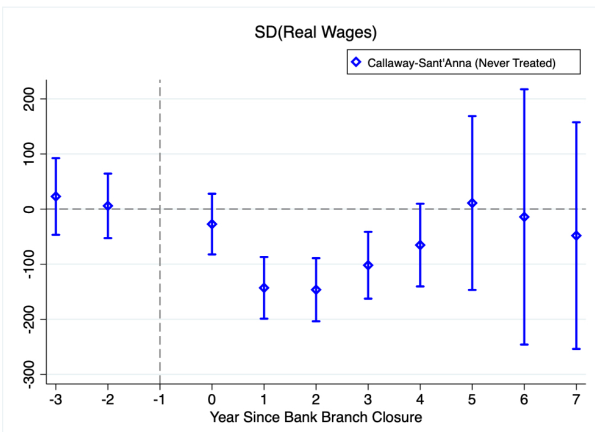


(a)

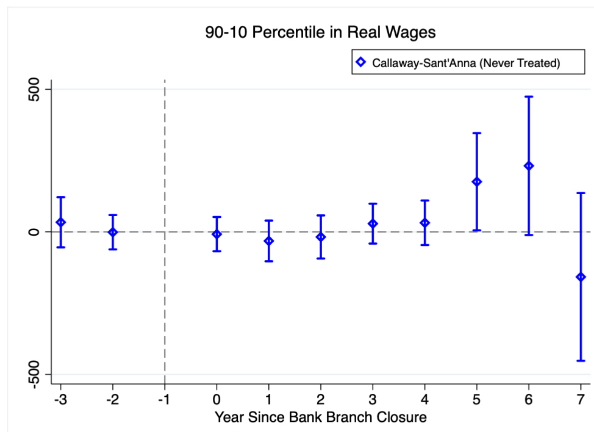


(b)

Panel B. Wage Disparities



(c)



(d)

Figure 4: Effect of Exposure to Bank Branch Closure on Local Levels of Employment and Wages

Note: This figure shows estimates from equation (7) regarding the Log(Number of Employed People), Log(Real Wages), SD (Real Wages), and P90-10 Real Wages. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors are computed by wild bootstrap. We use the "long2" option under "csdid" in Stata according to Roth's (2014) suggestion, making the pre-treatment estimates comparable with dynamic TWFE model and visual checks for pre-treatment effects possible. We use municipality-level data to conduct this analysis. We include the following covariates to narrow down the confidence intervals: female share of workers, average education level, average weekly hired hours, average establishment size in groups, time in employment, and whites as a share of workers. Real wages are calculated by adjusting nominal wages by Brazil's annual CPI. The unit for real wages is 2011 reais. Source: RAIS, authors' calculations.

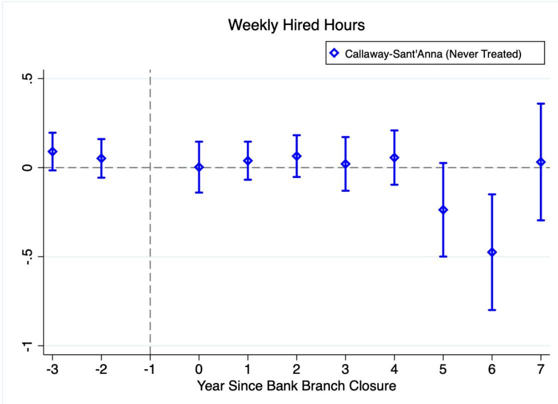
negative effect. For the number of employed workers, the CS estimator with never-treated as controls generally shows a potential long-term decreasing trend despite its point estimates being statistically insignificant. For the average wage, it shows a long-term decrease of 1.5 to 1.7 percent and an inconclusive short-term effect. In this analysis, both CS estimators show a similar trend, while the TWFE estimator has a slightly different pattern. The TWFE suggests a null effect on the number of employed workers and a small positive effect on wages. We do not find evidence of violation of PT.

To better understand the impact of bank branch closures on local employment dynamics, we delve into wage disparities. We employ two distinct measures to assess the effects on wage disparities: the standard deviation of real wages, to gauge overall wage variability among workers, and the difference between the 90th and 10th percentiles of real wages, to examine disparities between high- and low-paid jobs.

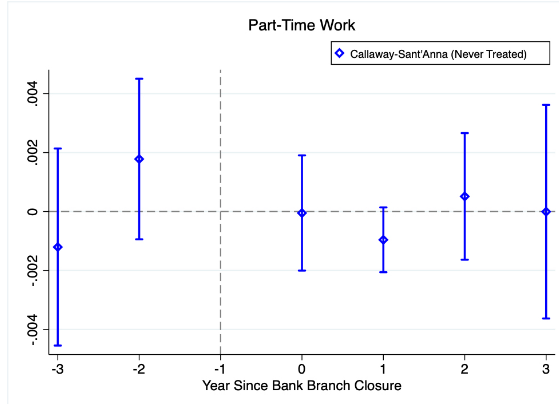
We present our estimates in Figure 4 Panel B. For the standard deviation of real wages, we note a short-term decrease of 142 reais one year after a closure, persisting for two years before gradually diminishing over approximately five years. In contrast, the gap between the 90th and 10th percentile wages initially shows no significant short-term effect. This hints at a potential long-term widening, beginning three years post-closure, with an increase of 28 reais, and reaching a difference of 231 reais six years after a closure. These observations suggest that in the short term, bank branch closures do not significantly affect the wage gap between high- and low-paid jobs, but they do lead to a notable reduction in overall wage disparities among workers, potentially through the middle-income wage bracket. In the long term, however, the loss of a bank branch appears to contribute to increasing wage disparities between high- and low-paid positions, even as overall wage disparities among workers become less pronounced.

Finally, we are interested in determining whether bank branch closures impact firms' employment patterns in other ways. For instance, we examine whether firms maintain the same number of employees but reduce their working hours, or if part-time positions are being used as substitutes for full-time jobs. Our analysis utilizes weekly contracted hours and the proportion of part-time work as metrics. The results are reported in Figure 5. We observe a decrease in contracted hours 5 to 6 years following a branch closure. However, upon examining the event-study plot for part-time work metrics, we do not find a clear impact due to bank branch closures.

Finally, we study whether local bank branch closures have an impact on economic output. If bank branch closures lead to reduced firm operations and employment levels, it is possible that impacted firms would produce less output. Here we rely on municipality-level GDP data and value-added accounts in services (excluding public administration, education, etc.),



(a)



(b)

Figure 5: Effect of Exposure to Bank Branch Closure on Other Local Employment Patterns
Note: This figure shows estimates from equation (7) regarding weekly hired hours and a binary variable of part-time work. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors are computed by wild bootstrap. We use the "long2" option under "csdid" in Stata according to Roth's (2014) suggestion, making the pre-treatment estimates comparable with the dynamic TWFE model and visual checks for pre-treatment effects possible. We use municipality-level data to conduct this analysis. We include the following covariates to narrow down the confidence intervals: female share of workers, average education level, average weekly hired hours, average establishment size in groups, time in employment, and whites as a share of workers.
Source: RAIS, authors' calculations.

industry, and agriculture to conduct our analysis. We adjust prices to 2011 reais and present the effect pattern in Figure 10. In services, we find a short-term decreasing trend in the first 3 years after closure, although the estimates are imprecise. We estimate that bank branch closures decrease valued added in services by 3,366 thousand reais by the 3rd year. In industry and agriculture, we do not find significant short-term patterns but a potential long-term decreasing trend.

