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COVID-19, policy interventions and credit: The Brazilian experience

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\textbf{A R T I C L E  I N F O}

\textbf{JEL classification:} G01, G18, G21, G32, H12, H51, H75, Q54

\textbf{Keywords:} COVID-19 crisis, Policy interventions, Credit, Banks, Loans

\textbf{A B S T R A C T}

The COVID-19 pandemic caused a global health and economic crisis to which governments responded with massive policy interventions. Using Brazil as a testing ground, we investigate the influence of the pandemic and ensuing policy interventions on local credit markets. First, we find that the pandemic has a significantly negative impact on local credit. Second, using a novel manually collected database on the staggered municipal government policy interventions, we show heterogeneous effects of interventions: positive effects of soft interventions (e.g., social distancing and mass gathering restrictions) and late reopening, and negative effects of hard interventions (e.g., closure of non-essential services) and early reopening. Third, we find that state-owned banks grant more local credit than privately owned banks during the COVID-19 crisis but this difference is less pronounced than it was in the 2008 Financial Crisis. We confirm our results using pre-pandemic local political preference as instrument for policy interventions and orthogonalized policy intervention indicators, and in placebo tests.

\section{1. Introduction}

The COVID-19 pandemic has caused a global health crisis that rapidly transformed to a full-scale economic crisis, creating a “perfect storm” particularly for emerging economies (Hevia and Neumeyer, 2020). There have been more than 196.5 million confirmed cases of infections and 4.1 million deaths worldwide as of July 31, 2021, and the global GDP growth tanked at $-4.4\%$ in 2020. International organizations and national governments responded with massive policy interventions, but there has been an increasing debate about the economic consequences of the pandemic itself and its ensuing differential policy interventions, especially on restrictive interventions and lockdowns.

In this paper, we investigate whether and how the COVID-19 pandemic and ensuing policy interventions affect local credit in Brazil. We refer to “local credit” as bank credit to firms at the municipality level. We focus on Brazil as a testing ground for the following reasons. First, Brazil is the third most severely affected country by the pandemic in the world after the U.S. and India, in which the number of new cases and deaths have kept growing and maintained high levels for months, reaching 19.9 million confirmed cases and 556,370 deaths as of July 31, 2021. Second, there has been fundamental disagreement between the Brazilian federal government and state/municipal governments about how to react to the COVID-19 pandemic.\footnote{Different from the Coronavirus Aid, Relief, and Economic Security (CARES) Act in the U.S., the Brazilian federal government financially supported mainly small businesses (next to much larger programs for low income households and unemployed workers, e.g., BEm and Auxílio Emergencial) with the Working Capital Program (CGPE, BRL 127 billion) and the Emergency Employment Support Program (PESE, BRL 40 billion). These two programs together only correspond to 4.4\% (Sep 2020) to 5.9\% (Jan 2018) of total local credit in Brazil.}

\footnote{We investigate the effect of policy interventions in response to the COVID-19 pandemic until September 2020 since approved vaccines or medical treatments were not available in Brazil until that date. The discussion on the necessity and the impact of policy interventions continues in 2021 as mass vaccination tends to advance more slowly than expected due to various reasons.}

Importantly, policy intervention decisions in Brazil were ultimately taken at the municipality level, were implemented in a staggered way, and varied in several dimensions, such as speed, duration and intensity. Local governments implemented policy interventions such as closure of public venues and non-essential services,\footnote{We investigate the effect of policy interventions in response to the COVID-19 pandemic until September 2020 since approved vaccines or medical treatments were not available in Brazil until that date. The discussion on the necessity and the impact of policy interventions continues in 2021 as mass vaccination tends to advance more slowly than expected due to various reasons.} while the federal virus-control...
policies have been prominently decoupled from those of local governments (see, e.g., Nadanovsky and Santos, 2020). The Brazilian President Jair Bolsonaro, whose term continues until the end of 2022, has publicly downplayed the COVID-19 pandemic, and has been opposed to interventions and in favor of early reopening (Ponce, 2020). Third, the COVID-19 crisis has severely disrupted the economy and likely affected local credit considering the Brazilian local credit markets are characterized by notably high interest rates, high borrower default risk, a relatively weak legal environment with congested courts and low enforcement. Fourth, a single-country study enables us to exploit the cross-sectional and monthly time-series variation of the pandemic severity and local policy interventions across municipalities in Brazil, keeping the institutional and legal environment constant.

We base our analysis on a novel and unique dataset that combines information on the COVID-19 pandemic, policy interventions and local credit at the municipality level. In the first step, we perform panel data regression analysis at the bank-municipality level to examine how the case severity of the COVID-19 pandemic influences local credit. We measure the local case severity using the absolute and per capita numbers of new confirmed infections and deaths per municipality and month. In the second step, we employ a difference-in-difference (DiD) design to examine the heterogeneous effects of different types of policy interventions on local credit. For this purpose, we manually collect a novel dataset on local policy interventions and define indicator and intensity variables that indicate the enactment periods of these interventions for 920 major metropolitan municipalities in Brazil and interact these variables with case severity measures of the COVID-19 pandemic in a DiD regression model for local credit, with a comprehensive set of time-varying control variables and fixed effects.

We find three main results. First, we show that the COVID-19 pandemic has a significantly negative impact on local credit. Second, we document heterogeneous effects of municipal government policy interventions on local credit. On the one hand, we find positive effects of soft interventions (social distancing, mass gathering restrictions and closure of schools and universities) and late reopening. On the other hand, we find negative effects of hard interventions (closure of public venues and/or non-essential services) and early reopening. Third, we find that state-owned banks in Brazil grant more local credit than privately owned banks during the COVID-19 crisis but this difference is less pronounced than it was in the 2008 Global Financial Crisis.

In further checks, we first conduct an instrumental variable analysis, using the pre-pandemic local political preference in a municipality (share of votes in favor of President Bolsonaro in 2018) as instrument for local policy interventions. This analysis helps address the potential endogeneity between the pandemic and interventions as well as pandemic-induced economic contraction and policy interventions. In the first stage, we find that local political preference is significantly related to the likelihood and restrictiveness of policy interventions. In the second stage, we obtain results that are consistent with our previous findings in terms of economic and statistical significance. We also confirm our results with the policy intervention variables orthogonalized by the COVID-19 pandemic case severity measures and in placebo tests which indicates our results are not driven by unobserved contemporaneous shocks or random local and temporal confounders in our data. Furthermore, we show that the pandemic has a larger effect on the local credit to the rural agriculture sector, and a potential credit reallocation effect between urban and rural sectors under the enactment and removal of local intervention (soft and hard interventions) during the pandemic. Finally, we find evidence that the duration and reaction speed of local governments to adopt interventions influence our main results on local credit. Overall, our empirical findings highlight the pandemic-induced disruption in local credit and suggest the undocumented yet critical heterogeneous effects of the policy interventions in response to the COVID-19 pandemic, i.e., positive effects of soft interventions (e.g., social distancing and mass gathering restrictions) and late reopening, and negative effects of hard interventions (e.g., closure of non-essential services) and early reopening on local credit granted by banks in Brazil. Our paper has clear implications for policy makers and financial regulators that different types of restrictive policy interventions in the COVID-19 crisis may have differential, or even opposite, effects on local credit, and bank state-ownership, sectoral specification and policy intervention timing matter for the prospect of lenders and borrowers.

Our paper contributes to the literature on the economic consequences of the COVID-19 pandemic. Previous studies have found that the pandemic strongly affects labor markets (Coibion et al., 2020b), stock markets (Baker et al., 2020a; Fahlenbrach et al., 2020), consumer credit (Horvath et al., 2021), household consumption (Baker et al., 2020b; Coibion et al., 2020a), and overall economic activity (Ludvigson et al., 2020). Concerning credit markets, there is evidence that large firms rapidly drew on their existing lines of credit at the beginning of the pandemic because of precautionary motives (Acharya and Steffen, 2020). The effect is concentrated on the largest banks (Li et al., 2020). Berger et al. (2021) document that relationship borrowers fare worse during the COVID-19 crisis than non-relationship borrowers, which indicates that the dark side of close bank-firm relationships (hold up) due to market power dominates during the crisis. Beck and Kell (2021) show a decrease in syndicate lending and an increase of interest rates for banks that are more affected by the pandemic. Our study contributes to this literature by showing a negative and significant impact of the COVID-19 pandemic on local credit.

