The Leading Role of Bank Supply Shocks

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The Leading Role of Bank Supply Shocks*

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Abstract

This paper studies the impact of the Covid-19 pandemic on corporate credit in Colombia. We first exploit the geographic and temporal variation in the disease spread to estimate the effect of local exposure to the virus on credit. Our estimates indicate that neither local exposure to the virus, nor the sector-specific mobility restrictions had an impact on credit. We then assess the role of bank supply shocks. We create a measure of bank exposure, reflecting the geographic heterogeneity in pandemic vulnerability and deposits, and estimate its effect on credit. Results indicate that bank-supply shocks account for a credit contraction of approximately 5.2%. To further disentangle the role of bank supply shock, we control for the interaction between firm and time fixed-effects and restrict the sample to municipalities that were relatively spared from the pandemic, finding similar results. Most of the bank supply effects are driven by firms that are small, young, and have relatively low liquidity.

JEL Codes: G01, G21

Keywords: Credit, Covid-19 Pandemic, bank liquidity

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El rol dominante de los choques de oferta bancarios[*]

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Resumen

Este artículo estudia el impacto de la pandemia del Covid-19 en el crédito empresarial en Colombia. Primero, utilizamos la variación geográfica y temporal en la propagación de la enfermedad para estimar el efecto de la exposición local al virus sobre el crédito. Las estimaciones indican que ni la dinámica local de la enfermedad ni las restricciones de movilidad sectoriales tuvieron efectos importantes sobre el crédito. En seguida evaluamos el papel de los choques de oferta bancaria. Creamos una medida de exposición bancaria, basada en la distribución geográfica de la vulnerabilidad a la pandemia y los depósitos, y estimamos su efecto sobre el crédito. Los resultados indican que los choques de oferta bancaria redujeron el crédito en aproximadamente 5.2%. Para identificar plenamente el rol del choque de oferta bancaria, se incluyen en el modelo las interacciones entre los efectos fijos de firma y tiempo y se restringe la muestra a municipios que no fueron tan severamente afectados por la pandemia, encontrando resultados similares. La mayoría de los efectos se explican por firmas pequeñas, jóvenes y con relativamente baja liquidez.

Códigos JEL: G01, G21
Palabras clave: Crédito, pandemia de Covid-19, liquidez de bancos

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1 Introduction

The Covid-19 pandemic has been one of the deadliest and most disruptive events in history. Since the first outbreaks in 2020, most countries have, as a consequence, experienced severe economic downturns with estimated effects on global GDP of approximately 3.5% (Yeyati et al., 2021b). And, while it did not specifically center (nor originated) at the core of the financial sector, as for example was the case of the 2008-09 world crisis, the pandemic did affect both credit supply and demand. On the supply side, credit and risk channels are at play, i.e. factors such as credit risk, loan quality, and funding costs could have disproportionately affected credit disbursement in regions with high contagion rates. On the demand side, besides the direct effect of the disease on households and businesses, there were also lock-downs and disruptions in local and global supply chains. Moreover, differences in expectations regarding the magnitude and duration of the pandemic could have led to differences in credit behavior.

In this paper we take a fresh new look at financial sector effects brought forth by the pandemic, focusing on the relative impact of demand and supply-driven shocks. Specifically, we use the entire corporate credit registry in Colombia and employ a difference in differences estimation that exploits the geographic variation and intensity in the disease spread. We believe Colombia is an interesting case study. On the one hand, Latin America is one of the most affected regions in the world by the SARS-CoV-2 virus, where Colombia ranks third in the region with the most cases and deaths. For identification purposes, Colombia has significant geographic differences in the incidence of the disease and the timing of the spread. On the other hand, while aggregate credit dropped during the first months of the pandemic, deposits increased considerably, therefore aggregate liquidity constraints were not the main drivers of the credit crunch.

Our contribution is twofold. First, we add to the empirical literature that disentangles and quantifies the relative importance of supply and demand related factors within the financial sector. While survey-based studies (mostly qualitatively) and macro-econometric models (DSGE, VAR models) have been most often employed in this strand of literature, there are only a handful of papers that rely on granular micro data, at the loan level, to establish a causal link between credit and the supply or demand nature of the shock (Huber, 2018; Amiti et al., 2017; Altavilla et al., 2022; Alfaro et al., 2021). In almost all cases, studies focus on only one type of shock and are thus silent about the joint identification and relative comparison. This is important since the differential effect on each shock carries direct implications on issues ranging from financial stability to monetary policy transmission. More broadly, we contribute to the growing literature on the mechanisms through which the pandemic affected the economy, particularly in developing countries.[1]

Second, our paper also contributes to the literature on the heterogeneous effects of bank liquidity shocks (Holmstrom and Tirole, 1997; Siriwardane, 2019; Chodorow-Reich et al., 2021). Namely, we test whether the impact of the bank supply shock varies depending on firm characteristics. To this end we estimate a triple differences model, in which we interact the bank supply shock with different variables reflecting firms' size, age, and liquidity. We also test the heterogeneous effect of the supple shock along the distribution of Covid cases.

We begin our analysis by assessing the effect of local exposure to the virus on corporate credit, driven by local demand. In our main specification, the explanatory variables are continuous measures of Covid cases and deaths –by municipality and week–, which capture the geographic variation in both the timing and the intensity of the outbreaks. We control for mobility restrictions, which were implemented by the government to control the disease spread, and affected some industries and not others. The main specification

[1] See Brodeur et al. (2020); Barua (2020); Chetty et al. (2020); Fernandes (2020); Maliszewska et al. (2020); Ozili (Ozili); del Rio-Chanona et al. (2020); Engzell et al. (2021); Psacharopoulos et al. (2021); Yeyati et al. (2021a); Jordà et al. (2022).

of our model accounts for time and firm-bank fixed effects. While the former account for the epidemiological and economic shocks that homogeneously affected credit across municipalities and banks, the latter account for observed and unobserved time-invariant characteristics of the bank-firms pairs. To fully purge supply shocks from the demand channel, we also interact time and firm fixed effects. Our results indicate that neither the local exposure to the pandemic, nor the mobility restrictions had a significant effect on credit. The estimated coefficients are economically small and are precisely estimated.

We then assess the extent to which credit contraction could have been driven by bank supply shocks. We base our analysis on the empirical strategy of Khwaja and Mian (2008), which tracks the credit decisions of a same firm with differently exposed banks. In this setting, given than some banks were more exposed to the pandemic this could, in turn, translate into a heterogeneous response in credit supply.

To test this hypothesis, we create a pre-pandemic bank exposure measure based on the geographic distribution of pandemic vulnerability and deposits. Notice that a key feature of this measure is to be unaffected by the observed change in bank deposits and credits during the crisis. For this we consider different metrics, including the share of elderly population, population density, and urban density. In sum, our time-invariant measure of bank exposure is defined as the banks' average predicted changes in deposits, weighted by the pre-pandemic share of deposits in each municipality. As expected, exposed banks experienced a sharper liquidity shock during the pandemic, reflected in considerably slower growth of total deposits and a sharp reduction in term deposits.

Our results indicate that bank exposure significantly predicts credit contraction during the pandemic, with estimated coefficients between -0.113 and -0.115. A back-of-the-envelope calculation indicates that, on average, supply shocks account for at least 5.2% in credit reduction. For robustness, we estimate alternative specifications varying the fixed effects structure, including municipal fixed-effects, and using a discrete credit measure as outcome. Additionally, to fully disentangle the supply-side effects we include the interaction between firm and time fixed effects. We further test the supply mechanism by dropping the municipalities most affected by the pandemic. Intuitively, by focusing on highly exposed banks but in low exposed regions, we are able to tune out the pandemic-driven changes in local demand and hence focus exclusively on supply. We also test whether the supply shocks vary depending on the local intensity of the virus, finding insignificant coefficients for the gradient coefficient. Overall, our results confirm that the pandemic highly affected the credit market through a heterogeneous effect on bank's liquidity.