4.3 Heterogeneity Analysis

In this section, we evaluate how the impact of bank branch closures differs by firm size and economic sector.

Knowing the average effect of closing bank branches on firm operations, it will be valuable to learn what kind of firms are more vulnerable to these effects. We consider two dimensions: firm size and main economic sector. There are different ways to categorize firms by number of employees in Brazil (Carneiro et al., 2020). IBGE classifies the size of firms in certain sectors using the number of employees. We use IBGE's employee count-based firm size categorization for firms/establishments in manufacturing and services (see Table 4). In the absence of a settled classification for the remaining sectors, such as agriculture, we adopt Cravo et al. (2018)'s classification scheme. [5]

We classify firms into four main sectors: industry and construction, referred to as manufacturing by Carneiro et al. (2020); trade and services, referred to as services; agriculture; and all other sectors.

Table 2: Estimates of the Effect of Bank Branch Closure on Firm Operations, by Firm Size

Outcome Variable	Active Establishments			
	Micro Firms (1)	Small Firms (2)	Medium Firms (3)	Large Firms (4)
Panel A. TWFE				
δ_{twfe}	-0.009	-0.000	-0.001	0.002
	(0.005)	(0.000)	(0.002)	(0.002)
Panel B. CS-Never				
δ_{csnev}	-0.014***	-0.000	-0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.000)
Panel C. CS-Notyet				
δ_{csny}	-0.012***	-0.000	-0.000	-0.000
	(0.002)	(0.000)	(0.000)	(0.000)
Baseline Mean	0.785	0.996	0.997	0.996
Observations	3,158,958	208,168	26,725	5,189

Note: This table presents the impact of a bank branch closure on firm operations by firm size, using equations (5), (7) and (8). The standard errors are reported in parentheses. The standard errors for the static TWFE estimates are clustered at both the municipality and year level. The standard errors for the CS estimates are computed by wild bootstrap. The significance level in this table is represented by: *** p<0.01, ** p<0.05, * p<0.10. The baseline mean represents the mean of the outcome variables for all observations in the sample during 2011-2013. We use establishment-level data to conduct this analysis. Observations denote the number of firms per size category.

Source: Authors' calculations

We first study the effect of a bank branch closure on firm operations across different firm sizes. Table 2 presents the results. We find that micro firms bear almost the full impact on operations from local bank branch closures, while the effects are roughly zero for firms of all other sizes. This could be due to their high level of active operation status: small, medium, and large firms are all more than 99.6% active in the baseline years (between 2011

[5] An alternative approach for firms in agriculture and all other sectors is to apply IBGE's categorization for manufacturing firms. The results are qualitatively similar.

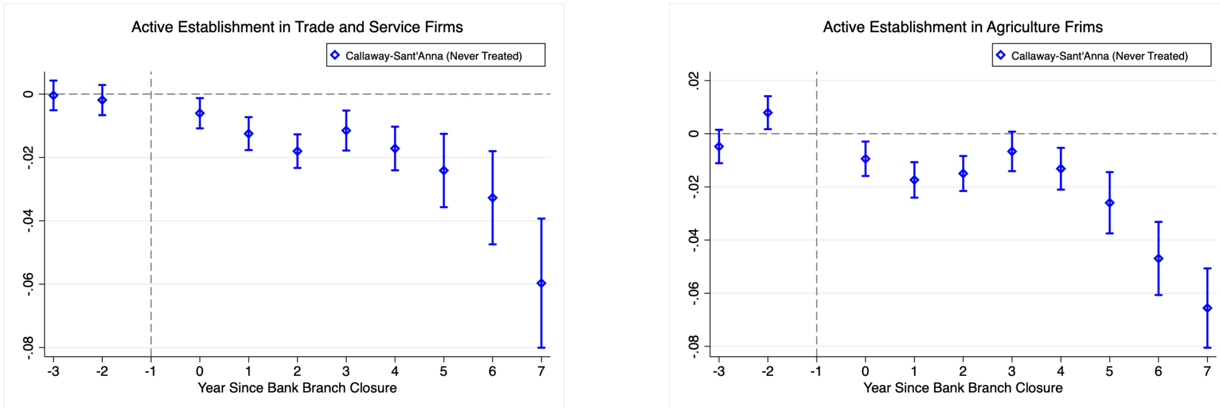
to 2013). The results confirm our previous hypothesis that larger firms have greater financial access and are less likely to be disrupted by a local bank branch closure. Micro firms play a dominant role (92.9%) in our sample and are sensitive to local branch closures, which could imply that micro firms' banking demands are more localized. We include an event-study plot of this effect in Appendix B (see Figure 14). The effect is similar to the impact pattern for our entire sample (see Figure 11).

Table 3: Estimates of the Effect of Bank Branch Closure on Firm Operations, by Sector

Outcome Variable	Active Establishments			
	Trade & Service (1)	Industry & Construction (2)	Agriculture (3)	All Other (4)
Panel A. TWFE				
δ_{twfe}	-0.008	-0.003	-0.013	0.017
	(0.005)	(0.006)	(0.008)	(0.052)
Panel B. CS-Never				
δ_{csnev}	-0.014***	0.002	-0.018***	0.000
	(0.002)	(0.005)	(0.003)	(0.053)
Panel C. CS-Notyet				
δ_{csny}	-0.013***	0.003	-0.016***	0.000
	(0.002)	(0.005)	(0.003)	(0.054)
Baseline Mean	0.768	0.790	0.914	0.858
Observations	2,315,624	415,022	665,012	3,757

Note: This table presents the impact of a bank branch closure on firm operations by firm sector, using equations (5), (7) and (8). The sectors are: trade and services, industry and construction, agriculture, and all other firms. The standard errors are reported in parentheses. The standard errors for the static TWFE estimates are clustered at both the municipality and year level. The standard errors for the CS estimates are computed by wild bootstrap. The significance level in this table is represented by: *** p<0.01, ** p<0.05, * p<0.10. The baseline mean represents the mean of the outcome variables for all observations in the sample during 2011-2013. We use establishment-level data to conduct this analysis. Observations denote the number of firms per sector.
Source: Authors' calculations

We now turn to the impact of bank branch closures on firm operations by sectors. The results are presented in Table 3. While the TWFE estimates suggest null effects across different sectors, the CS estimates imply that bank branch closures depress the operations of firms in trade and services as well as in agriculture. Overall effects on agriculture firms are somewhat more severe than on trade and service firms despite agriculture firms' higher rate of active establishment status in the baseline year. We present event-study plots for the trade and service sector as well as the agriculture sector in Figure 6.