We also add to the research on government policy interventions during the COVID-19 pandemic. Goel and Thakor (2020) develop a two-period production-consumption model in which the government can choose to either invest in shock mitigation to attenuate the effects of a shock or simply shut down the economy when facing a pandemic crisis. They show that investing in mitigation (soft interventions) while keeping the economy open is Pareto-optimal and can be superior to a lockdown because it leads to higher consumption. Eichenbaum et al. (2021) show that the policy interventions in response to the COVID-19 pandemic deepen the economic recession as they reduce consumption and labor supply. Empirical research provides evidence for a significantly negative impact of restrictive interventions on economic activity (Carletti et al., 2020; Coibion et al., 2020a; Kong and Prinz, 2020; Horvath et al., 2021). Coibion et al. (2020a) show that restrictive policy interventions have a negative effect on real economic activity and household spending. Horvath et al. (2021) document that both the COVID-19 pandemic case severity and policy interventions have negative effects on consumer credit in the early stage of the COVID-19 crisis in the U.S. Spiegel and Tookes (2021) find heterogeneous effects of business restriction policies on COVID-19 fatalities. Our study contributes to this literature by analyzing the effects of government policy interventions on local credit empirically and providing novel evidence on the heterogeneous effects of different policy interventions in Brazil during the COVID-19 pandemic.

Finally, our study contributes to the growing literature on the macroeconomic policies and their financial outcomes in the 2020 COVID-19 crisis relative to previous crisis, in particular the 2008 Global Financial Crisis (e.g., Cortes et al., 2021; Sedunov, 2021). We document that state-owned banks in Brazil grant relatively more credit than privately owned banks in both crises, but the difference was substantially smaller during the COVID-19 crisis. We show that lending by state-owned banks was countercyclical in the 2008 crisis and less cyclical in the 2020 crisis. This differential response can be explained with the different nature of the two crises, bank governance issues and political influence on state-owned banks and the recovery after the first COVID-19 wave in Brazil.

The remainder of this paper is organized as follows. Section 2 discusses the theoretical background and develops three main hypotheses. Section 3 describes our data and methodology. Section 4 presents our main results. Section 5 reports further findings. Section 6 concludes.
2. Theory and hypotheses

The COVID-19 pandemic has caused a substantial economic disruption. It has reduced economic output (Furceri et al., 2021), employment (Coibion et al., 2020b), consumer spending (Baker et al., 2020b), and significantly contributed to an overall decrease of economic activity (Ludvigson et al., 2020). Credit demand might have temporarily surged significantly, contributing to an overall decrease of economic activity (Coibion et al., 2020b), consumer spending (Baker et al., 2020b), and economic activity, drop in firm revenues, temporary shut-down or suspension of investments. Regarding credit supply, higher probability of default should lead banks to tighten their lending standards, especially for riskier borrowers (Berger et al., 2021; Beck and Keil, 2021). We expect that the overall effect of the COVID-19 pandemic on local credit is negative and driven by a simultaneous decrease of credit supply and credit demand. We therefore hypothesize:

Hypothesis 1. The COVID-19 pandemic has a negative impact on local credit.

During the COVID-19 pandemic, governments have implemented a series of policy interventions, ranging from soft interventions that are less restrictive to local economic activities such as social distancing and mass gathering restrictions, to hard interventions that are more restrictive ones such as closure of public venues and closure of non-essential services. These policy interventions have a significant impact on local markets (see, e.g., Coibion et al., 2020a; Carletti et al., 2020). We hypothesize that they also have significant and heterogeneous effects on local credit during the COVID-19 crisis. Our theoretical reasoning closely relates to Goel and Thakor’s (2020) model, which establishes sufficient conditions under which less restrictive policy interventions can result in higher consumption and lower mortality relatively to lockdown measures. We expect a heterogeneous impact also on local credit. Less restrictive policy interventions should not severely affect local economic activities, and could further help mitigate the pandemic and, in turn, their effect on local credit. In contrast, more restrictive interventions impose more constraints to local economic activities, which should negatively affect local credit. Consequently, relaxing or revoking these restrictive interventions to reopen the economy should have a positive effect on local credit. Echoing our hypothesis, for instance, Kong and Prinz (2020) provide evidence on this heterogeneous impact of policy interventions on employment, which closure of non-essential services is associated with increase in unemployment insurance claims, whereas there is no association for less restrictive interventions, such as mass gathering restriction. We therefore hypothesize that restrictiveness of policy interventions matters for its impact on local credit:

Hypothesis 2. Policy interventions have heterogeneous effects on local credit during the COVID-19 pandemic. Soft interventions (social distancing, mass gathering restrictions and closure of schools and universities) have a positive effect (H2a), hard interventions (closure of public venues and/or non-essential services) have a negative effect (H2b), and the revoking of restrictive policy interventions (reopening) has a positive effect on local credit during the pandemic (H2c).

State-owned banks are historically important in Brazil and account for almost half of total credit during the last three decades. Research shows that state-owned banks help to sustain credit expansions and avoid credit crunches (see, e.g., Coleman and Feler, 2015; Cortes et al., 2019). Coleman and Feler (2015) find that Brazilians state-owned banks increased lending compared to privately owned banks in the 2008 Global Financial Crisis. Cortes et al. (2019) also show that Brazilian banks had greater access to credit from state-owned banks after the bankruptcy of Lehman Brothers. Based on this research, we expect that state-owned banks have a less cyclical pattern in granting local credit in the COVID-19 crisis. We therefore hypothesize:

Hypothesis 3. Lending by state-owned banks helps stabilize local credit during the COVID-19 crisis in Brazil.

3. Data and methodology

3.1. Data and variables

We collect data from three main sources and gather additional control variables from further sources. First, we gather data on the COVID-19 pandemic. We consider the data of daily new confirmed infection and death cases of the COVID-19 pandemic in Brazil as of Sep 2020 at the municipality level from the Ministry of Health of Brazil (Ministério da Saúde do Brasil). Fig. 1 displays the new infection cases and deaths in Brazil over time as of September 30, 2020 on the daily (past 15 days moving average) basis. New cases is the absolute number of new infection cases confirmed in a municipality during a given month, and New cases per population is the number of new cases per 1000 local population in a given municipality during a given month. Similarly, we define two other variables that indicate the number of death cases caused by the COVID-19 pandemic at the municipality level, i.e., Deaths and Deaths per population. Fig. 2 shows a heatmap displaying the dynamics of the COVID-19 pandemic across municipalities in Brazil in March, June and September of 2020 respectively, using New cases per population as the severity measure. We set the value of case severity variables to 0 for observations before February 2020 as comparison group in the pre-crisis time period. We use these local case severity measures of New cases, New cases per population, Deaths and Deaths per population to quantify the impact of the COVID-19 crisis across municipalities in Brazil as of September 2020.

Second, we manually assemble a novel dataset about the policy interventions in response to the COVID-19 pandemic in Brazil. According to the Brazilian Federal Constitution, the federal, state and municipal governments share the authority to legislate on public health matters due to the regional disparities across Brazil’s territory, which allows local public administrators to adopt different legislative and administrative measures depending on the pandemic’s progression in respective administrative area (Alves et al., 2020). Along with the COVID-19 crisis unfolded with extreme speed, local governments have enacted various policy interventions to flatten the curve of the COVID-19 pandemic cases and also relaxed these restrictions to promote economic activity over time. Following the Ministry of Health of Brazil, we classify the government policy interventions enacted in response to the COVID-19 pandemic across municipalities into seven types including social distancing (SD), mass gathering restrictions (MGR), closure of schools and universities (CSU), closure of public venues (CPV), closure of non-essential services (CINES), stay-at-home orders (i.e., lockdown or shelter-in-place orders) and phased reopening. We hand-collect and assemble the starting and ending date of these policy interventions in response to the COVID-19 pandemic enacted by local legislatures for 920 major metropolitan municipalities in Brazil as of September 2020. We conduct a manual textual search with reference to local government legislative decrees, gazettes, official notices (Diário Oficial), health secretory websites, local regulations and public media reports at the municipality and state level.