Lastly, we assess heterogeneous effects based on firm's balance sheet information including: size, age, and various measures of liquidity based on the corporate registry, current ratio, acid test, and debt-to-equity ratio. Results indicate that the impact of the bank supply shocks on corporate credit are mostly driven by firms that are small, young, and have relatively low liquidity.

Overall, our findings confirm a leading role of bank supply shocks. These findings contrast with previous studies such as (Beck and Keil, 2021; Norden et al., 2021; Çolak and Öztekin, 2021; Altavilla et al., 2022), which also exploit the geographic variation of the disease to identify the effect of the pandemic on credit, and find important negative effects. A potential explanation, as stated in Dursun-de Neef and Schandlbauer (2020), is that in the United States deposits increased in the hardest-hit regions, which in turn led the more exposed banks to increase loans. In Colombia, while liquid assets grew, term deposits fell. Moreover, there is a negative and significant relationship between municipality pandemic vulnerability and deposits. Given that the geographic distribution of deposits varies across banks, this led to a heterogeneous bank supply shock which partly explains the variation in bank liquidity and corporate credit.

The remaining of the paper is organized as follows. Section 2 describes the Covid pandemic in Colombia and the performance of the credit market during this period. Section 3 presents the data and the empirical strategy. Section 4 presents the results and Section 5 concludes.

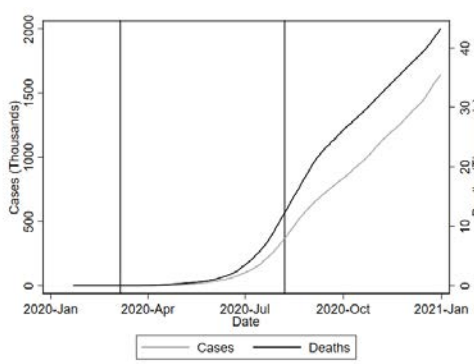
2 Pandemic and Credit in Colombia

While the Covid-19 pandemic did not specifically center (nor originated) at the core of the financial sector, it was nonetheless affected by the crisis. On the one hand, the recession increased default rates; affecting credit risk, funding costs, and liquidity (Acharya et al., 2021; Barua and Barua, 2021; Kapan and Minoiu, 2021; Li et al., 2020). On the other hand, consumption fell and precautionary savings increased, which translated into a large influx of deposits (Dursun-de Neef and Schandlbauer, 2020; Levine et al., 2020). While credit increased during the first months of the pandemic, partly driven by existing credit lines drawdowns, in most cases it contracted soon afterwards. The impact varied depending on the intensity of the health crisis and the policy responses, as well as institutional factors such as the regulatory environment and the financial conditions of the banking sector (Beck and Keil, 2021; Bosshardt and Kakhbod, 2020; Çolak and Öztekin, 2021; Dursun-de Neef and Schandlbauer, 2021; Norden et al., 2021). This has led to an increase in bank systemic risk, particularly for riskier and highly leveraged banks (Duan et al., 2021).

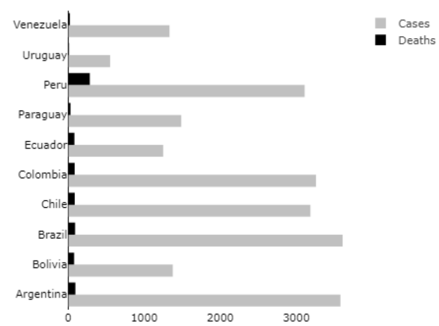
The first confirmed case of Covid-19 in Colombia was reported in early March 2020. Less than 3 weeks later, and with relatively few cases, the government enacted a strict national lockdown. While the measure was initially set to last for a few weeks, it was extended multiple times, lasting until August 2020. In addition to the domestic and international travel ban, the government enforced mobility and activity restrictions, allowing only a few essential industries to operate. These include, among others, public administration, financial sector, agriculture, and public utilities. Since then, the government has transitioned towards more flexible policies, allowing municipalities with low contagion rates and ICU occupation to gradually reopen. Nonetheless, despite the stringent lockdown policies, the first wave hit the country hard in July 2020, killing over 7,250 people in 24 days. As shown in Figure 1, by December 2020 Colombia ranked third in the region with most cases (1.6 million) and deaths (43,000).

Figure 1: Covid in Colombia and Latin America

(a) Cumulative cases and deaths in Colombia



(b) Cumulative cases and deaths by country (Dec-2020)

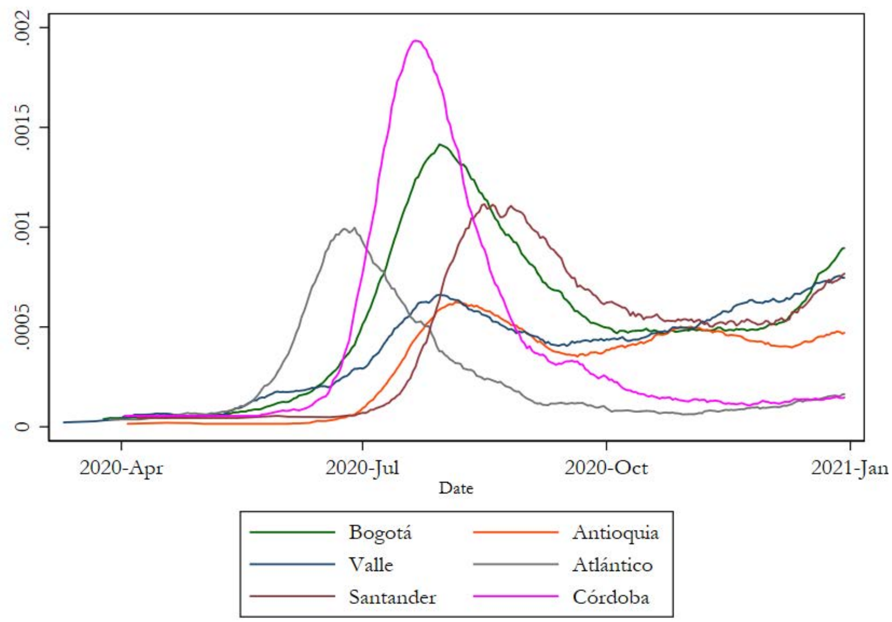


Notes: Confirmed Covid cases (gray) and deaths (black) are expressed in per thousand people. In Panel A, the vertical lines denote the beginning and end of the strict lockdown policy.

A key aspect of the epidemic in Colombia is that it was not homogeneous across regions. While some departments like *Atlantico* were hit by the first wave in June, other departments such as *Santander*, *Norte de Santander*, and *Antioquia*, exhibited their initial effects only until August (Figure 2). There is also variation in the intensity of the disease, with some departments peaking at 0.0005 deaths per thousand per week, while others reaching 0.002.

We exploit this spatial and temporal variation to identify the effect of local exposure to the virus on credit.

Figure 2: Covid Deaths by Department

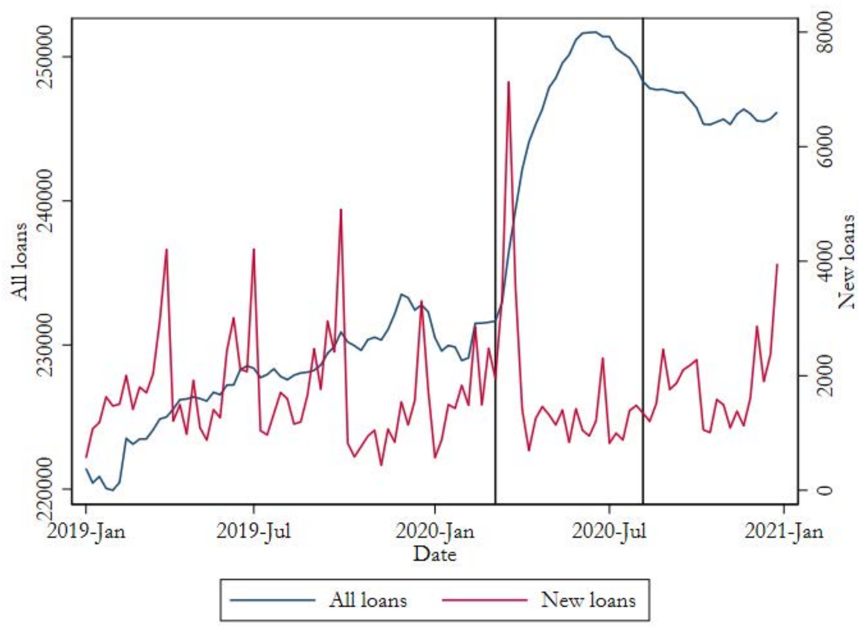


Notes: Each line represents the 1-month moving average of the weekly number of Covid-related deaths per thousand people in the ten most populated departments in Colombia.