(a) (b)

Figure 6: Effect of Exposure to Bank Branch Closure on Firm Operations in Two Sectors
Note: This figure shows estimates from equation (7) regarding the "active establishment" variable in two sectors: trade and services, and agriculture. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors are computed by wild bootstrap. We use the "long2" option under "csdid" in Stata according to Roth's (2014) suggestion, making the pre-treatment estimates comparable with the dynamic TWFE model and visual checks for pre-treatment effects possible. We use municipality-level data to conduct this analysis.
Source: RAIS, authors' calculations.

5 Conclusions

This paper studies whether a shrinking local banking supply through physical branch closures impacts firm operations, labor market outcomes, and the local economy. Our analysis focuses on Brazilian municipalities with one bank branch between 2011-2021 and on private sector firms in these municipalities. We employ a difference-in-differences design with variation in treatment timing, where the treatment is the branch closure. We use both the traditional TWFE estimator and the more recent CS estimators to provide credible effects of local branch closures. We find that roughly 1 percent of establishments become inactive in the first 3 years after a bank branch closure, and the share of inactive establishments increases from 1.2 percent to 8.1 percent between years 4 and 7 after a closure. We also find that a bank branch closure is followed by a decrease in weekly hours worked and a compression of the wage distribution.

Bank decisions to reduce their branch networks in this period are primarily driven by rapid digitalization in the banking industry. Nevertheless, at the margin, some of the closure decisions may be based on local economic conditions. We mitigate endogeneity concerns by also using "not-yet-treated" municipalities as a control group, that is, municipalities that experience a closure at a later time. The resulting estimates are similar to those those that use "never-treated" municipalities as controls, suggesting that selection issues are minor and do not threaten the PT assumption in this context. Second, firms' access to financial services may be imperfectly approximated by the presence of a bank branch in their municipality. Due to data availability constraints, we conduct our analyses using the municipality level to proxy for access to financial services. Third, the effects we observe in Brazil may be shaped by the country's highly concentrated banking industry. In countries with more diffuse industrial organization in the banking sector, the effects of bank branch closures may be different.

Our study has important policy implications. First, it highlights the importance of physical bank branches in providing financial access, particularly for small firms. This suggests the need for policies that balance digital banking growth with preservation of adequate physical banking infrastructure, especially in underserved areas. Second, our study shows that demand for financial services among certain types of firms, particularly in services and agriculture, is highly localized. Recognizing this, providing local financial access becomes vital to fostering inclusive regional growth. This suggests the importance of a policy focus on strengthening financial ecosystems that support small-scale local-economy businesses.

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Online Appendix

Appendix A. Additional Tables and Figures

Table 4: Classification of Firms by Sector, using CNAE 2.0

Industry and Construction	Trade and Services	Agriculture	Others
05-09, 10-33, 35, 36-39, 41-43	45-47, 49-53, 55-56, 58-63, 64-66, 68, 69-75, 77-82, 85, 86-88, 90-93, 94-96	01-03	84, 97, 99

Note: This table shows our classification of firms by sector using CNAE categories.

Definition of firm size

Sector	Size	Microfirms	Small firms	Medium firms	Large firms
Manufacturing		< 19 employees	Between 20 and 99	Between 100 and 499	> 500 employees
Service		< 9 employees	Between 10 and 49	Between 50 and 99	> 100 employees

Source: Sebrae. Available at: <https://bit.ly/2DiBvMg>. Accessed on: Oct. 20, 2015.
Authors' elaboration.

Figure 7: IBGE Categorization of Firms (Establishments) by Number of Employees

Source: Table 3, Carneiro, Douglas Mesquita, Carlos Eduardo Lobo, and Geoffrey JD Hewings. "Firm Size and Economic Development: Evidence for the Brazilian Municipalities." Planejamento e Políticas Públicas (2020).

Table 5: Summary Statistics for Sample Variables Across Groups

	Never-Treated Group Mean	N	Treatment Group Mean	N	Difference	
	(1)	(2)	(3)	(4)	(5)	
Establishment-Level Data						
Active Establishment	0.939	2,337,785	0.926	1,138,674	0.013	***
	(1.146)		(1.115)		(0.001)	
Establishment Size (Groups)	1.585	2,337,785	1.573	1,138,674	0.012	***
	(0.965)		(0.969)		(0.001)	
Municipality-Level Data						
Number of Establishments	307.770	7,436	233.222	4,763	74.548	***
	(176.866)		(128.248)		(2.963)	
P(SME)	0.995	7,436	0.996	4,763	0.000	**
	(0.007)		(0.008)		(0.000)	
P(Ag Firm)	0.175	7,436	0.196	4,763	-0.021	***
	(0.163)		(0.198)		(0.003)	
Log(Real Wages)	6.812	6,963	6.791	4,367	0.021	***
	(0.172)		(0.170)		(0.003)	
SD (Real Wages)	845.087	6,963	795.49	4,367	49.597	***
	(434.860)		(410.458)		(8.216)	
Real Wages_P90	1591.892	6,963	1514.931	4,367	76.961	***
	(496.044)		(525.198)		(9.796)	
Real Wages_P10	627.451	6,963	628.28	4,367	-0.83	
	(69.203)		(71.615)		(1.354)	
P(Female)	0.309	6,963	0.302	4,367	0.007	*
	(0.096)		(0.101)		(0.002)	
Time Employed (Months)	35.384	6,963	34.891	4,367	0.493	*
	(11.027)		(10.803)		(0.211)	
Weekly Hired Hours	42.913	6,963	42.974	4,367	-0.061	***
	(0.957)		(0.899)		(0.018)	
Age	33.789	6,963	33.868	4,367	-0.080	*
	(1.828)		(2.011)		(0.037)	
Average EstSize	3.672	6,963	3.593	4,367	0.080	***
	(0.910)		(0.939)		(0.018)	
P(Part-Time Work)	0.002	6,963	0.002	4,367	0.000	
	(0.008)		(0.009)		0.000	
Education Level	5.922	6,963	5.87	4,367	0.052	***
	(0.601)		(0.664)		(0.012)	
Number of Employed People	1017.736	6,963	736.796	4,367	280.94	***
	(886.796)		(669.004)		(15.632)	
Race: White	0.522	6,963	0.533	4,367	-0.011	*
	(0.267)		(0.264)		(0.005)	
Population	10237.16	6,963	8624.363	4,367	1612.797	***
	(6884.674)		(6277.038)		0.000	
Valued Added: Ag	30494.07	7,436	21364.62	4,763	9129.45	***
	(49670.360)		(27651.030)		(787.917)	
Value Added: Ind	21514.61	7,436	13793.65	4,763	7720.96	***
	(59695.790)		(35852.060)		(959.715)	
Value Added: Services	35166.9	7,436	25079.69	4,763	10087.21	***
	(35294.550)		(29811.660)		(617.299)	

[Continue for table notes]

Note: This table presents summary statistics for all the variables in our sample. Firm size is categorized into 9 groups in terms of number of employees. Firm sector categories are industry and construction, trade and services, and all other sectors. Real wages are deflated using the annual consumer price index; their units are 2011 Brazilian reais. Education level consists of 11 groups according to categories in the RAIS dataset. The partial work status is only available from 2017. Value added is deflated using the annual consumer price index; its units are thousands of 2011 Brazilian reais. The significance level in this table is represented by: $*p < 0.1 * *p < 0.5, * * *p < 0.01$.