We create indicator variables to denote the enactment period of each

Data on the COVID-19 pandemic in Brazil are publicly available at the official website of the Ministry of Health of Brazil (https://covid.saude.gov.br/), and the OpenDATASUS website (https://opendatasus.saude.gov.br/). Data on the policy interventions during the COVID-19 pandemic in Brazil is available from the corresponding author on reasonable request.
type of policy interventions for a given municipality in Brazil as of September 2020. That is, we make these indicators equal 1 only between the starting and ending date of according policy interventions for a given municipality during our sample period, and 0 otherwise. We start by constructing the indicators of three relatively less restrictive ("soft") policy interventions, which are mainly imposed on individuals and less likely to restrict local economic activities, i.e., social distancing (SD), mass gathering restrictions (MGR), closure of schools and universities (CSU). We create the variable Soft intervention to indicate the enactment period of these local soft policy interventions during which either SD, MGR or CSU equals 1 for a given municipality in a given month. Second, we construct the indicators of two more restrictive ("hard") policy interventions imposed on local social and economic activities, i.e., closure of public venues (CPV) and closure of non-essential services (CNES). Similarly, we create the variable Hard intervention to indicate the enactment period of local hard policy interventions during which either CPV or CNES equals 1 for a given municipality in a given month. Third, we use the variable Lockdown to indicate the stay-at-home orders, lockdown or shelter-in-place orders that impose transport restrictions and mandate people should shelter in their homes except for essential reasons. Finally, we define the indicators of local phased reopening process across municipalities in Brazil over time using New cases per population as the case severity measure, in which New cases per population is grouped into 6 groups: 0 new case, [0, 0.01 new case per 1000 people], [0.01 new case per 1000 people, 1 new case per 1000 people], [1 new case per 1000 people, 5 new cases per 1000 people], [5 new cases per 1000 people, 10 new cases per 1000 people], and more than 10 new cases per 1000 people.

Since our merged bank financial data are on the monthly basis, we count the intervention starting month with a date before 15th in each month as the current month and after 15th to be the following month to avoid overstatements of their enactment periods.

Thereby, Intervention intensity index indicates an intensity average of local policy interventions in a given municipality over the month with an index value ranging from 0 to 3.

Third, we collect monthly data on bank credit to firms at the municipality level from the Central Bank of Brazil (Banco Central do Brasil, Fig. 1. COVID-19 new cases and deaths in Brazil. This figure shows the severity of the COVID-19 pandemic in 2020 using the number of daily (past 15 days moving average) newly confirmed infection cases and deaths in Brazil. The black line indicates the number of new cases shown on the left vertical axis and the gray line indicates the number of deaths shown on the right vertical axis. Fig. 2. COVID-19 new cases per population by municipality. This figure shows the temporal evolution of the COVID-19 pandemic at the municipality level in Brazil over time using New cases per population as the case severity measure, in which New cases per population is grouped into 6 groups: 0 new case, [0, 0.01 new case per 1000 people], [0.01 new case per 1000 people, 1 new case per 1000 people], [1 new case per 1000 people, 5 new cases per 1000 people], [5 new cases per 1000 people, 10 new cases per 1000 people], and more than 10 new cases per 1000 people.

Fig. 3 displays the number of the metropolitan municipalities that adopted individual policy interventions in Brazil from February to September of 2020. Furthermore, we also construct an intervention intensity index Intervención intensity to proxy and quantify the restrictive scale of local government policy interventions for a given municipality in a given month by summing up the three restrictive intervention indicators Soft intervention, Hard intervention and Lockdown while subtracting the phased reopening indicators. Thereby, Intervention intensity index indicates an intensity average of local policy interventions in a given municipality over the month with an index value ranging from 0 to 3.
Credit to firms is largely local in Brazil since most of Brazilian firms are locally operating micro and small businesses, through a highly concentrated bank-based financial system involving five large banks, a large number of relatively small banks and credit unions (Cortes and Marcondes, 2018). We gather the financial statement data of all commercial banks in Brazil from the Monthly Banking Statistics per Municipality data (Estatística Bancária Mensal por município, or ESTBAN) of the Central Bank of Brazil (BCB) at the granular bank-municipality level. We merge these data with our manually assembled policy intervention data. The merged dataset covers 920 major metropolitan municipalities that account for 94.04% of the total bank assets in Brazil. We focus on the total amount of outstanding credit for each bank and also differentiate by credit to the local corporate, agricultural and housing sectors. The granularity of the ESTBAN data allows for a geographic identification on the effect of the COVID-19 crisis on local credit across municipalities in Brazil. To be more specific, we take the ratio of monthly bank outstanding loan amount granted over total book assets for a given bank within a given municipality in a given month as the main local credit measure \( \frac{\text{Loans}}{\text{Assets}} \). Moreover, in order to further analyze variations in local credit to different sectors, we differentiate local credit with the variables \( \frac{\text{Corporate loans}}{\text{Assets}} \), \( \frac{\text{Agriculture loans}}{\text{Assets}} \) and \( \frac{\text{Mortgage loans}}{\text{Assets}} \). We thereby compare variations in local credit across municipalities with varying case severity of the COVID-19 pandemic between the pre- and crisis period to examine how the local credit responds to the pandemic severity over time. Fig. 4 shows the evolution of the bank local credit measure in Brazil during January to September of 2020. Local credit significantly decreased after the outbreak of the pandemic in Brazil, and then slightly rebounded which coincides with the reopening periods.

Fourth, we add a comprehensive set of control variables regarding bank financial controls and local economic and demographic characteristics. We first include a vector of bank financial variables including the bank asset growth rate \( \frac{\text{Asset growth}}{} \) to proxy the variation dynamics in local bank asset size, the deposits over assets ratio \( \frac{\text{Deposits over assets}}{\text{Assets}} \) as the ratio of bank customer deposits over total book assets to proxy local funding conditions, the forward-looking bank credit risk-risk measure \( \frac{\text{Loan loss provision ratio}}{\text{Assets}} \) as the ratio of bank loan loss provisions over total book assets, the bank profitability measure ROA as the ratio of bank gross profit over total book assets and the bank liquidity ratio \( \frac{\text{Liquidity}}{\text{Assets}} \) as the ratio of bank cash holdings and short-term liquid assets over total book assets. Moreover, we include a variety of municipality-level and state-level controls. To start, we control for the state-level retail sales index with a base value of 100 in Fig. 3.
level. Our baseline regression model is specified as follows: in terms of local case severity on local credit at the bank-municipality level. Our baseline regression model is specified as follows: September 2020. We start by examining the effect of the COVID-19 crisis directly affects the local credit in Brazil. We thus compare the variations in local credit before and during the crisis, bank-specific temporal interventions on local credit, using monthly bank-municipality data from different Brazilian states have rather heterogenous intervention intensities over time but all peaked around April-May and decreased after July.

3.2. Summary statistics

Table 1 presents the summary statistics of the variables for our sample of 920 major metropolitan municipalities in Brazil for the full sample period, pre-crisis period (Jan 2018 to Jan 2020) and crisis period (Feb 2020 to Sep 2020) respectively. Our main local credit measure Loans over assets has an average of 27.784% across banks and municipalities in Brazil from Jan 2018 to Sep 2020. The mean is 28.132% in the pre-crisis period and decreases to 26.669% during the crisis. Regarding the COVID-19 case severity and policy interventions, during the crisis period, the average monthly number of new cases is around 1953 per municipality, which corresponds to 2.810 cases per 1000 local population, and the average monthly number of deaths is 85 per municipality, which is 0.077 deaths per 1000 population. The intervention intensity index has an average of 0.847. We note that municipalities from different Brazilian states have rather heterogenous intervention intensities over time but all peaked around April-May and decreased after July.