The pandemic had devastating effects on the economy. Colombia's GDP contracted by 15.7% in the second quarter of 2020, its deepest economic recession in history. Unemployment reached a maximum of 20.9% in May 2020, and in December it was still 4 percentage points (pp) above the pre-pandemic level. Lockdown policies are partially responsible for the economic downturn. According to Morales-Zurita et al. (2021), approximately one-fourth of the initial job losses can be attributed to sector-specific mobility restrictions. The remaining three-quarters of job losses are related to the disease itself, as well as the sharp decrease in international trade and domestic consumption.

The volume of new corporate credit expanded considerably between February and March 2020, which reflects some degree of anticipation based on the news of the pandemic abroad. After this, credit fell gradually until August. Hence, the recovery only begins in September 2020 when lockdown policies were relaxed (pre-pandemic credit levels were reached by the end of the year as shown in Figure 3).

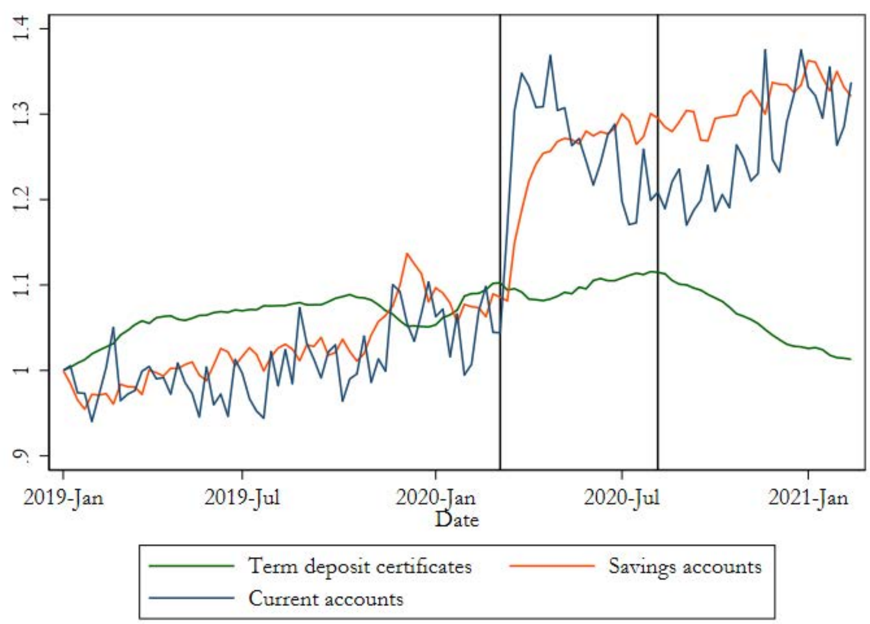
Figure 3: Volume of corporate credits



Notes: The volume of corporate credit is expressed in COP billions (10^9) per week. The two vertical lines represent the beginning and the end of the strict lockdown policy.

Total bank deposits also increased at the beginning of the pandemic and stayed at high levels during the rest of the year. This is the result of a sharp reduction in consumption and an increase in precautionary savings, combined with an expansionary monetary policy and additional measures to guarantee financial stability Cabrera-Rodríguez and Rodríguez-Novoa (2020). However, the increase in deposits was mostly driven by liquid assets such as savings and current accounts. In contrast, term deposits experienced a relatively slow growth during the first months of the pandemic, and fell afterwards, ending 2021 7 pp below pre-pandemic levels (Figure 4). Such recomposition of bank liabilities may have also affected credit supply, particularly in banks that were more exposed to the pandemic (we further explore this mechanism in Section 4.2).

Figure 4: Bank deposits growth



Notes: Total bank deposits are the sum of liquid (savings and current accounts) and illiquid assets (term deposits). Deposit values are expressed in percentage changes with respect to January 2019. The two vertical lines represent the beginning and the end of the strict lockdown policy.

3 Data and Empirical Strategy

3.1 Data

Our main analysis is based on the entire credit registry from the Financial Regulator, the *Superintendencia Financiera de Colombia* - SFC. The dataset contains individual credit records at the firm-bank level, with detailed information on credit issuance date, volume, interest rate, and maturity. We match these data with the corporate registry from the Business Regulator, the *Superintendencia de Sociedades* - SS.[2] Out of 22,420 firms that reported to SS between 2000 and 2020, we were able to match 15,398, which in turn account for 64,7% of total corporate assets. We measure the volume of new credits by firm, bank, and week between January 2018 and December 2020.

The National Health Institute (INS) provides detailed information on the Covid-19 epidemic in Colombia. Based on their official daily records, we compute the number of confirmed cases and deaths by municipality and week. In our main analysis, we normalize this measure by the municipal population in the 2018 Population Census, from the National Department of Statistics (DANE). We use the Decree 457 of 2020, issued by the National government, to identify industries at the 4-digit level with strict mobility restrictions.

To assess the role of bank supply shocks, we create a measure of bank exposure based on bank deposits and municipal urban density. Bank deposits data are also provided by the SFC. Total deposits include term deposits, savings accounts, and current accounts. While bank deposits are reported weekly, deposits by bank and municipality are only available quarterly. Urban density, expressed in inhabitants per squared kilometer, is calculated using the urban population from the 2018 Population Census and the area

[2] Corporations are under surveillance and control of SS when annual total gross income surpasses 3,500 monthly minimum wages (MMW). Small businesses are exempted if assets are smaller than 500 MMW and have less than 10 employees. When a firm operates in multiple cities, we use the headquarter location.

of urban land, which is computed from the official 2018 cartography from DANE. Alternative municipal characteristics, such as population density and the share of the elderly population are also measured in 2018, based on data from DANE.

In the last section, we estimate the heterogeneous effects of the pandemic on corporate credit by firms' characteristics. We combine multiple datasets to compute eight measures reflecting firms' size, age, and liquidity in 2019. First, we use the SS records, which provide yearly information on the firms' balance sheets, including basic data on sales, assets, liabilities, and equity to measure firms total assets and age, and compute three measures of liquidity: current ratio (current assets / current liabilities), acid test (current assets - inventory / current liability), and debt-to-equity ratio (total liability / total equity). We then combine the SS and the SFC credit records from December 2019 to compute the financial debt ratio (total financial debt/ total equity) and a dummy variable that takes value one if the firm did not miss any credit payments in 2019, and zero otherwise. Finally, we match the firms social security records from the Ministry of Health to measure the average number of workers in 2019.

Table 1 reports the descriptive statistics of the main variables. The volume of new credits by bank and municipality is expressed in logarithms. The average municipality reports 209 Covid cases and 7 deaths per week between March and December 2020.