Source: Authors' calculations

Table 6: Population and GDP Comparisons Across Groups

	Year	Never-Treated (1)	Treatment (2)	Other Mun (3)
Population	*2011-2013*	10688.15	9037.55	41421.61
		(159.66)	(177.69)	(2002.94)
	2014-2017	11075.77	9295.07	43427.09
		(144.78)	(159.00)	(1805.63)
	2018-2021	11138.72	9268.61	44695.30
		(149.08)	(160.02)	(1854.50)
Real GDP	*2011-2013*	117566.50	85692.04	976888.10
		(2300.79)	(1808.36)	(79505.82)
	2014-2017	123471.40	91513.17	965289.10
		(2159.20)	(1650.16)	(66289.58)
	2018-2021	135178.90	96514.38	972079.40
		(2518.69)	(1889.33)	(61537.83)
RGDP per capita	*2011-2013*	13.99	13.12	14.92
		(0.29)	(0.35)	(0.16)
	2014-2017	14.10	13.31	14.82
		(0.25)	(0.30)	(0.12)
	2018-2021	15.20	14.02	15.95
		(0.27)	(0.33)	(0.14)

Note: This table presents the average municipal population, real GDP, and real GDP per capita of each sample and time period. The simple average is presented and the standard deviations within groups are provided in parentheses. The unit of population is number of individuals, and the unit for real GDP and real GDP per capita are thousands of reais. Real GDP is deflated using Brazil's GDP deflator from FRED and IMF; the base year is 2011. Municipal populations are IBGE estimates, not counts. RGDP per capita is calculated by the authors using the estimated population.

Source: IBGE, authors' calculations

Table 7: Involved Banks: Treatment and Never-Treated Group

BANK	Treatment	Never-Treated	Total	Public-Owned
BCO BANESTES S.A.	0	18	18	X
BCO BRADESCO S.A.	9	157	166	
BCO DO BRASIL S.A.	332	271	603	X
BCO DO EST. DE SE S.A.	1	12	13	X
BCO DO EST. DO PA S.A.	0	1	1	X
BCO DO ESTADO DO RS S.A.	0	57	57	X
BCO DO NORDESTE DO BRASIL S.A.	0	1	1	X
BCO SANTANDER (BRASIL) S.A.	29	51	80	
CAIXA ECONOMICA FEDERAL	0	11	11	X
ITAò UNIBANCO S.A.	62	97	159	
Total	433	676	1,109	703

Note: This table presents the banks and the number of their branches in the treatment and control groups. The right column indicates whether a bank is publicly owned (i.e., owned by the state or federal government). We include the “Total” row and column to indicate the number of bank branches in each group and each bank.
Source: Authors’ calculations

Table 8: Patterns of Bank Branch Closures by Year

Year	Freq.	Percent	Cum.
2014	29	2.61	2.61
2015	21	1.89	4.5
2016	27	2.43	6.93
2017	155	13.98	20.91
2018	34	3.07	23.98
2019	104	9.38	33.36
2020	2	0.18	33.54
2021	61	5.5	39.04
Not Lost	676	60.96	100
Total	1109		

Note: This table shows the pattern of bank branch closures in our sample. Our sample consists of municipalities with one bank branch from 2011 to 2013. We exclude municipalities whose branch count doesn’t fall into the absorbing stage from 2014. A branch is considered lost when the only branch closes and doesn’t reopen till the end of the study period. ”Not Lost” municipalities are those that retain one bank branch from 2011 to 2021. The frequency in the timing of branch loss is shown for our sample, including their shares and cumulative percentage.
Source: Authors’ calculations

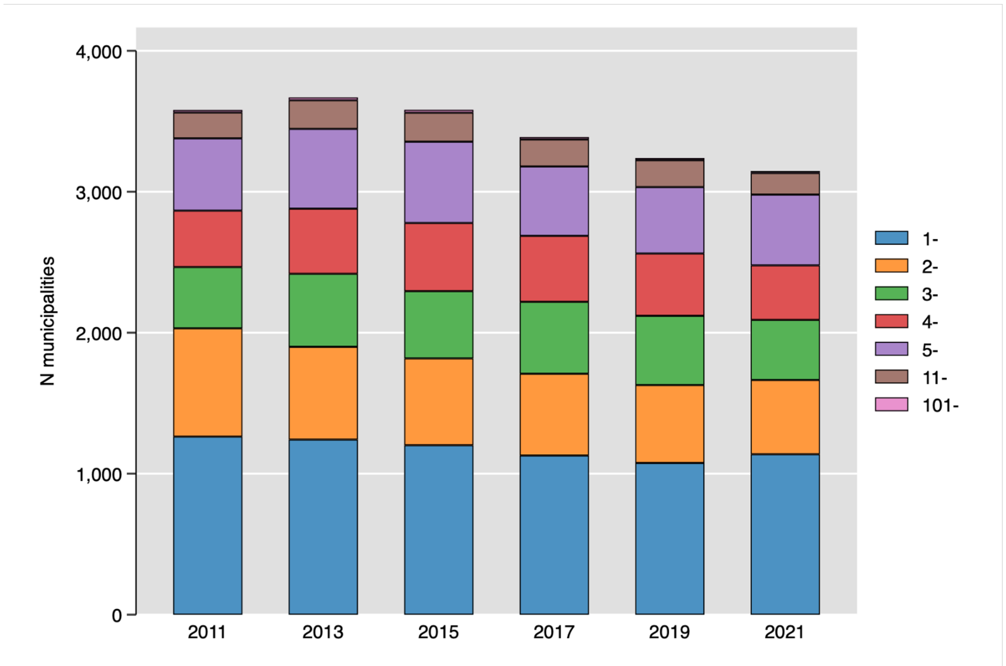


Figure 8: Distribution of Municipalities by Number of Bank Branches, 2011-2021

Note: This figure shows the distribution of municipalities by number of bank branches located in each municipality in each year. The colors for each category are marked in the right legend. This figure only presents the distributions for banked municipalities. During the study period, Brazil had 5,570 municipalities in total.
Source: Authors' calculations, ESTBAN dataset.