3.3. Methodology

We study the effects of the COVID-19 pandemic and ensuing policy interventions on local credit, using monthly bank-municipality data from the period from January 2018 to September 2020. The COVID-19 pandemic was unexpected and exogenous to local credit markets and local governments, since it was neither caused by lenders or borrowers, nor were local governments prepared to contain its outbreak. First and foremost, we examine whether and how the COVID-19 pandemic directly affects the local credit in Brazil. We thus compare the variations in local credit in pre-crisis period granted between the pre-crisis period from January 2018 to January 2020 and crisis period from February 2020 to September 2020. We start by examining the effect of the COVID-19 crisis in terms of local case severity on local credit at the bank-municipality level. Our baseline regression model is specified as follows:

\[ \text{Loans over assets}_{i,m,t} = \beta_0 + \beta_1 \text{Case severity}_{i,m,t} + \gamma Z_{i,m,t-1} + \nu_{i,t} + \theta_{i} + \epsilon_{i,m,t}, \]  

(1)

where \( i \) indexes a bank, \( m \) indexes a municipality, \( s \) indexes a state and \( t \) indexes a time unit of year-month; \( \text{Loans over assets}_{i,m,t} \) is the ratio of loans over assets of bank \( i \) in municipality \( m \) at time \( t \); Case severity\(_{i,m,t}\) is the local case severity measure of the COVID-19 pandemic for municipality \( m \) during year-month \( t \), which is one of our four main explanatory variables: New cases, New cases per population, Deaths and Deaths per population. We saturate the model with \( Z_{i,m,t-1} \) that is a vector of time-varying control variables including bank financial controls and local economic and demographic characteristics as defined before lagged by one year-month. We take the one-month lag setting for the control variables to mitigate the potential endogeneity and simultaneity between bank loan lending and local socioeconomic characteristics; \( \nu_{i,t} \) are bank-time fixed effects accounting for aggregate temporal variations in local credit before and during the crisis, bank-specific temporal lending dynamics, such as idiosyncratic lending seasonality in credit demand, and aggregate economic cycle, such as the temporal variations in the benchmark interest rate and nationwide liquidity relief policies; \( \theta_{i} \) are state fixed effects accounting for the state-level time-invariant fundamental characteristics. Standard errors are robust and clustered at the bank-municipality level to allow for temporal autocorrelations within bank and municipality groups. \( \epsilon_{i,m,t} \) is the error term. In Eq. (1), \( \beta_1 \) is the coefficient of our interest that captures the extent to which the COVID-19 pandemic impacts local credit granted.

Next, we examine whether and how the COVID-19 crisis and different policy interventions jointly affect local credit across municipalities over time using a staggered difference-in-difference (DiD) design, following Goodman-Bacon and Marcus (2020). We hypothesize that the spread of the COVID-19 pandemic may impose negative effects on local credit while specific types of policy interventions may either alleviate or deteriorate this negative effect on local credit. We interact the COVID-19 case severity measure with the vector of intervention indicators as the main explanatory variable that resembles DiD-like interaction terms capturing the joint effect of the COVID-19 crisis and ensuing policy interventions across municipalities over time. We estimate the regression model specified as follows:

\[ \text{Loans over assets}_{i,m,t} = \beta_0 + \beta_1 \text{Case severity}_{i,m,t} \times \text{Intervention}_{i,m,t} + \beta_2 \text{Intervention}_{i,m,t} + \gamma Z_{i,m,t-1} + \nu_{i,t} + \theta_{i} + \epsilon_{i,m,t}, \]  

(2)

where \( \text{Intervention}_{i,m,t} \) is the vector of policy intervention indicator variables including Soft intervention, Hard intervention, Lockdown, Reopen-early phase and Reopen-late phase. All other variables are the same as defined before. \( \epsilon_{i,m,t} \) is the error term. Standard errors are robust and clustered at the bank-municipality level. In Eq. (2), \( \beta_1 \) is the vector of coefficients of our interest that indicates the amplification effect of each specific type of policy interventions on the relationship between the COVID-19 severity and local credit. We then investigate the effect of local policy intervention intensity on local credit across municipalities over time. We include the interaction term between the intervention intensity index \( \text{Intervention intensity} \) and the monthly policy intensity index at the municipality level, and the COVID-19 case severity measure as the main explanatory variable in the DiD model to estimate the extent to which the local intervention intensity amplifies the impact of the COVID-19 pandemic severity on local credit.

Finally, we investigate the role of state-owned banks during the COVID-19 pandemic and compare it with the 2008 Global Financial Crisis. We define the bank indicator variable State-owned that equals one if a bank is a state-owned bank and zero otherwise, and the time indicator variable \( Post \) that equals zero before and one during the crisis. We use the interaction term between State-owned and Post as the main explanatory variable in the DiD regression model for bank-specific local credit during these two crisis periods.

4. Main results

4.1. The COVID-19 pandemic and local credit

We study whether and how the COVID-19 pandemic impacts local credit using the regression model shown in Eq. (1). Table 2 reports the results for our final sample of 920 major metropolitan municipalities in Brazil, for which we manually collected the policy intervention data.\footnote{The results remain consistent when we include alternative sets of fixed effects, such as bank-state fixed effects, bank-municipality fixed effects and year-month fixed effects. We do not include state-time or municipality-time fixed effects because they are highly collinear with the COVID-19 crisis and policy intervention variables.}
and 95th percentile, respectively. Number of obs. is the number of observations. Variable definitions and according data sources are shown in Appendix A1.

The results are similar to the ones reported in Table 2.

Table 1

This table presents summary statistics for the variables used in this study. We winsorize Asset growth, Capital adequacy, and ROA at the 1st and 99th percentile to account for outliers. The unit of observation is at the bank-municipality level. The full sample period spans from Jan 2018 to Sep 2020. The pre-crisis period spans from Jan 2018 to Jan 2020 and the crisis period spans from Feb 2020 to Sep 2020. Std. Dev. is the standard deviation. P5 and P95 are the values at the 5th and 95th percentile to account for outliers. The unit of observation is at the bank-municipality level. The full sample period spans from Jan 2018 to Sep 2020. The pre-crisis period spans from Jan 2018 to Jan 2020 and the crisis period spans from Feb 2020 to Sep 2020. Std. Dev. is the standard deviation. P5 and P95 are the values at the 5th and 95th percentile, respectively. Number of obs. is the number of observations. Variable definitions and according data sources are shown in Appendix A1.

| Variable                  | Full sample period | Pre-crisis period | Crisis period |
|---------------------------|--------------------|-------------------|---------------|
|                           | Mean               | Median            | Mean          | Median          | Mean          | Median          |
|                           | Std. Dev.          |                   | Std. Dev.     | Number of obs.  | Std. Dev.     | Number of obs.  |
|                           | P5                 | P95               | obs.          |                  | P5            | P95            | obs.          |
| Loans over assets (%)     | 27.784             | 23.832            | 22.294        | 1.235            | 73.146        | 28.132          | 22.477        | 84.593          | 26.669          | 21.658          | 26.374          |
| Corporate loans over assets (%) | 13.631             | 10.943            | 11.668        | 0.444            | 35.895        | 11.906          | 13.683        | 11.580          | 84.593          | 13.466          | 11.945          | 26.374          |
| Agriculture loans over assets (%) | 5.935             | 0                 | 14.711        | 6.030            | 46.129        | 110,967         | 14.847        | 84.593          | 5.628           | 14.261          | 26.374          |
| Mortgage loans over assets (%) | 5.680             | 0                 | 11.127        | 31.383           | 110,967       | 5.760           | 11.268        | 84.593          | 5.424           | 10.662          | 26.374          |

Policy intervention variables:

Soft intervention (SD/MGR/CSU) | 0.188 | 0 | 0.390 | 0 | 1 | 110,967 | 0 | 0 | 84,593 | 0.789 | 0.408 | 26,374 |

Hard intervention (CPV/CNES) | 0.169 | 0 | 0.375 | 0 | 1 | 110,967 | 0 | 0 | 84,593 | 0.710 | 0.454 | 26,374 |

Lockdown | 0.004 | 0 | 0.060 | 0 | 0 | 110,967 | 0 | 0 | 84,593 | 0.015 | 0.122 | 26,374 |

Reopen-early phase | 0.114 | 0 | 0.317 | 0 | 1 | 110,967 | 0 | 0 | 84,593 | 0.478 | 0.500 | 26,374 |

Reopen-late phase | 0.055 | 0 | 0.229 | 0 | 1 | 110,967 | 0 | 0 | 84,593 | 0.233 | 0.243 | 26,374 |