3.2 Empirical Strategy

3.2.1 Demand factors

We begin our analysis on the effect of the Covid-19 pandemic on credit by exploiting the geographic variation of the disease spread using the following panel regression model with fixed effects:

Table 1: Descriptive Statistics

	Obs	Mean	Std.Dev	Min	Max
New credits (log)	1,059,864	0.012	0.127	0	6.772
New credits (discrete)	1,059,864	0.019	0.136	0	1
Cases	26,000	0.209	0.575	0	10.29
Cumulative cases	26,000	2.611	7.052	0	63.39
Deaths	26,000	0.007	0.023	0	0.614
Cumulative deaths	26,000	0.093	0.250	0	2.36
Urban Pop. density	1,134	20.70	86.51	0.052	1487
Population density	1,134	7.09	3.56	0.508	20.81
Share of elderly population	1,134	14.04	4.32	4.7	33.9

Notes: All statistics are computed between March and December 2020. Cases and deaths are expressed in thousands of citizens. Population density and Urban population density are measured in inhabitants per square kilometer. The share of elderly population is the population over 60 years of age over inhabitants per municipality.

$$Credit_{ibt} = \beta Covid_{mt} + \gamma lockdown_{st} + \delta_t + \phi_{ib} + \epsilon_{ibt} \tag{1}$$

where $Credit_{ibt}$ is the log volume of new credits of firm i, which belongs to industry s and is located in municipality m, with bank b, in week t. $Covid_{mt}$ is a time-varying measure of either new confirmed cases or Covid-related deaths in municipality m and week t. These measures capture the geographic variation in both the timing and the intensity of the outbreaks. $lockdown_{st}$ is a dummy variable that is one for the industries affected by mobility restrictions between March and August 2020, and zero otherwise. Our main specification includes time (δ_t) and firm-bank fixed effects ($\phi_{b,m}$). Time fixed-effects account for the epidemiological and economic shocks that homogeneously affected credit across municipalities and banks. These include the aggregate effect of the disease and the lockdown policies on credit, as well as indirect effects related to shifts in consumption and trade. Firm and bank fixed effects account for observed and unobserved time-invariant characteristics of the firms and banks pairs. Errors are clustered at the firm level.

Coefficients β and γ in equation (1) can be interpreted as the effect of local exposure to the virus and the lockdown, driven by local factors (mostly from the demand side). For instance, businesses can be directly affected by the virus or mobility restrictions, or indirectly through cuts and disruptions in the supply chain and consumption. On the supply side, local bank branches can be directly affected by the virus, e.g. risk assessment could disproportionately affect credit provision in regions with high contagion rates. Also, loan quality and funding costs could weigh in. Note that the local shocks could be correlated with bank supply shocks. To fully isolate them from the bank supply shocks, we also estimate the model including the interaction between banks and time fixed effects and firm fixed effects.

We complement this analysis with an event-study specification, in which municipalities switch from control to treatment status when they are first hit by the pandemic, i.e. when their number of accumulated cases per capita exceeds a certain threshold. Specifically, we use the 5^{th} percentile of the accumulated per capita cases in all municipalities between March and December 2020, which is 0.056 cases per thousand people. The following equation describes this specification:

$$Credit_{b,m,t} = \alpha + \sum_{\tau=-q}^{-2} \beta_\tau D_{m,t+\tau} + \sum_{\tau=0}^{r} \beta_\tau D_{m,t+\tau} + \delta_t + \phi_{b,m,t} + \epsilon_{b,m,t} \tag{2}$$

The event period, in which each municipality surpasses the threshold of cases, is zero ($t = 0$). Dummy variables $D_{m,t}$ denote the leads and lags of the event dummy. We include 10 anticipatory and 15 post-treatment periods. As in the main specification, regressions control for time and bank-municipal fixed effects and errors are clustered at the municipal level.

The staggered treatment nature of this specification could lead to biased estimates (Goodman-Bacon, 2021).[3] We address this concern by using

[3] In fact, the two-way fixed effect estimator is the weighted sum of different 2×2

the Callaway and Sant'Anna (2020) estimator, which corrects for potential treatment effect heterogeneity. As robustness checks, we estimate alternative specifications that include separate fixed effects for firms and banks, and municipality fixed-effects instead of firm fixed-effects. We also estimate the model with a discrete credit measure: a dummy variable switched on if firm i receives new credit with bank b in period t, and zero otherwise.

3.2.2 Supply factors

In the second part of our analysis, we assess whether some of the effects of the pandemic on credit are driven exclusively by bank supply shocks. We base our analysis on the empirical strategy of Khwaja and Mian (2008), which tracks the credit decisions of a same firm with differently exposed banks. In this setting, we exploit the fact that, given the heterogeneous geographic distribution of deposits and pandemic vulnerability, some banks were more exposed to the pandemic than others. This could, in turn, translate into a heterogeneous bank supply shock.[4] We are interesting in this mechanism given the high correlation between banks' deposits and credit in Colombia.

We proceed by estimating the relationship between different types of deposits and total credit volume at the bank and week level in 2019, the year before the pandemic began. The coefficients are positive and significant in all cases, with an elasticity as high as 0.877 for total deposits (Appendix Table A3).

To estimate the role of bank supply shocks, we create a measure of bank exposure that reflects the abnormal changes in deposits that are predicted by pandemic vulnerability. The first step in creating this measure is finding a municipal characteristic that accurately predicts pandemic vulnerability but is not directly affected by the observed change in bank deposits and credits during this period. For this we consider different metrics, including

treatment effects, and the presence of negative weights can lead to biased results.

[4] Chodorow-Reich et al. (2021) follow a similar approach, using abnormal industry employment growth to isolate firm demand factors.

the share of elderly population, population density, and urban density. To select which is the best predictor, we regress the number of cases and deaths on the interaction between the municipal characteristics and a post dummy that is switched on in the third week of March, when the national government announced the lockdown policies. Results indicate that the best predictor is urban density, with the highest R^2 and a negative and significant effect that is robust across specifications (Appendix Table A1).

We then regress log deposits, measured at the bank and municipality level, on the interaction between urban density and the third week of March post-term. Regressions include time and bank-municipality fixed effects, and errors are clustered at the municipal level. In an alternative specification, we replicate the analysis using exclusively deposit term certificates as outcomes. Results are presented in Table A2 of the Appendix. The estimated coefficient for urban density, our preferred measure, is -0.003 for total deposits, and -0.0027 for term deposits. These estimates reflect the heterogeneous response of bank deposits depending on the municipal vulnerability to the pandemic.

The time-invariant measure of *bank exposure* is defined as the banks' average predicted changes in deposits, weighted by the share of deposits in each municipality in 2019. For ease of interpretation, we multiply it by -1 so that the banks with higher values are those more exposed. The bank exposure measures based on total deposits and term deposits are almost identical, with a correlation of 1; therefore, we base our analysis on the first one.[5] As expected, exposed banks experienced a sharper liquidity shock during the pandemic, reflected in considerably slower growth of total deposits and a sharp reduction in term deposits (Appendix Figure A2).

3.2.3 Heterogeneous effects

Finally, we estimate the heterogeneous effects of the pandemic by bank exposure. Specifically, we interact the exposure measure with with a post-term

[5]The distribution of the resulting bank exposure measures is presented in Figure A1.

that takes value one in the third week of March. Since we want to identify borrowing behavior changes in borrowing behavior of the same firm, from different banks, we restrict the sample to firms borrowing from at least two banks. The main specification controls for covid-related cases and deaths, industry-specific mobility restrictions, as well as time and firm-bank fixed effects:

$$Credit_{ibt} = \theta Exposure_b \times post_t + \beta Covid_{mt} + \gamma lockdown_{st} + \delta_t + \phi_{ib} + \epsilon_{ibt} \tag{3}$$

The estimated θ coefficients reflect the extent to which banks' liquidity affect credit from a specific firm, in the spirit of Khwaja and Mian (2008). In an additional exercise, we estimate event study specifications that interact the exposure variable to a set of time dummies. Unlike equation 1, this is not a staggered treatment specification. In fact, all units are treated in the third week of March, reflecting that the bank supply shock that we intent to capture does not vary across regions. This specification allows us to measure the dynamic effect of the bank supply shocks.

For additional robustness, we estimate alternative specifications varying the fixed effects structure, including municipal fixed-effects, and using a discrete credit measure as outcome. Additionally, we include the interaction between firm and time fixed effects, while controlling for bank fixed effects. This allows us to fully disentangle the supply-side effects from local demand or supply shocks.