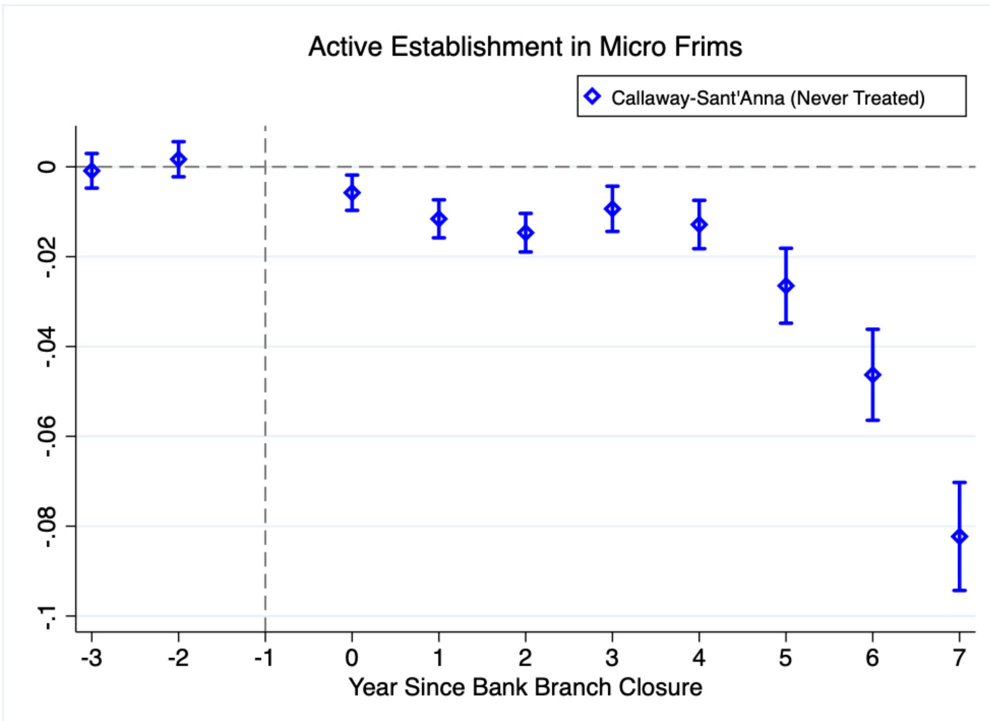
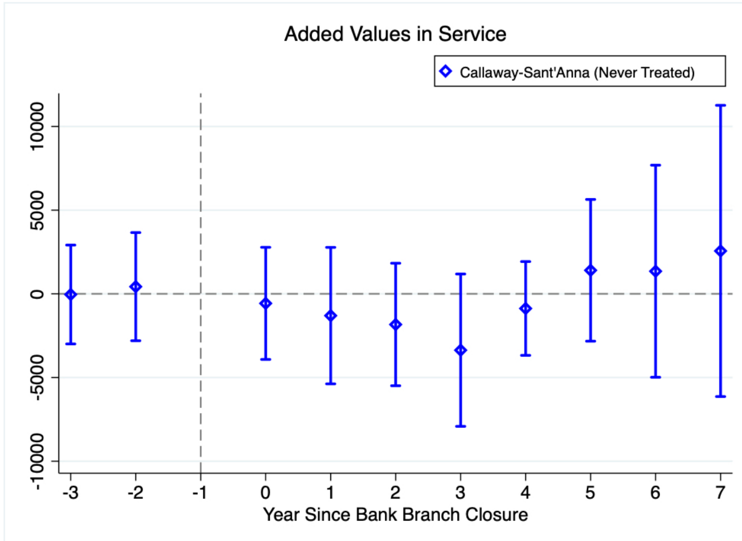
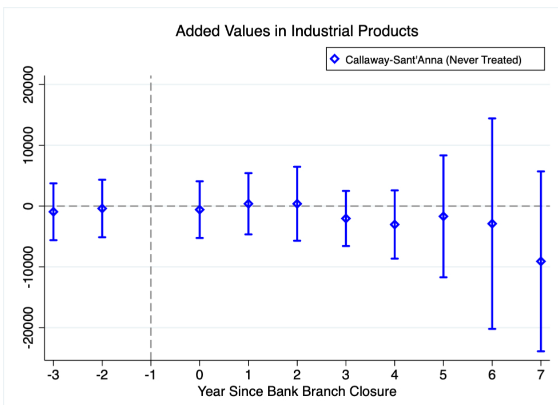


Figure 9: Effect of Exposure to Bank Branch Closure on Firm Operations: Micro Firms

Note: This figure shows estimates from equation (7) regarding the "active establishment" variable among micro firms. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors are computed by wild bootstrap. We use the "long2" option under "csdid" in Stata according to Roth's (2014) suggestion, making the pre-treatment estimates comparable with the dynamic TWFE model and visual checks for pre-treatment effects possible. We use municipality-level data to conduct this analysis.
Source: RAIS, authors' calculations.



(a)



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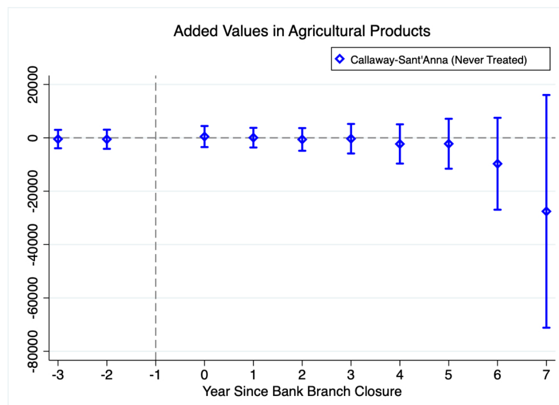


(c)

Figure 10: Effect of Exposure to Bank Branch Closure on Economic Output

Note: This figure shows estimates from equation (7) regarding value added in services (excluding administration, education, public health, and social security), industry, and agriculture. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors for the dynamic TWFE estimates are clustered at both the municipality and year level. The standard errors for the CS estimates are computed by wild bootstrap. Prices are deflated using the reference year's average consumer price index. The unit of measurement is thousands of 2011 Brazilian reais.

Source: Brazil's GDP by Municipality, authors' calculations.

Appendix B. Event-Study Plots with Three Estimators

In this section, we provide event-study plots with results from all three estimators for equations (5), (7) and (8). The estimators are dynamic TWFE, CS-never-treated, CS-not-yet-treated, respectively.