Intervention intensity | 0.201 | 0 | 0.555 | 0 | 2 | 110,967 | 0 | 0 | 84,593 | 0.847 | 0.864 | 26,374 |

Control variables

Bank controls:

Asset growth | 0.014 | 0.010 | 0.067 | –0.067 | 0.109 | 110,967 | 0.011 | 0.068 | 84,593 | 0.024 | 0.066 | 26,374 |

Deposits over assets | 0.305 | 0.297 | 0.198 | 0 | 0.624 | 110,967 | 0.301 | 0.195 | 84,593 | 0.318 | 0.204 | 26,374 |

Loan loss provision ratio | 0.005 | 0 | 0.011 | 0 | 0.025 | 110,967 | 0.005 | 0.011 | 84,593 | 0.005 | 0.011 | 26,374 |

ROA | 0.014 | 0.009 | 0.015 | 0 | 0.044 | 110,967 | 0.014 | 0.016 | 84,593 | 0.011 | 0.013 | 26,374 |

Liquidity | 0.018 | 0.006 | 0.055 | 0 | 0.054 | 110,967 | 0.018 | 0.056 | 84,593 | 0.016 | 0.052 | 26,374 |

Local controls:

HHI deposit | 0.393 | 0.337 | 0.195 | 0.222 | 1 | 110,967 | 0.393 | 0.195 | 84,593 | 0.392 | 0.193 | 26,374 |

Retail sales index | 97.572 | 96.800 | 12.465 | 77.700 | 121.700 | 110,967 | 97.463 | 10.722 | 84,593 | 97.923 | 16.877 | 26,374 |

Average income | 2.539 | 2.632 | 0.565 | 1.548 | 3.379 | 110,967 | 2.478 | 0.543 | 84,593 | 2.732 | 0.589 | 26,374 |

Unemployment rate (%) | 6.870 | 6.420 | 3.418 | 3.304 | 15.100 | 110,967 | 5.606 | 1.513 | 84,593 | 10.922 | 4.501 | 26,374 |

Labor turnover (%) | 0.012 | 0.033 | 0.152 | –0.240 | 0.183 | 110,967 | 0.028 | 0.101 | 84,593 | –0.041 | 0.246 | 26,374 |

Instrumental variable

Political preference | 0.623 | 0.661 | 0.166 | 0.265 | 0.826 | 110,967

We find that the coefficients of Case severity are negative and statistically significant across our four case severity measures (New cases, New cases per population, Deaths and Deaths per population). These results remain robust when we add the vector of control variables and bank-time and state fixed effects. The economic magnitude estimated of the COVID-19 pandemic effect on local credit is also large. For instance, an increase of deaths by one per 1000 local population during the pandemic corresponds to a drop of 4.07 percentage points in the loans over assets ratio, as shown in column (8) of Table 2. This impact corresponds to 14.4 percent decrease of the pre-crisis mean of the loans over assets ratio (i.e., \(-4.07/28.13=–0.144\)). These results suggest that the COVID-19 pandemic has a significantly negative impact on local credit, which is consistent with our Hypothesis 1.

4.2. Policy interventions and local credit during the COVID-19 crisis

We employ a DiD design to investigate whether and how the policy interventions in response to the COVID-19 pandemic affect local credit using the model in Eq. (2). Table 3 reports the corresponding results.

We note that the model specifications in Table 3 include a full set of interacted bank-time fixed effects, which absorbs any effect due to differences in bank lending in the cross-section and over time. We find the
coefficient of the interaction term Soft intervention $\times$ Case severity is positive and statistically significant, which indicates that less restrictive interventions that focus on restricting individual activities increase local credit. This result is consistent in all specifications. Furthermore, the coefficient of Hard intervention $\times$ Case severity is negative and statistically significant, which indicates that the more restrictive interventions, which heavily disrupt local economic activities, amplify the local “credit drain” effect induced by the COVID-19 pandemic. The effect of lockdown is weakly or not significant, probably because the preceding hard interventions absorbed most of the negative impact on local credit. Moreover, the coefficient of Reopen-early phase $\times$ Case severity is negative and statistically significant but the coefficient of Reopen-late phase $\times$ Case severity goes to the opposite direction as it is positive and statistically significant. These differential effects of revoking local restrictive interventions at different temporal stages suggest early-stage reopening in Brazil further constrains the local credit granting under the overall deteriorating pandemic conditions, while late-stage reopening alleviates this local credit constraint under improved local pandemic-control conditions. These findings are broadly consistent using different case severity measures, in line with the theoretical model of Goel and Thakor (2020) and support our Hypothesis 2.

We also examine how the invention intensity in response to the pandemic correlates with local credit using a similar DiD model to Eq. (2). As shown in Table 3, we find the coefficient of Intervention intensity $\times$ Case severity is positive and statistically significant. This finding indicates that the positive amplification effects of soft interventions to contain the pandemic spread and reopening outweigh the negative effects of hard interventions to restrict local economic activities on local credit under the pandemic.

We find the economic magnitudes of the heterogenous intervention effects on local credit, which are calculated by multiplying the estimated coefficients with the mean of the COVID-19 case severity measures in the crisis period, are also large. For instance, using Deaths per population as the case severity measure and the DiD analysis results shown in column (7) of Table 3, we show that the loans over assets ratio decreases by 0.506 percentage points (i.e., $-0.506 \times 0.077 = -0.0387$) on average per bank and municipality after the hard interventions, and decreases by 0.387 percentage points (i.e., $-0.387 \times 0.077 = -0.0298$) on average per bank and municipality after early-stage reopening, holding all other factors constant.

### 4.3. State-owned banks in the COVID-19 crisis vis-à-vis the 2008 global financial crisis

We further examine the role of state-owned banks in local credit granting during the 2020 COVID-19 crisis (hereafter the 2020 crisis) vis-à-vis the 2008 Global Financial Crisis (hereafter the 2008 crisis). Following the prior research such as Coleman and Feler (2015) and Cortes et al. (2019), we construct a sample period of 12 months for the 2008 crisis with March 2008 to August 2008 (6 months) as the pre-crisis period and September 2008 to February 2009 (6 months) as the crisis period, using September 2008, when Lehman Brothers filed for bankruptcy, as the break point for the start of the crisis in Brazil. To better compare these two crises, we adopt a similar sample period of 12 months for the 2020 crisis with August 2019 to January 2020 (6 months) as the pre-crisis period and February 2020 to July 2020 (6 months) as the crisis period.

| Dependent variable | Loans over assets (%) | New cases | New cases per population | Deaths | Deaths per population |
|--------------------|-----------------------|-----------|--------------------------|--------|-----------------------|
| Case severity      | -0.311***             | -0.110*   | -0.244***                | -0.097*** | -7.110***             | -19.426*** | -4.076***                 |
|                     | (0.029)               | (0.064)   | (0.035)                  | (0.028) | (0.669)               | (1.290)    | (1.321)                   | (0.960) |

Table 2

Regression analysis results using new cases and deaths as the COVID-19 severity measure. This table reports the regression analysis results using new cases and deaths as the measure for the COVID-19 pandemic severity for the sample of 920 metropolitan municipalities for which we have collected data of local policy interventions. Column (1) - (8) report results using New cases, New cases per population, Deaths and Deaths per population as the COVID case severity measure respectively. The unit of observation is at the bank-municipality level. The sample period spans from Jan 2018 to Sep 2020. Results are estimated using the regression model shown in Eq. (1). Control variables are lagged by one month. Standard errors are shown in parentheses and clustered at the bank-municipality level. * * * indicate statistical significance at the 10, 5, and 1 percent level, respectively. Details on variable definitions and according data sources are shown in Appendix A1.
We conduct a DiD analysis of the local credit granted by state-owned and privately owned banks during the 2020 crisis and the 2008 crisis. We define the bank indicator variable State-owned that equals one if a bank is a state-owned bank and zero otherwise, and the time indicator variable Post that equals zero before and one during the crisis. We use the interaction term between State-owned and Post as the main explanatory variable and estimate the DiD regression model for bank-specific local credit. We report the results in Panel A of Table 4. For the 2020 crisis, we find positive and statistically (borderline) insignificant coefficients of State-owned × Post for loans over assets ratio during the 2020 crisis period. For the 2008 crisis, we find positive and highly significant coefficients of State-owned × Post for loans over assets ratio during the 2008 crisis period and these results remain when we add the vector of control variables and bank, time and state fixed effects. 