The main advantage of using this bank exposure measure is that it is largely exogenous from the observed disease spread. First, we estimate the effect on deposits using a good predictor of the pandemic vulnerability (urban density) instead of the actual number of cases or deaths. Second, these regression also control for time and firm-bank fixed effects, accounting for common shocks and time-invariant characteristics of the firm and bank pairs that could be potentially correlated with both deposits and pandemic vulnerability. Third, the exposure measure is added at the bank level, and we use pre-pandemic measure of the geographic distribution of deposits as weights. Finally, results presented in the following section show that simultaneously including the heterogeneous effect by bank exposure and the observed Covid cases and deaths has little or no effect on the estimated coefficients. These results indicate that the exposure measure is in fact exogenous. They also indicate that the local demand and supply shocks and the bank supply shocks are for the most part independent.

In the last section, we assess the heterogeneous effects of the pandemic on corporate credit by firm characteristics. In total, we use 8 measures reflecting firm size, age, and liquidity. We estimate triple difference models that interact the different shocks in equation 3 with a dummy variable that takes value one if the firm is above the median of the respective measure, and zero otherwise.

4 Results

4.1 Effects of local demand shocks

The first set of estimates, based on continuous measures of Covid cases and deaths by municipality, indicate that neither the local exposure to the virus, nor the mobility restrictions, have an impact on corporate credit. As can be seen in Table 2, we find economically small and statistically non-significant effects for all specifications. With the main fixed effect structure, column 1 measures local exposure with Covid cases, column 3 with deaths, and column 5 with both. Results are fairly similar when we use separate firm and bank fixed effects (columns 2, 4, and 6). Likewise, in all estimations, we also find small and non-significant coefficients for the sector-specific mobility restrictions.

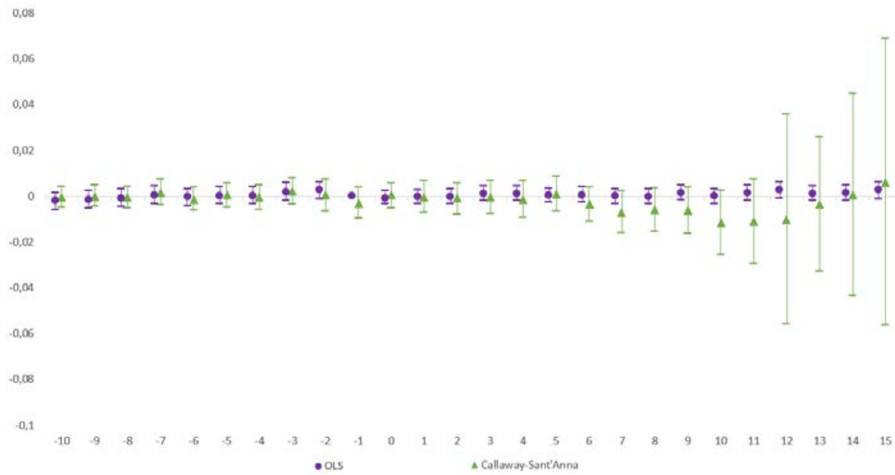
Table 2: Local supply and demand shocks

	(1)	(2)	(3)	(4)	(5)	(6)
New Cases/hab.	-0.000304	-0.000305			-0.000339	-0.000339
	(0.000186)	(0.000186)			(0.000259)	(0.000259)
New Deaths/hab.			-0.00522	-0.00523	0.00138	0.00137
			(0.000492)	(0.00492)	(0.00685)	(0.00685)
Lockdown	-6.45e-05	2.13e-05	-6.49e-05	2.09e-05	-6.52e-05	2.06e-05
	(0.000407)	(0.000411)	(0.000407)	(0.000411)	(0.000407)	(0.000411)
Observations	2,563,392	2,563,392	2,563,392	2,563,392	2,563,392	2,563,392
R-squared	0.015	0.023	0.015	0.023	0.015	0.023
Time FE	✓	✓	✓	✓	✓	✓
Firm FE	✓		✓		✓	
Bank FE	✓		✓		✓	
Bank*Firm FE		✓		✓		✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. New Deaths/inhab and New Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

Results are overall similar with OLS and Callaway and Sant'Anna (2020) event study specifications. The estimated effects are economically small and non-significant in all periods, indicating that credit is overall unaffected by the local spread of the disease. Moreover, the null coefficients in the pre-treatment period show that there are no relevant differences in credit before the pandemic hit, confirming that the parallel trends assumption holds (Figure 5).

Figure 5: Event Study Estimates of Local Demand and Supply Shocks



Notes: Lines represent the point estimates and 95% confidence bands from the OLS and the Callaway and Sant'Anna (2020) estimators. All models control for time and bank-municipal fixed effects and errors are clustered at the municipal level. The Callaway and Sant'Anna (2020) inference is based on 1000 bootstrap replications.

As a robustness check, we estimate the model using as outcome a discrete measure of credit. Results are overall similar, with the exception of the estimated effect of Covid cases that are statistically significant at the 10% in columns 1 and 2 (Appendix Table A4). We also replicate the model replacing firm fixed-effects with municipal fixed-effects (Appendix Table A5). In this case, the effect of local exposure to the virus remains small and non-significant. However, we do find a negative and significant effect for the mobility restrictions, with estimated coefficients near -0.001. This effect is absorbed by the firm fixed-effect in our main specification, which suggests that it mainly reflects time-invariant characteristics of the firms.

In the last set of regressions of this section, we control for any potential bank supply shocks by including the interaction between time and bank fixed-effects. Results are presented in Appendix Table A6. Odd (even) columns include firm (municipal) fixed effects. Results are overall similar to those reported in Tables 2 and A5, implying that the correlation between the local shocks and bank supply shocks is overall small.

4.2 Effects of bank supply shocks

While total deposits grew during the first months of the pandemic and remained high throughout 2020, there could be some heterogeneity in liquidity supply across banks, driven by their differential exposure to the pandemic. To assess this mechanism, we create a time-invariant measure of bank exposure, which reflects abnormal changes in deposits that can be explained by pandemic vulnerability. We then estimate the heterogeneous effects of bank exposure on credit, by interacting the exposure measure with the third week of March post-term in a sample of firms with credit relationships with at least two banks. For more details on the bank exposure measure and the estimation, see section 3.2.

Results are presented in Table 3. The $Exposure_b \times post_t$ coefficient is consistently negative and significant, indicating that bank supply shocks did contribute to the contraction of credit during the pandemic. The estimated coefficient varies between -0.113 and -0.115 across specifications. Given an average bank exposure level of 0.45, the effect of the supply shock would account for a 5.2% credit contraction. It is worth noting that the estimated coefficients for Covid cases or deaths and mobility restrictions are overall similar when controlling for the bank exposure term. The fact that including the local demand and bank supply shocks simultaneously has such little effect on the first set of estimated coefficients confirms that the correlation between these two shocks is not affecting our main results. It also validates the fact that our bank exposure measure is largely exogenous from the actual disease spread.