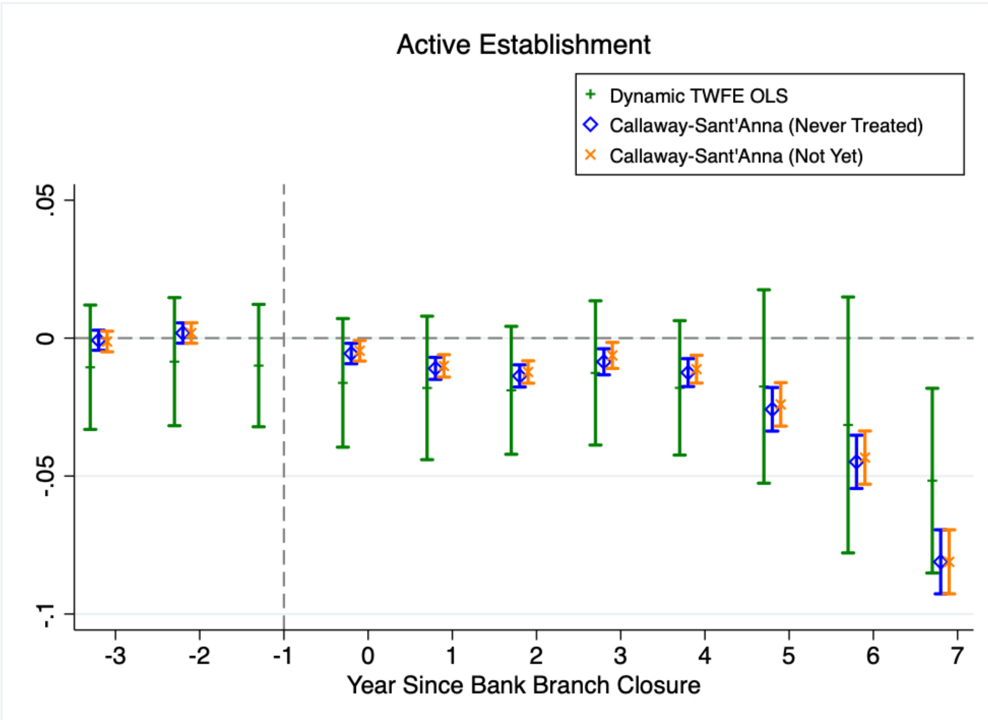
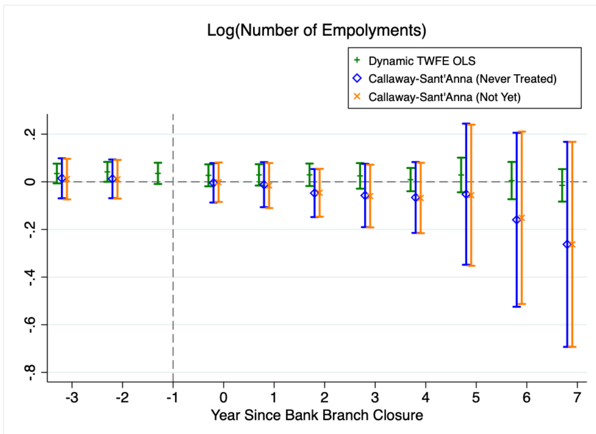


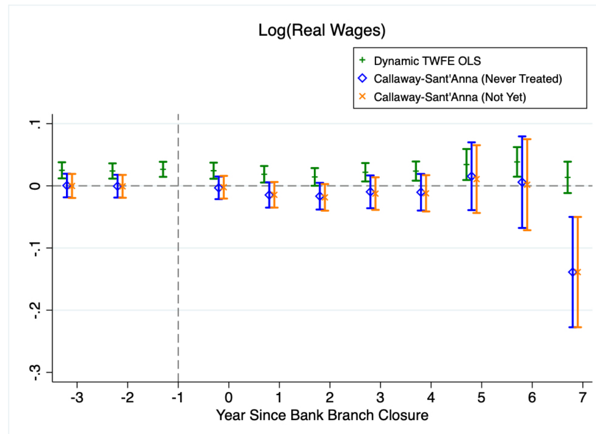
Figure 11: Effect of Exposure to Bank Branch Closure on Firm Operations at the Local Level, Three Estimators

Note: This figure shows estimates from equations (5), (7) and (8) regarding the "active establishment" variable. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors for the TWFE estimates are robust standard errors clustered by both year and municipality. The standard errors for the CS estimates are computed by wild bootstrap.
Source: RAIS, authors' calculations.

Panel A. Local Level of Employment and Real Wage

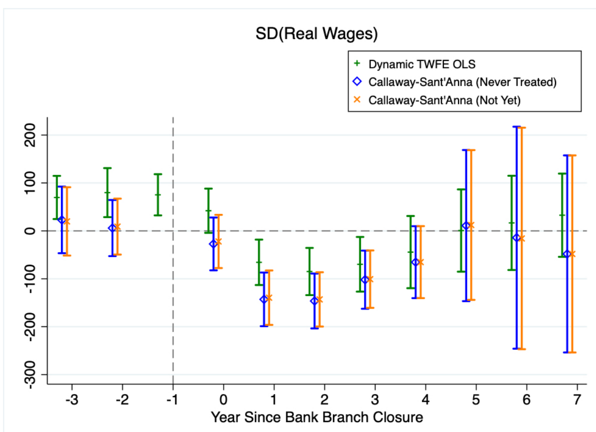


(a)

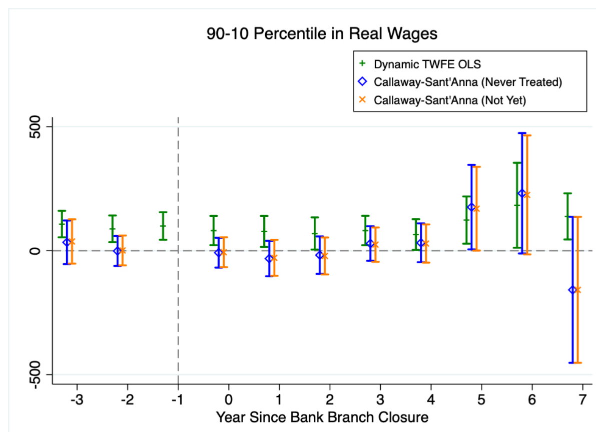


(b)

Panel B. Wage Disparities



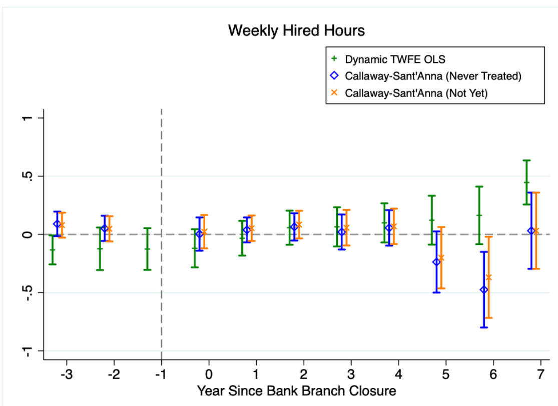
(c)



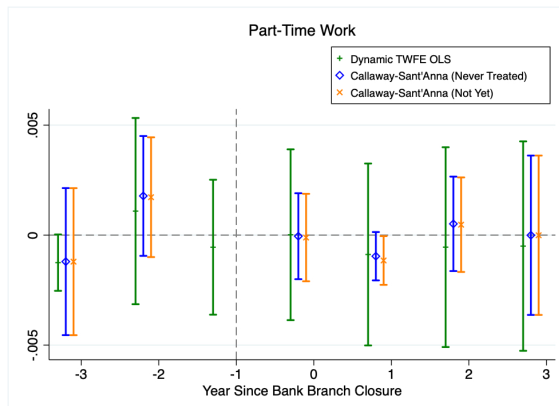
(d)

Figure 12: Effect of Exposure to Bank Branch Closure on Local Levels of Employment and Wages, Three Estimators

Note: This figure shows estimates from equations (5), (7) and (8) regarding the variables Log(Number of Employed People), Log(Real Wages), SD (Real Wages), and P90-10 Real Wages. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors for the TWFE estimates are robust standard errors clustered by both year and municipality. The standard errors for the CS estimates are computed by wild bootstrap.
Source: RAIS, authors' calculations.