Echoing the findings of Coleman and Feler (2015) and Cortes et al. (2019), we find that state-owned banks grant relatively more local credit than privately owned banks in Brazil during both the 2020 crisis and the 2008 crisis. We calculate the relative credit supply elasticity between Brazilian state-owned and privately owned banks as the ratio of our DiD estimation over the mean difference in our local credit measure between these two groups of banks during the respective crisis period. The relative credit supply elasticity during the 2020 crisis equals 0.05% (i.e., 0.013/(40.344×0.005)) and the one during the 2008 crisis 4.5% (i.e., 0.722/(41.469−25.598)=0.045). The relative credit supply elasticity between state-owned and privately owned banks is substantially smaller in the 2020 crisis than the 2008 crisis.

We see three possible explanations for this difference. First, the two

| Dependent variable | Loans over assets (%) | | | | | | |
|--------------------|-----------------------|---|---|---|---|---|---|
|                    | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| New cases          |       |       |       |       |       |       |       |       |
| New cases per population |       |       |       |       |       |       |       |       |
| Soft intervention × Case severity | 25.636*** | 50.266*** | 1223.377*** | 363.266*** |
| (9.365) | (9.414) | (550.260) | (69.919) |
| Hard intervention × Case severity | −0.087** | −0.168** | −1.185 | −6.377** |
| (0.040) | (0.085) | (1.044) | (3.729) |
| Lockdown × Case severity | 0.041 | 0.190* | 1.072 | 5.175* |
| (0.152) | (0.095) | (1.806) | (3.231) |
| Reopen-early phase × Case severity | −0.102 | −0.174*** | −0.342 | −5.020*** |
| (0.056) | (0.059) | (1.064) | (1.926) |
| Reopen-late phase × Case severity | 0.004 | 0.108** | −1.243 | 3.420 |
| (0.020) | (0.055) | (0.879) | (2.219) |
| Intervention intensity × Case severity | 0.002 | 0.056** | 0.808* | 2.080** |
| (0.017) | (0.023) | (0.425) | (0.820) |
| Case severity | −25.660*** | −0.112* | −50.115*** | −0.147*** | −1224.993*** | −3.113* | −359.052*** | −6.739*** |
| (9.359) | (0.063) | (9.416) | (0.035) | (550.114) | (1.758) | (69.837) | (1.569) |
| Soft intervention | −1.732*** | 50.266*** | −1.688*** | −1.673*** |
| (0.403) | (9.414) | (0.039) | (0.410) |
| Hard intervention | 0.298 | −0.168** | 0.205 | 0.860 |
| (0.430) | (0.085) | (0.434) | (0.558) |
| Lockdown | −0.391 | 0.190** | −0.427 | −1.399 |
| (0.802) | (0.095) | (0.700) | (1.247) |
| Reopen-early phase | 0.498 | −0.174*** | 0.516 | 0.814** |
| (0.330) | (0.059) | (0.323) | (0.407) |
| Reopen-late phase | −0.803*** | 0.108* | −0.738** | −1.273*** |
| (0.298) | (0.055) | (0.303) | (0.438) |
| Intervention intensity | −0.054 | −0.187 | −0.096 | −0.186 |
| (0.165) | (0.194) | (0.167) | (0.202) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Local controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank-time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.705 | 0.705 | 0.705 | 0.705 | 0.705 | 0.705 | 0.705 |
| Number of obs. | 110,967 | 110,967 | 110,967 | 110,967 | 110,967 | 110,967 | 110,967 | 110,967 |
Table 4
State-owned and privately owned banks in the COVID-19 crisis vis-à-vis the 2008 Global Financial Crisis. This table reports the regression analysis results for the local credit of state-owned and privately owned banks in Brazil and their subgroups during the 2020 COVID-19 crisis and the 2008 Global Financial Crisis for the sample of 920 metropolitan municipalities in Brazil. *CEF is a dummy variable that equals one if the bank is Caixa Econômica Federal and zero if the bank is Banco do Brasil. Foreign is a dummy variable that equals one if the bank is a foreign private bank and zero if the bank is a domestic private bank. The unit of observation is at the bank-municipality level. We drop local control variables Average income and Unemployment rate from regressions due to the data limit in the years before 2012. Control variables are lagged by one month. Standard errors are shown in parentheses and clustered at the bank-municipality level. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

| Dependent variable | Loans over assets (%) | | |
|--------------------|-----------------------|-------|-------|
|                     | 2020 COVID-19 Crisis  | 2008 Financial Crisis |
| Panel A: All state-owned and privately owned banks | | |
| State-owned × Post | 0.043 | 0.013 | 1.768*** | 0.722*** |
|                     | (0.148) | (0.141) | (0.220) | (0.203) |
| Bank controls: No | Yes | No | Yes |
| Local controls: No | Yes | No | Yes |
| Bank FE | No | Yes | No | Yes |
| Time FE | No | Yes | No | Yes |
| State FE | No | Yes | No | Yes |
| Adjusted R-squared | 0.339 | 0.687 | 0.123 | 0.632 |
| Number of obs. | 39,801 | 39,801 | 47,044 | 47,044 |

Panel B: Two major state-owned banks: Caixa Econômica Federal and Banco do Brasil

| CEF × Post | 0.559*** | 0.906*** | 0.556** | 0.807*** |
|           | (0.160) | (0.162) | (0.291) | (0.309) |
| Bank controls: No | Yes | No | Yes |
| Local controls: No | Yes | No | Yes |
| Bank FE | No | Yes | No | Yes |
| Time FE | No | Yes | No | Yes |
| State FE | No | Yes | No | Yes |
| Adjusted R-squared | 0.304 | 0.536 | 0.281 | 0.452 |
| Number of obs. | 16,154 | 16,154 | 14,472 | 14,472 |

Panel C: Foreign private and domestic private banks

| Foreign × Post | 1.201*** | 1.039*** | 1.607*** | 1.329*** |
|               | (0.230) | (0.231) | (0.227) | (0.196) |
| Bank controls: No | Yes | No | Yes |
| Local controls: No | Yes | No | Yes |
| Bank FE | No | Yes | No | Yes |
| Time FE | No | Yes | No | Yes |
| State FE | No | Yes | No | Yes |
| Adjusted R-squared | 0.002 | 0.569 | 0.055 | 0.627 |
| Number of obs. | 20,944 | 20,944 | 30,269 | 30,269 |

crises differ. The negative health shock due to the COVID-19 pandemic in 2020 significantly reduced economic activity, increased economic uncertainty and credit risk. As a result, credit demand decreased and credit supply followed. In contrast, the 2008 crisis is mainly characterized by a large negative bank credit supply shock, in which state-owned banks were better capable of granting credit than privately owned banks. Second, this difference may be attributed to the contrasts between two major state-owned banks in Brazil, i.e., Caixa Econômica Federal and Banco do Brasil, regarding their internal bank governance and political influence from the Brazilian federal government, since we find that Caixa Econômica Federal granted more local credit than Banco do Brasil during both crises but with a larger extent in the 2020 crisis. Banco do Brasil deviated from the “classic role” of state-owned banks which may be due to the market discipline effect (see, e.g., Flannery, 2001; Flannery and Bliss, 2019) since 49.6% of Banco do Brasil’s capital is held by private shareholders. Banco do Brasil had notoriously intense political conflicts with President Bolsonaro’s government on its credit expansion since the outbreak of the pandemic. Third, we observe that the local credit increased again during June to September 2020 when the economy experienced a temporary recovery in Brazil and privately owned banks increased credit supply again, which made the credit expansion of state-owned banks in the 2020 crisis relatively less pronounced compared to the 2008 crisis.