Table 3: Bank Supply Shocks

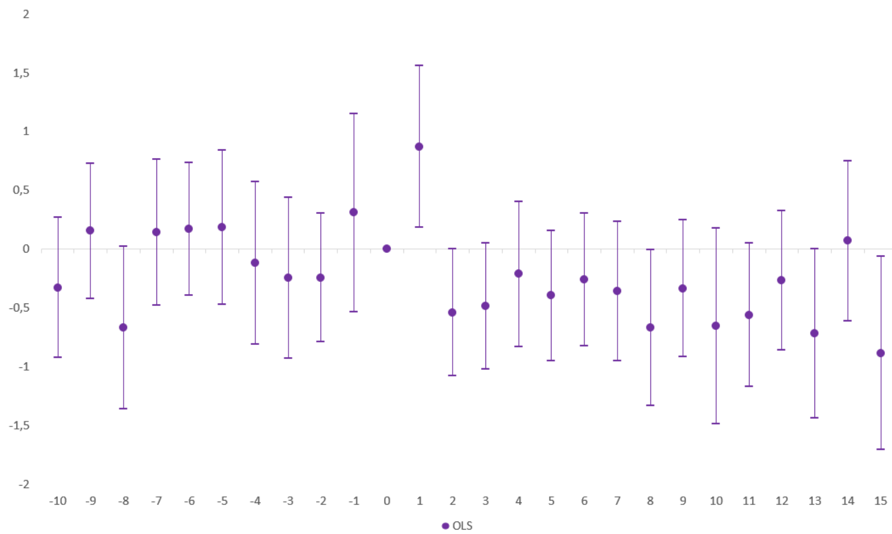
	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000333		-0.000331
		(0.000224)		(0.000313)
New Deaths/inhab.			-0.00650	-7.98e-05
			(0.00589)	(0.00823)
Lockdown	0.000468	0.000476	0.000477	0.000476
	(0.000513)	(0.000513)	(0.000514)	(0.000513)
Exposure*Post	-0.115***	-0.113***	-0.115***	-0.113***
	(0.0399)	(0.0399)	(0.0399)	(0.0399)
Observations	1,956,864	1,956,864	1,956,864	1,956,864
R-squared	0.023	0.023	0.023	0.023
Time FE	✓	✓	✓	✓
Bank*Firm FE	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced). Bank exposure denotes the average expected change in deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019. New Deaths/inhab and New Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

We estimate the model with the discrete credit outcome in Appendix Table A7. The effect for the bank supply shock are considerably larger. The estimated coefficients oscillate between 0.360 and 0.362, which implies that the probability of getting a new credit felt by approximately 16.2% for the average bank. In this case we find significant, although small effects for new Covid cases (-0.0005) and the mobility restriction (0.0016). As an additional robustness check, we replace the firm fixed effects for municipal fixed effects in Appendix Table A8. Results are overall similar, except for the mobility restrictions which are now statistically significant (Appendix Table A5).

To observe the dynamic effect of bank supply shocks, we estimate an event study specification in which we interacts the exposure variable with a set of time dummy variables. In this case all units are treated simultaneously in the third week of March. Results are presented in Figure 6. We observe a short surge in credit in the first week, followed by a negative and significant effect that extends for approximately 4 months.

Figure 6: Event Study Estimates of Local Demand and Supply Shocks



Notes: Lines represent the point estimates and 95% confidence bands from the OLS and the Callaway and Sant'Anna (2020) estimators. All models control for time and bank-municipal fixed effects and errors are clustered at the municipal level. The Callaway and Sant'Anna (2020) inference is based on 1000 bootstrap replications.

To further disentangle the effect of bank supply shocks, we control for any potential pandemic-driven changes in local supply and demand in Table 4. We do this by including the interaction between firm and time fixed-effects (odd columns), and the interaction between municipal and time fixed effects (even columns). Results are overall similar. In the firm and time fixed-effects specification, the bank supply shock effects are only slightly larger than in the main specification, with an estimated coefficient of -0.152. These results confirm, once again, that the correlation between the local shocks and the bank supply shock is negligible.

Table 4: Bank Supply Shocks (control for firm and time FE)

	(1)	(2)
Lockdown	-0.000305	-0.00106*
	(0.000888)	(0.000554)
Exposure*Post	-0.152***	-0.116***
	(0.0483)	(0.0302)
Observations	1,937,832	1,956,864
R-squared	0.272	0.011
Bank FE	✓	✓
Time*Firm FE	✓	
Time*Municipality FE		✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced). Bank exposure denotes the average expected change in deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

As an alternative way to account for local demand and supply shocks, we drop the municipalities that were most affected by the pandemic. The new samples include 90% and 75% of the municipalities with fewer accumulated cases in December 2020, respectively. Results are presented in Table 5. Notice that the estimated coefficients for Covid cases and deaths are non-significant and even small in magnitude in the restricted samples. This is consistent with the fact that the local effects of the pandemic are mitigated in municipalities that were relatively spared from it. In contrast, the bank exposure effect remains large and significant, which confirms that the bank supply shock did affect corporate credit. Moreover, the impact is larger in the most restricted sample, with estimated coefficients between -0.178 and -0.186. In part, this could reflect that large cities were more affected by the pandemic, and excluding them from the analysis leaves us with firms that are smaller and less liquid, and therefore more likely to be vulnerable to bank supply shocks.

Table 5: Bank Supply Shocks in Less Affected Municipalities

	Full sample		90%		75%	
	(1)	(2)	(3)	(4)	(5)	(6)
New Cases/inhab.	-0.000331		-0.000292		0.00153	
	(0.000313)		(0.000538)		(0.00145)	
New Deaths/inhab.	-7.89e-05		-0.0117		-0.0139	
	(0.00823)		(0.0110)		(0.0272)	
Lockdown	0.000476		0.00168**		0.00121	
	(0.000513)		(0.000779)		(0.00127)	
Exposure*Post	-0.113***	-0.114***	-0.130***	-0.125***	-0.186***	-0.178**
	(0.0399)	(0.0398)	(0.0588)	(0.0589)	(0.0873)	(0.0870)
Observations	1,956,864	1,956,864	700,544	700,544	289,536	289,536
R-squared	0.023	0.023	0.022	0.022	0.023	0.023
Time FE	✓	✓	✓	✓	✓	✓
Bank*Firm FE	✓	✓	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced). Bank exposure denotes the average expected change in deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019. New Deaths/inhab and New Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

Finally, we test whether the impact of the bank supply shock varies depending on the local incidence of the pandemic. We estimate a triple differences model, interacting the bank supply shock with the municipal accumulated cases in December 2020 (Appendix Table A9). The triple interaction term reflects the gradient of the bank supply shock along the distribution of Covid accumulated cases. While the point estimate of the supply shock is larger in magnitude, it is statistically non-significant. The coefficient of the triple interaction is economically small and non-significant, indicating that, even if banks' credit policies varied regionally, they are not driven by the local incidence of the pandemic. These findings further confirm that the local demand and supply shocks are overall independent from the bank supply shock.

4.3 Heterogeneous effects by firm characteristics

In the last set of results, we assess the heterogeneous effects of both local demand and supply shocks and bank supply shocks, by firm characteristics. We observe firms characteristics in 2019, before the pandemic begins, using the following eight indicators reflecting firms' size, age, and liquidity: total assets, number of workers, age, current ration, acid test, debt to equity ratio, financial debt ratio, and no late (moratorium) payment. For ease of interpretation, we multiply debt to equity ratio and financial debt ratio by -1, so that higher values reflect more liquidity. We then identify firms above and below the median of the respective measure, and estimate triple difference models that interact the different shocks with the above-median dummy. The p-values for the estimated effect on firms above the median are computed with linear test and presented in brackets.

Results are presented in Table 6. The bank supply shock affects almost exclusively firms that are small, young, and have low liquidity. The estimated coefficients for these firms are larger in magnitude and statistically significant for all characteristics except debt to equity ratio. In contrast, the impact on larger, older, and more liquid firms is consistently insignificant. These findings are in line with previous literature showing that some firms are more vulnerable to bank supply shocks than others (Chodorow-Reich et al., 2021). On the local demand and supply side, the estimated effects remain small and insignificant in most cases. However, there are two dimensions in which there is some heterogeneity across firms. On one hand, mobility restrictions increase the volume of credit in smaller and, for some measures, more liquid firms. On the other hand, the number of Covid deaths have a negative and significant effect on younger firms.[6]

[6]There are also some significant coefficients for Covid cases and deaths for firms bellow the assets median, however the effects are compensating each other.