(a)



(b)

Figure 13: Effect of Exposure to Bank Branch Closure on Other Local Employment Patterns, Three Estimators

Note: This figure shows estimates from equations (5), (7) and (8) regarding weekly hired hours and a binary variable of part-time work. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors for the TWFE estimates are robust standard errors clustered by both year and municipality. The standard errors for the CS estimates are computed by wild bootstrap.
Source: RAIS, authors' calculations.

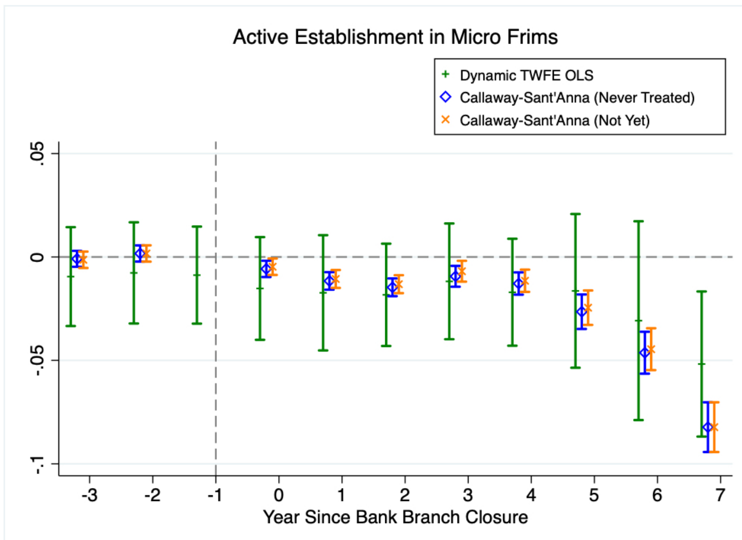
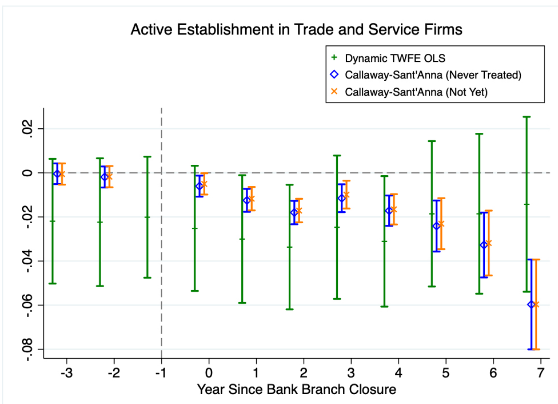
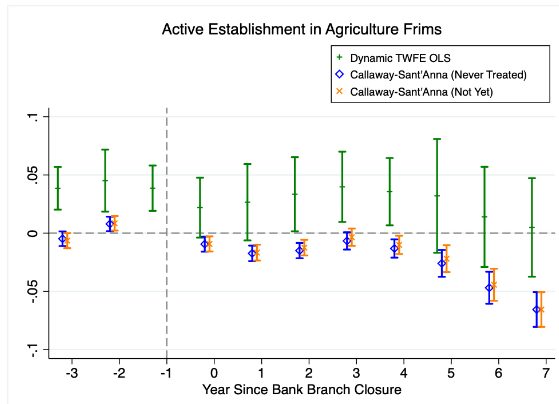


Figure 14: Effect of Exposure to Bank Branch Closure on Firm Operations: Micro Firms, Three Estimators

Note: This figure shows estimates from equations (5), (7) and (8) regarding the "active establishment" variable among micro firms. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors for the TWFE estimates are robust standard errors clustered by both year and municipality. The standard errors for the CS estimates are computed by wild bootstrap. Source: RAIS, authors' calculations.



(a)

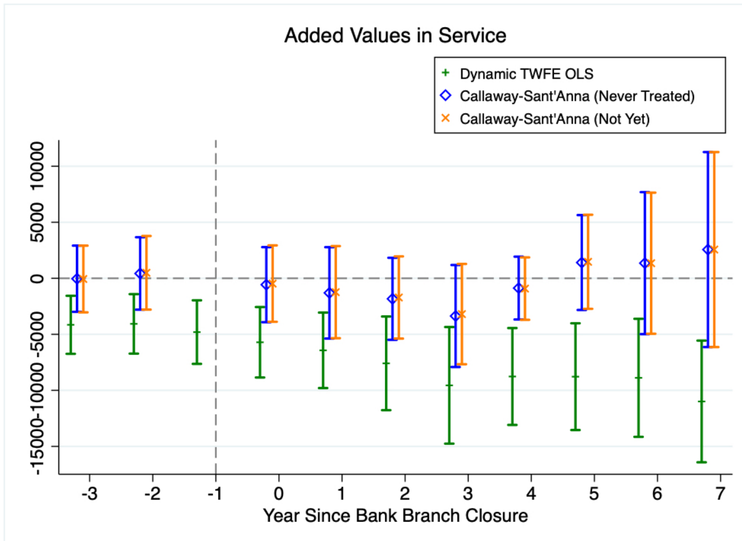


(b)

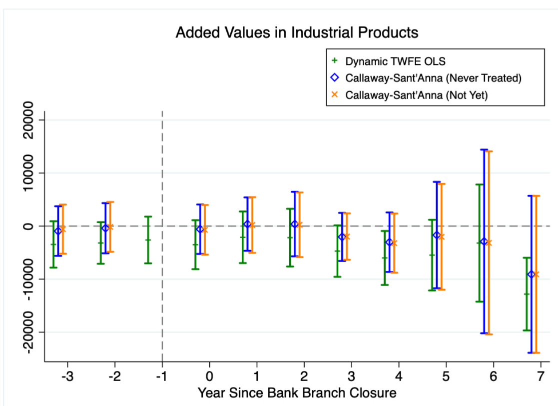
Figure 15: Effect of Exposure to Bank Branch Closure on Firm Operations in Two Sectors, Three Estimators

Note: This figure shows estimates from equations (5), (7) and (8) regarding the "active establishment" variable for firms in two sectors: trade and services, and agriculture. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors for the TWFE estimates are robust standard errors clustered by both year and municipality. The standard errors for the CS estimates are computed by wild bootstrap.