5. Further checks and robustness tests

5.1. Instrumental variable analysis, orthogonalization test and placebo tests

One important challenge in our analysis is that the enactment and revoking of policy interventions are directly related to the local COVID-19 pandemic severity and economic activities. To address this potential reverse causality, we first conduct an instrumental variable (IV) analysis. We hypothesize that local political preferences for President Bolsonaro influence the likelihood of local policy interventions during the COVID-19 pandemic in Brazil since President Bolsonaro has publicly downplayed the severity of the pandemic, refused more restrictive interventions and promoted early reopening (Ajzenman et al., 2020; Ponce, 2020). We use Political preference, the ratio of popular votes for President Bolsonaro over total votes in a municipality in the 2018 Brazilian general election, as the instrument for municipal policy interventions. This variable is pre-determined and uncorrelated with local credit that is largely determined by economic factors. Higher Political preference should correlate with lower likelihood of restrictive interventions and higher likelihood for reopening.

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7 We plot the local credit of Caixa Econômica Federal and Banco do Brasil during the 2008 crisis and 2020 crisis in Panel A and Panel B of Online Appendix Figure A2 respectively and report the according DiD analysis results in Panel B of Table 4. In addition, we plot the local credit of foreign private and domestic private banks in Brazil during the two crises in Panel A and B of Online Appendix Figure A3 respectively and report the according DiD analysis results in Panel C of Table 4. We find that foreign private banks granted more local credit than domestic private banks during both the COVID-19 crisis and the 2008 Global Financial Crisis.

8 We note the former CEO of Banco do Brasil, Rubem Novaes conflicts with President Bolsonaro’s government, especially regarding the eventual privatization of Banco do Brasil, which was supported by Novaes but dismissed by Bolsonaro. Explaining his formal resignation in Sep 2020, Novaes stated in interviews that he had trouble “adapting to the culture of privilege, cronyism and corruption” due to the political inference on Banco do Brasil. Meanwhile, consistent with our results on the credit contraction of Banco do Brasil during the first months of the 2020 crisis, Novaes publicly claimed that it was impossible to supply enough credit to the “unhealthy demand” induced by the COVID-19 crisis, and the toolbox available to expand credit of Banco do Brasil was much limited.
Results for the instrumental variable (IV) analysis. This table reports the instrumental variable (IV) analysis results following the control function (CF) approach (Wooldridge, 2015). Panel A reports the first stage results using Political preference as the instrument and the IV diagnosis statistics. Political preference is the share of popular votes cast for Jair Bolsonaro in the 2018 Brazilian general election at the municipality level. Panel B reports the final stage results with the policy intervention indicators (Soft intervention, Hard intervention, Lockdown, Reopen-early phase, Reopen-late phase) and the intervention intensity index using Loans over assets as the dependent variable. Details on variable definitions and according data sources are shown in Appendix A1. The unit of observation is at the bank-municipality level. The sample period spans from Jan 2018 to Sep 2020. Control variables are lagged by one month. Standard errors are shown in parentheses and clustered at the bank-municipality level. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

### Panel A: First stage results using Political preference as the instrument

| Dependent variable | Soft intervention | Hard intervention | Lockdown | Reopen-early phase | Reopen-late phase | Intervention intensity |
|--------------------|-------------------|-------------------|----------|--------------------|------------------|-----------------------|
|                    | (1)               | (2)               | (3)      | (4)                | (5)              | (6)                   |
| Political preference | 0.003             | −0.010**          | −0.004** | 0.031***           | 0.040***         | −0.078***             |
|                    | (0.002)           | (0.004)           | (0.002)  | (0.006)            | (0.006)          | (0.010)               |
| Case severity      | Yes               | Yes               | Yes      | Yes                | Yes              | Yes                   |
| Bank controls      | Yes               | Yes               | Yes      | Yes                | Yes              | Yes                   |
| Local controls     | Yes               | Yes               | Yes      | Yes                | Yes              | Yes                   |
| Bank-time FE       | Yes               | Yes               | Yes      | Yes                | Yes              | Yes                   |
| State FE           | Yes               | Yes               | Yes      | Yes                | Yes              | Yes                   |
| Adjusted R-squared | 0.960             | 0.919             | 0.140    | 0.823              | 0.650            | 0.804                 |
| Number of obs.     | 110,967           | 110,967           | 110,967  | 110,967            | 110,967          | 110,967               |

### IV diagnosis statistics:

- Under-identification test: Kleibergen-Paap rk LM statistic
  - IV-Soft intervention: 33.656***
  - IV-Hard intervention: −18.093***
  - IV-Lockdown: −35.614**
  - IV-Reopen-early phase: −37.548**
  - IV-Reopen-late phase: 5.579*

- Weak identification test: Cragg-Donald Wald F statistic
  - IV-Soft intervention: 1079.763***
  - IV-Hard intervention: 4772.765***
  - IV-Lockdown: 1368.374***
  - IV-Reopen-early phase: 1382.829***
  - IV-Reopen-late phase: 570.038***

### Panel B: Final stage results with the policy intervention indicators and intervention intensity index

| Dependent variable | Soft intervention × Case severity | Hard intervention × Case severity | Lockdown × Case severity | Reopen-early phase × Case severity | Reopen-late phase × Case severity | Intervention intensity × Case severity |
|--------------------|----------------------------------|----------------------------------|--------------------------|-----------------------------------|----------------------------------|---------------------------------------|
|                    | (1)                              | (2)                              | (3)                      | (4)                               | (5)                              | (6)                                   |
| Loans over assets  |                                |                                |                          |                                   |                                  |                                      |
|                    | (1)                              | (2)                              | (3)                      | (4)                               | (5)                              | (6)                                   |
|                    | 0.283                            | 0.364***                         | 6.042                    | 2.657                             |
|                    | (0.356)                          | (0.117)                          | (10.181)                 | (7.042)                           |

- Case severity: 0.626
  - (2.345)
  - 0.225
  - (0.196)
  - 39.882***
  - (13.817)
  - −0.598***
  - (0.127)
  - 11.778
  - (68.313)
  - −4.429
  - (4.931)
  - 832.395***
  - (279.509)

(continued on next page)
In the first step, we regress the policy intervention variables on the Political preference with all controls and fixed effects. Panel A of Table 5 reports the results. Political preference is significantly related to intervention variables in five of six models with expected coefficient signs. It is negatively correlated with the likelihood of more restrictive interventions and lockdown, positively correlated with the likelihood of local reopening and also negatively correlated with the intervention intensity index. The IV diagnosis statistics indicate the instrument is econometrically not weak. In the next step, we use the instrumented intervention variables and include all residuals from the first stage in the final stage IV regressions. We adopt this control function (CF) approach since the variable of interest is an interaction term (Wooldridge, 2015). Panel B of Table 5 reports the final stage results. The coefficients of the instrumented interaction terms between the case severity measures and intervention indicators are statistically significant and consistent in terms of sign and magnitude with our baseline results. In sum, we continue to find positive effects of soft interventions and late-stage reopening while negative effects of hard interventions and early-stage reopening on local credit.

Second, we further address the endogeneity problem by performing an orthogonalization test (Hendry and Nielsen, 2007; Hastie et al., 2009). We first regress the intervention variables on the severity measures and include the resulting residuals as new orthogonalized intervention variables. These orthogonalized intervention variables capture the intervention effect that cannot be explained with the severity measures. Online Appendix Table A2 reports the results. All results remain consistent and statistically significant across different severity measures.

Third, we employ a placebo test design with placebo severity measures and policy intervention variables that are similarly distributed but take randomly assigned values. Online Appendix Table A3 reports the results. Panel A shows that the falsified severity measure does not have significant coefficients. Panel B and C show that the interaction terms between falsified policy intervention variables and severity measure are mostly insignificant. Hence, our findings are not driven by unobserved contemporaneous shocks or random local and temporal confounders in the data.

5.2. Sectoral dependence of local credit: corporate, agriculture and housing sector

We study whether the main effects on local credit differ across the corporate, agricultural and housing sector. The sectoral difference is relevant for Brazil since it has a large, labor-intensive and fast-growing agriculture industry. The lower productivity induced by the negative labor shock and market disruption may decrease the local credit to the agriculture sector from both the demand and supply side (Bustos et al., 2020). Online Appendix Table A4 reports the results. The coefficients of Case severity are negative for local credit to firms from all three sectors, while the magnitude for agriculture sector is larger than others. We also find the local credit to agriculture sector increases after the pandemic outbreak and enactment of the soft interventions in urban regions and late-stage reopening, but decreases after early-stage reopening. These findings indicate that the pandemic has a larger negative impact on local credit to the agriculture sector and also suggest a credit reallocation between the rural agricultural sector and other sectors under different policy interventions in Brazil.