Table 6: Heterogeneous effect of the bank Supply Shocks by firm characteristics

	Firm size		Firm	Firm liquidity				
	Workers	Assets	Age	Current ratio	Acid test	Debt to equity ratio	Financial debt ratio	No late payment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Cases/hab.	-0.000447	-0.00115***	-3.01e-05	0.000285	-0.000125	0.000302	-0.000495	-0.000435
	(0.000416)	(0.000358)	(0.000474)	(0.000510)	(0.000502)	(0.000494)	(0.000471)	(0.000471)
New Cases/hab.×high	5.41e-05	0.00148**	-0.000729	-0.00132**	-0.000436	-0.00143**	0.000333	0.000200
	(0.000632)	(0.000600)	(0.000659)	(0.000649)	(0.000652)	(0.000638)	(0.000652)	(0.000653)
p-value (high)	[0.467]	[0.553]	[0.144]	[0.0266]	[0.242]	[0.0184]	[0.752]	[0.648]
New Deaths/hab.	0.00886	0.0201*	-0.0239**	-0.00470	-0.00266	-0.00922	0.00484	-0.00337
	(0.00973)	(0.00816)	(0.0120)	(0.0150)	(0.0146)	(0.0139)	(0.0133)	(0.0130)
New Deaths/hab.×high	-0.0212	-0.0388**	0.0447**	0.00530	0.00105	0.0164	-0.0165	0.00278
	(0.0179)	(0.0169)	(0.0185)	(0.0183)	(0.0183)	(0.0179)	(0.0180)	(0.0184)
p-value (high)	[0.427]	[0.221]	[0.153]	[0.956]	[0.889]	[0.543]	[0.356]	[0.965]
Lockdown	0.00177***	0.00236***	-3.76e-05	0.0000213	-0.000175	-0.000137	-0.000713	-2.09e-05
	(0.000635)	(0.000541)	(0.000762)	(0.000796)	(0.000812)	(0.000773)	(0.000735)	(0.000732)
Lockdown×high	-0.00246***	-0.00365***	0.00102	0.000338	0.00127	0.00132	0.00259***	0.000842
	(0.000861)	(0.000824)	(0.000898)	(0.000886)	(0.000885)	(0.000880)	(0.000896)	(0.000896)
p-value (high)	[0.403]	[0.126]	[0.189]	[0.421]	[0.100]	[0.0949]	[0.0134]	[0.284]
Exposure×Post	-0.167***	-0.140***	-0.163**	-0.152***	-0.153***	-0.107	-0.162***	-0.114**
	(0.0423)	(0.0320)	(0.0721)	(0.0693)	(0.0637)	(0.0653)	(0.0597)	(0.0568)
Exposure×Post×high	0.0685	0.0569	0.0636	0.0868	0.0924	-0.0139	0.111	0.00112
	(0.0889)	(0.0840)	(0.0929)	(0.0909)	(0.0921)	(0.0909)	(0.0941)	(0.0941)
p-value (high)	[0.210]	[0.284]	[0.0899]	[0.269]	[0.360]	[0.0564]	[0.489]	[0.131]
Observations	1,582,256	1,620,112	1,582,256	1,620,112	1,620,112	1,620,112	1,620,112	1,620,112
R-squared	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank*Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. New Deaths/inhab and New Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020. Bank exposure denotes the average expected change in deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019. High is a dummy variable equal to 1 if the respective measure is above the median.

5 Conclusions

The Covid-19 pandemic has been one of the deadliest and most disruptive crisis in history. And, while it did not specifically center (nor originated) at the core of the financial sector, as for example was the case of the 2008-09 world crisis, the pandemic did affect both credit supply and demand. On the supply side, factors such as credit risk, loan quality, and funding costs affected the disbursement of credit. This occurred in a period of global monetary expansion, where the credit and risk channels are at play. On the demand side, besides the direct effect on households and businesses (e.g. lock-downs and disruptions in local and global supply chains), there were also differences in expectations regarding the magnitude and duration of the pandemic, which led to differences in credit behavior; in some cases to over-borrowing.

In this paper we take a fresh new look at financial sector effects brought forth by the pandemic, focusing on the relative magnitudes of demand and supply-driven shocks. To measure overall effects, we use a difference in differences framework that exploits both the timing and the geographic variation in the disease spread. We find that neither the local exposure to the virus, nor the mobility restrictions have an impact of corporate credit.

We then evaluate effects driven by bank-supply shocks. To do so, we construct a pre-pandemic bank exposure variable, based on the geographic distribution of deposits and urban density. We estimate the heterogeneous effects of the pandemic by bank exposure, finding negative and significant effects on credit and almost unaltered results for local exposure and mobility restrictions. The effect of the supply shock accounts for a 5.2% contraction in corporate credit. Results hold when we control for any potential local supply or demand shock and when we drop the municipalities that were more affected by the pandemic. Moreover, the impact of the bank supply shock does not vary depending on the local intensity of the pandemic.

In the final section of the paper, we estimate the heterogeneous effects, finding that most of the effects are driven by firms that are small, young, and with relatively low liquidity.

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6 Appendix

Table A1: Municipal Characteristics Predicting Local Intensity of Covid Cases

	Cases			Deaths		
	(1)	(2)	(3)	(4)	(5)	(6)
Elderly population*Post	-67.43***			-1.666***		
	(15.90)			(0.419)		
Population density*Post		2,130***			47.70***	
		(0.184)			(0.005)	
Urban pop. density*Post			285.35***			6.626***
			(16.143)			(0.420)
Observations	21,859	21,940	18,342	21,859	21,940	18,342
R-squared	0.598	0.601	0.606	0.537	0.539	0.555
Time FE	✓	✓	✓	✓	✓	✓
Municipality FE	✓	✓	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Population density and Urban population density are measured in inhabitants per square kilometer. The share of elderly population is the population over 60 years of age over inhabitants per municipality. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced).

Table A2: Bank Deposits and Covid Predictors

	All deposits			Term deposits		
	(1)	(2)	(3)	(4)	(5)	(6)
Elderly Population*Post	0.000341			0.000758		
	(0.000989)			(0.00142)		
Population density*Post		-0.163***			-0.100***	
		(0.056)			(0.0198)	
Urban pop. Density*Post			-0.003**			-0.00277**
			(0.001)			(0.00129)
Observations	6,327	6,354	6,354	6,300	6,327	6,327
R-squared	0.994	0.994	0.994	0.993	0.993	0.992
Time FE	✓	✓	✓	✓	✓	✓
Bank*Municipality FE	✓	✓	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Population density and Urban population density are measured in inhabitants per square kilometer. The share of elderly population is the population over 60 years of age over inhabitants per municipality. Post is a dummy that is switched on after after the third week of March (when the lockdown measures were announced).

Table A3: Baseline Relationship between Banks' Deposits and Credit

	(1)	(2)	(3)	(4)
Term deposits	0.582***			
	(0.0967)			
Savings accounts		0.335***		
		(0.0645)		
Current accounts			0.204***	
			(0.0495)	
All Deposits				0.877***
				(0.0908)
Observations	1,266	1,215	1,074	1,266
Number of banks	30	28	21	30
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. All variables are in logarithms.

Table A4: Local demand and supply shocks (discrete outcome)

	(1)	(2)	(3)	(4)	(5)	(6)
New Cases/hab.	-0.000390*	-0.000390*			-0.000442	-0.000442
	(0.000201)	(0.000201)			(0.000290)	(0.000290)
New Deaths/hab.			-0.00651	-0.00653	0.00209	0.00208
			(0.00548)	(0.00548)	(0.00793)	(0.00793)
Lockdown	0.000290	0.000378	0.000290	0.000377	0.000289	0.000376
	(0.000446)	(0.000454)	(0.000446)	(0.000454)	(0.000446)	(0.000454)
Observations	2,563,392	2,563,392	2,563,392	2,563,392	2,563,392	2,563,392
R-squared	0.013	0.017	0.013	0.017	0.013	0.017
Time FE	✓	✓	✓	✓	✓	✓
Firm FE	✓		✓		✓	
Bank FE	✓		✓		✓	
Bank*Firm FE		✓		✓		✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Deaths/inhab and Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

Table A5: Local demand and supply shocks (Municipal FE)