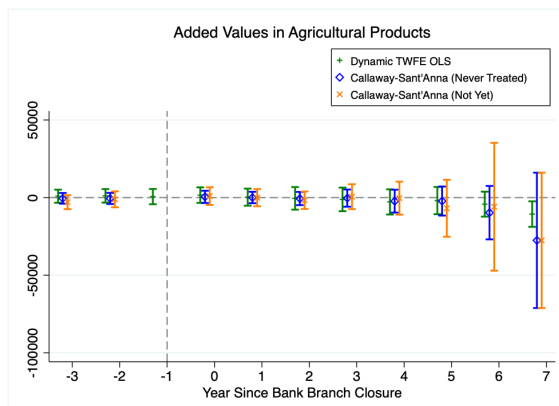
Source: RAIS, authors' calculations.



(a)



(b)



(c)

Figure 16: Effect of Exposure to Bank Branch Closure on Economic Output, Three Estimators

Note: This figure shows estimates from equations (5), (7) and (8) regarding value added in services (excluding administration, education, public health, and social security), industry, and agriculture. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors for the TWFE estimates are robust standard errors clustered by both year and municipality. The standard errors for the CS estimates are computed by wild bootstrap.
Source: RAIS, authors' calculations.

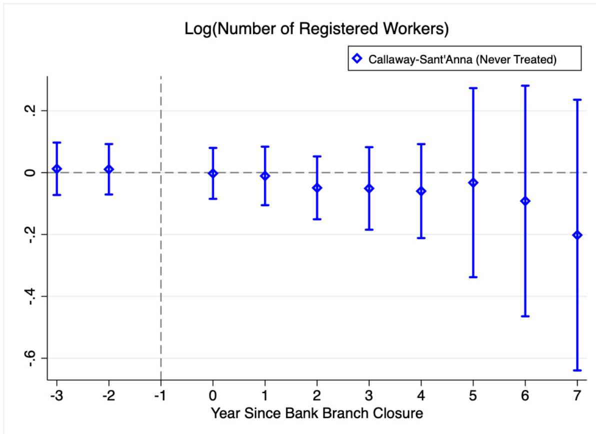
Appendix C. Robustness Checks

In this section, we conduct robustness checks regarding a key issue that appeared in the context of this study. To investigate if sample selection will threaten the validity of this study, we show the relationship between bank branch closures and earnings using both paid and unpaid workers.

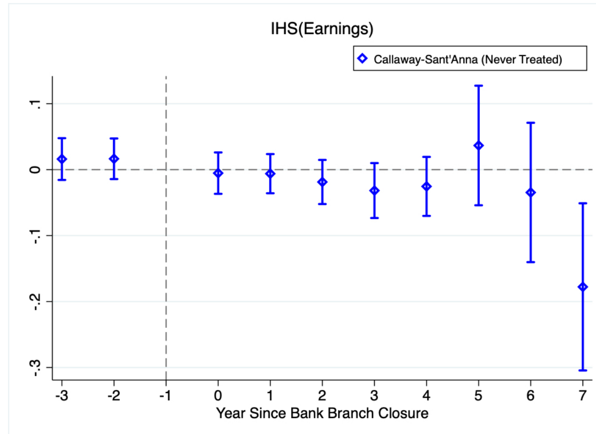
We replicate the employment and wage analyses using samples consisting of both paid and unpaid workers. We use "number of registered workers" to refer to the total number of paid and unpaid workers within an establishment. Similarly, we use "earnings" to refer to the real wages of both groups of workers. We report the event-study results in Figure 17. Using earnings and registered workers does not substantially change the pattern of the effect.

We provide inverse hyperbolic sine estimates for earnings. According to Chen and Roth (2024), the estimates should not be interpreted as percentages but decrease for units of inverse hyperbolic sine (earnings).

Panel A. Local Level of Employment and Real Wage

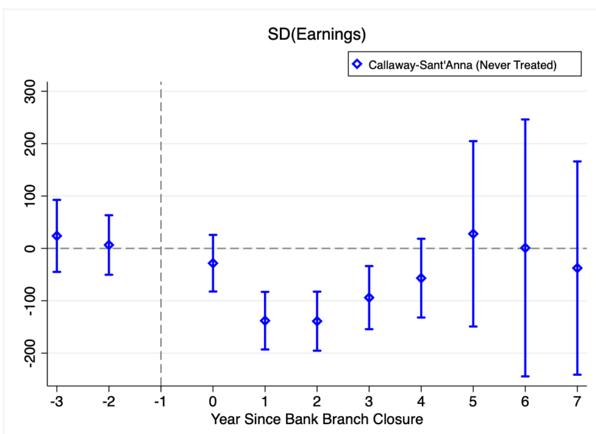


(a)

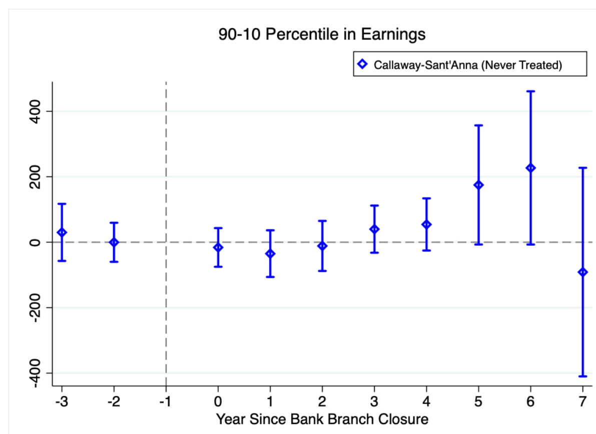


(b)

Panel B. Wage Disparities



(c)



(d)

Figure 17: Effect of Exposure to Bank Branch Closure on Local Levels of Registered Workers and Earnings

Note: This figure shows estimates from equation (7) regarding the Log(Number of Registered Workers), IHS (Earnings), SD (Earnings), and P90-10 Earnings. The bar shows the 95% confidence interval. Years since bank branch closure equals 0 in the year the municipality loses its sole bank branch. We report pre-treatment trends starting from period -3. The panel is balanced between periods -3 and 0; other periods are estimated using incomplete samples. The standard errors are computed by wild bootstrap. We use the "long2" option under "csdid" in Stata according to Roth's (2014) suggestion, making the pre-treatment estimates comparable with dynamic TWFE model and visual checks for pre-treatment effects possible. We use municipality-level data to conduct this analysis. We include the following covariates to narrow down the confidence intervals: female share of workers, average education level, average weekly hired hours, average establishment size in groups, time in employment, and whites as a share of workers. Real wages are calculated by adjusting nominal wages by Brazil's annual CPI. The unit for real wages is 2011 reais. Source: RAIS, authors' calculations.