5.3. Duration and reaction speed of policy interventions and local credit

We further study whether and how the duration and reaction speed of local policy interventions enacted by the local governments in Brazil as of September 2020 influence our results. Online Appendix Table A5 reports the results. Panel A reports the results that longer duration of more restrictive interventions amplifies the negative shocks of these interventions on local credit under the crisis. Panel B reports the results that higher reaction speed of local governments increases the positive effect of soft interventions on local credit.

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We show the first stage results using the case severity measure New cases per population as an example in Panel A of Online Appendix Table A2 for simplicity because we use the intervention variables orthogonalized by the respective case severity measure in the final stage tests shown in each column of Panel B of Online Appendix Table A2. We also obtain both qualitatively and quantitatively similar results of the orthogonalization test if we orthogonalize the intervention variables with the lagged case severity measures by one month as shown in Panel C and D of Online Appendix Table A2.
6. Conclusions

We investigate whether and how the COVID-19 pandemic and ensuing policy interventions impact the local credit in Brazil. Using a novel and unique dataset that combines monthly information on local COVID-19 pandemic case and deaths, municipal government policy interventions, and local bank credit to firms, we analyze the impact of the pandemic and ensuing policy interventions on credit during the period from January 2018 to September 2020.

We find consistent evidence that the COVID-19 pandemic has a significantly negative impact on local credit. We also find that the policy interventions have heterogeneous effects on local credit during the COVID-19 pandemic. Specifically, we find positive effects of soft interventions (less restrictive interventions focused on individual activities such as social distancing and mass gathering restrictions) and late-stage reopening. In contrast, we find negative effects of hard interventions (more restrictive interventions focused on local economic activities such as closure of public venues and/or non-essential services), and early-stage reopening. We further find that state-owned banks grant more local credit than privately owned banks during both the COVID-19 crisis and the 2008 Global Financial Crisis in Brazil. However, the differential response of state-owned banks is less pronounced in the COVID-19 crisis, which can be explained with the different nature of the crises, bank governance issues and political influence and the recovery after the first COVID-19 wave in Brazil. We confirm the main results in an instrumental variable analysis, in which we use local pre-pandemic activities such as closure of public venues and/or non-essential services), and late-stage reopening. We further find that state-owned banks grant more local credit than privately owned banks during both the COVID-19 crisis and the 2008 Global Financial Crisis in Brazil. However, the differential response of state-owned banks is less pronounced in the COVID-19 crisis, which can be explained with the different nature of the crises, bank governance issues and political influence and the recovery after the first COVID-19 wave in Brazil. We confirm the main results in an instrumental variable analysis, in which we use local pre-pandemic political preference as instrument for local policy interventions. Our results are upheld in a policy intervention orthogonalization test and placebo tests. We also show that the effects on local credit are sector-dependent and stronger with longer intervention duration and higher intervention speed. Our findings suggest undocumented yet critical heterogeneous effects of the COVID-19 pandemic and ensuing policy interventions on local credit.

CRediT authorship contribution statement

Lars Norden: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Project administration. Daniel Mesquita: Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. Weichao Wang: Conceptualization, Methodology, Data curation, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Acknowledgement

The authors thank Murilo Campello (the editor), one co-editor and an anonymous referee for extremely useful comments and suggestions. They also thank participants at the Brazilian Finance Society 2021 Annual Meeting (EBFin). Corresponding author: Lars Norden, Brazilian School of Public and Business Administration, Getulio Vargas Foundation, Rua Jornalista Orlando Dantas 30, 22231-010 Rio de Janeiro, RJ, Brazil. Phone: +55 21 3083 2431. E-mail (Lars Norden): lars.norden@fgv.br. This paper represents the authors’ personal opinions and does not necessarily reflect the views of Getulio Vargas Foundation.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfi.2021.100933.

Appendix A. Variable definitions

This table presents the names, definitions and data sources of the variables used in this analysis.

| Variable name | Definition | Source |
|---------------|------------|--------|
| **Dependent variables** | | |
| Loans over assets (%) | Ratio of lending amount of bank loans granted over total book assets for a given bank in a municipality in percentage. | ESTBAN data |
| Corporate loans over assets (%) | Ratio of bank corporate loans granted over total book assets for a given bank in a municipality in percentage. | ESTBAN data |
| Agriculture loans over assets (%) | Ratio of bank agriculture loans granted over total book assets for a given bank in a municipality in percentage. | ESTBAN data |
| Mortgage loans over assets (%) | Ratio of bank mortgage loans granted over total book assets for a given bank in a municipality in percentage. | ESTBAN data |
| **Crisis variables** | | |
| New cases deaths per population | Number of new COVID-19 cases per 1000 local population in a municipality during a month. | Ministry of Health |
| Deaths per population | The absolute number of new COVID-19 cases per 1000 local population in a municipality during a month. | Ministry of Health |
| Soft intervention | Indicator variable that equals 1 during the enactment period of the policies of social distancing (i.e., social distancing mandate of at least 6 feet between people and work-at-home advice for the general population accompanied by local health disaster declarations), mass gathering restrictions (i.e., prohibition of public gatherings above a certain size) or closure of schools and universities for a given municipality, and 0 otherwise. | Authors’ collection |
| Hard intervention | Indicator variable that equals 1 during the enactment period of the policies intervention of closure of public venues or non-essential in-person services for a given municipality, and 0 otherwise. | Authors’ collection |
| Lockdown | Indicator variable that equals 1 during the enactment period of the policy of stay-at-home and lockdown orders for a given municipality, and 0 otherwise. | Authors’ collection |
| Reopen-early phase | Indicator variable that equals 1 after the enactment date of the 1st phase of reopening order for a given municipality, and 0 otherwise. This early stage reopening corresponds to the "orange phase" of local reopening plans and features, e.g., allowing street vendors back and a partial reopening of selected non-essential services. | Authors’ collection |
| Reopen-late phase | Indicator variable that equals 1 after the enactment date of the order of the 2nd or 3rd phase of reopening for a given municipality, and 0 otherwise. This late stage reopening corresponds to the "yellow phase" or "blue phase" of local reopening plans, and features, e.g., an amplified reopening of non-essential services such as bars and cinemas, and partial or full reopening of public venues such as beaches and parks. | Authors’ collection |

(continued on next page)
Intensity index measure variable to quantify the restrictive scale of local government interventions, which is calculated by summing up the indicators of soft interventions (SD/MGR/CSU), hard interventions (CPV/CNES) and lockdown while subtracting the reopening indicators, for a given municipality over time, with a value ranging from 0 to 3.

Control variables

Bank controls:
- **Asset growth**: Monthly bank total book asset growth rate in a municipality. ESTBAN data
- **Deposits over assets**: Ratio of bank customer deposits over total book assets. ESTBAN data
- ** Loans loss provision ratio**: Ratio of bank loan loss provisions over total book assets. ESTBAN data
- ** ROA**: Ratio of bank gross profits over total book assets. ESTBAN data
- ** Liquidity**: Ratio of bank cash holdings and short-term assets over total book assets. ESTBAN data

Local controls:
- **HFI deposit**: Municipality level Herfindahl-Hirschman Index calculated by bank customer deposits within a given municipality. ESTBAN data
- **Retail sales index**: State-level seasonally adjusted retail sales index with a base value of 100 in 2014. IPEA data
- ** Average income**: State-level average income amount in thousand BRL. IPEA data
- ** Unemployment rate (%)**: State-level unemployment rate in percentage. IPEA data
- ** Labor turnover (%)**: State-level labor turnover ratio calculated as the difference between the number of employee admissions and layoffs over total population within a given state in percentage. CAGED data

Instrumental variable
- **Political preference**: Ratio of popular votes cast for Jair Bolsonaro by voters over total votes in a given municipality in the 2018 Brazilian general election. Superior Electoral Court of Brazil

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