	(1)	(2)	(3)	(4)	(5)	(6)
New Cases/hab.	-0.000300	-0.000301			-0.000339	-0.000339
	(0.000214)	(0.000214)			(0.000220)	(0.000220)
New Deaths/hab.			-0.00505	-0.00506	0.00156	0.00154
			(0.00676)	(0.00676)	(0.00816)	(0.00816)
Lockdown	-0.00112***	-0.00104**	-0.00113***	-0.00104**	-0.00113***	-0.00104**
	(0.000446)	(0.000454)	(0.000446)	(0.000454)	(0.000446)	(0.000454)
Observations	2,563,392	2,563,392	2,563,392	2,563,392	2,563,392	2,563,392
R-squared	0.004	0.005	0.004	0.005	0.004	0.005
Time FE	✓	✓	✓	✓	✓	✓
Municipality FE	✓		✓		✓	
Bank FE	✓		✓		✓	
Bank*Municipality FE		✓		✓		✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Deaths/inhab and Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

Table A6: Local demand and supply shocks (Control for bank Supply Shocks)

	(1)	(2)	(3)	(4)	(5)	(6)
New Cases/hab.	-0.000294	-0.000289			-0.000314	-0.000314
	(0.000186)	(0.000230)			(0.000259)	(0.000221)
New Deaths/hab.			-0.00530	-0.00512	0.000810	0.000966
			(0.00494)	(0.00738)	(0.00686)	(0.00855)
Lockdown	1.33e-05	-0.00106**	1.31e-05	-0.00106**	1.28e-05	-0.00106**
	(0.000406)	(0.000446)	(0.000406)	(0.000448)	(0.000406)	(0.000448)
Observations	2,563,288	2,563,288	2,563,288	2,563,288	2,563,288	2,563,288
R-squared	0.018	0.006	0.018	0.006	0.018	0.006
Firm FE	✓		✓		✓	
Municipality FE		✓		✓		✓
Bank*Time FE	✓	✓	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Deaths/inhab and Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

Table A7: Bank Supply Shocks (discrete outcome)

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000500**		-0.000580*
		(0.000230)		(0.000337)
New Deaths/inhab.			-0.00807	0.00317
			(0.00629)	(0.00921)
Lockdown	0.00114**	0.00116**	0.00116**	0.00115**
	(0.000522)	(0.000522)	(0.000522)	(0.000522)
Exposure*Post	-0.362***	-0.360***	-0.362***	-0.360***
	(0.0468)	(0.0468)	(0.0468)	(0.0468)
Observations	1,956,864	1,956,864	1,956,864	1,956,864
R-squared	0.017	0.017	0.017	0.017
Time FE	✓	✓	✓	✓
Bank*Firm FE	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced). Bank exposure denotes the average expected change in deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019. Deaths/inhab and Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

Table A8: Bank Supply Shocks (Municipal FE)

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000327		-0.000333
		(0.000263)		(0.000262)
New Deaths/inhab.			-0.00622	0.000224
			(0.00763)	(0.00860)
Lockdown	-0.000943*	-0.000936*	-0.000936*	-0.000937*
	(0.000535)	(0.000536)	(0.000539)	(0.000539)
Exposure*Post	-0.112***	-0.110***	-0.112***	-0.110***
	(0.0283)	(0.0287)	(0.0284)	(0.0288)
Observations	1,956,864	1,956,864	1,956,864	1,956,864
R-squared	0.005	0.005	0.005	0.005
Time FE	✓	✓	✓	✓
Bank*Municipality FE	✓	✓	✓	✓

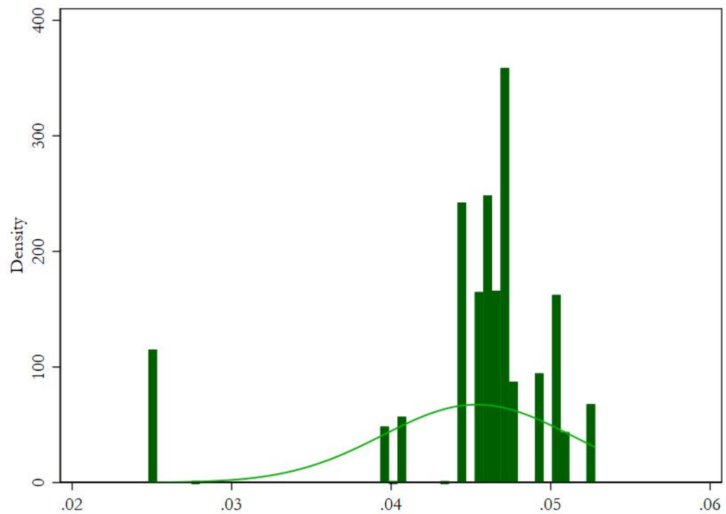
Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced). Bank exposure denotes the average expected change in deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019. Deaths/inhab and Cases/inhab are deaths and cases per thousand per week, respectively. Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

Table A9: Bank Supply Shocks (local pandemic gradient)

	(1)	(2)	(3)	(4)
New Cases/hab.		-0.000226		-0.000177
		(0.000237)		(0.000327)
New Deaths/hab.			-0.00502	-0.00182
			(0.00598)	(0.00824)
Lockdown	0.000498	0.000497	0.000503	0.000499
	(0.000514)	(0.000514)	(0.000514)	(0.000514)
Exposure×Post	-0.206	-0.206	-0.207	-0.207
	(0.134)	(0.134)	(0.134)	(0.134)
Exposure×Post×Cases	0.00202	0.00202	0.00202	0.00202
	(0.00278)	(0.00278)	(0.00278)	(0.00278)
Observations	1,956,864	1,956,864	1,956,864	1,956,864
R-squared	0.023	0.023	0.023	0.023
Time FE	✓	✓	✓	✓
Bank*Firm FE	✓	✓	✓	✓

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced). Bank exposure denotes the average expected change in deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019. Deaths/inhab and Cases/inhab are deaths and cases per thousand per week, respectively.Lockdown is a dummy variable equal to 1 if the sector was affected by the quarantines between week 13 and 31 of 2020.

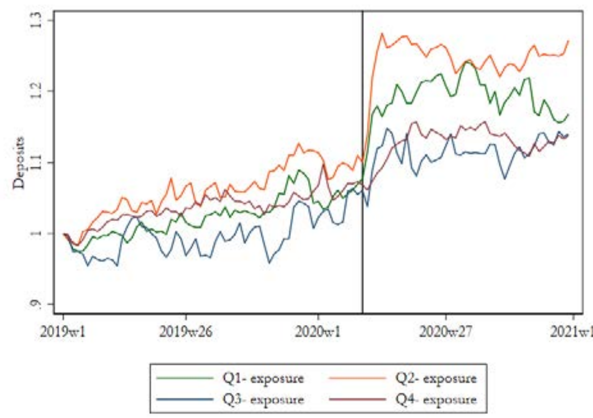
Figure A1: Bank Exposure



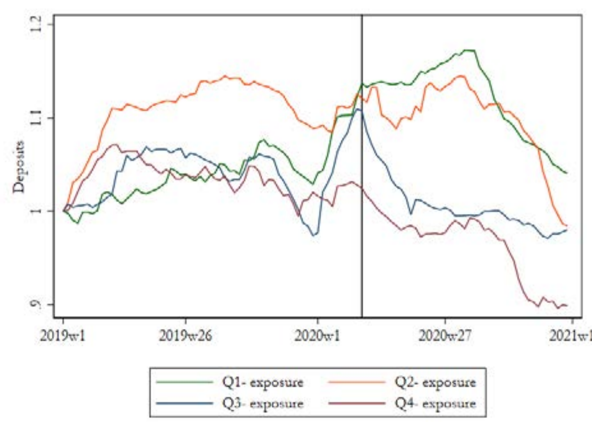
Notes: Bank exposure denotes the average expected change in total deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019.

Figure A2: Bank exposure and deposits

(a) Total deposits



(b) Term deposits



Notes: Banks are classified in 4 groups based on their estimated pandemic exposure using quartile values as cutoffs (see Section 3.2 for more details on the pandemic exposure measure). Total deposits (Panel A) and Tern deposit certificates (Panel B) are expressed in percentage changes with respect to January 2019.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