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The Leading Role of Bank Supply Shocks

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The Leading Role of Bank Supply Shocks*

Leonardo Bonilla-Mejía † Mauricio Villamizar-Villegas ‡

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Abstract

This paper explores the impact of demand and supply shocks on the credit market during major economic downturns. Using granular firm-bank credit data from Colombia during the Covid-19 pandemic, we assess the demand channel and find that neither local outbreaks nor mobility restrictions significantly affect corporate credit. We then examine the role of bank supply shocks, leveraging heterogeneous exposures of banks to the pandemic. Our results indicate that supply shocks contribute to a credit contraction of approximately 5.2%. These supply effects are predominantly transmitted to small, young firms with relatively low liquidity.

JEL Codes: G01, G21
Keywords: Credit shocks, liquidity constraints, bank-supply shocks, Covid-19 Pandemic

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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

1 Introduction

Large economic downturns generally lead to contractions in corporate credit; however, it is hard to disentangle the extent to which these are driven by demand or supply factors. While survey-based studies (mostly qualitative) 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 microdata, at the loan-level, to establish a causal link between credit and the supply or demand nature of the shock (Amiti and Weinstein, 2018; Huber, 2018; Alfaro et al., 2021; Cherry et al., 2021; Altavilla et al., 2022). 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.

In this paper, we take a fresh look at this question, assessing the relative impact of demand and supply shocks in the context of the Covid-19 crisis. The pandemic provides a unique framework for this study, as it affected both the demand and supply factors of the credit market (Li et al., 2020; Dursun-de Neef and Schandlbauer, 2022; Acharya et al., 2021; Barua and Barua, 2021; Kapan and Minoiu, 2021; Haddad et al., 2021; Levine et al., 2021; Goldstein et al., 2021). 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 impact of the disease on households and businesses, there were also stringent lockdown policies and disruptions in local and global supply chains. Moreover, different expectations regarding the magnitude and duration of the pandemic could have led to disparities in credit behavior.

Our analysis is based on administrative credit records at the firm-bank level matched

with the firms' corporate registry (balance sheet information). We use a difference-in-differences framework that exploits multiple sources of variation associated with the potential demand and supply factors. On the one hand, Colombia ranks among the countries most affected by the Covid-19 pandemic, with significant differences across regions in the disease's incidence and the timing of the spread. Furthermore, mobility restrictions implemented by the government to prevent the disease spread, affected some industries and not others. On the other hand, the pandemic led to a recomposition of bank liabilities that affected liquidity and credit supply during the pandemic. Hence, to identify the impact of supply shocks, we exploit the variation in banks that were more exposed to the pandemic.

We begin our analysis by assessing the demand-driven effects of the pandemic on corporate credit. We capture the geographic variation in both the timing and the intensity of the outbreaks with continuous measures of Covid cases and deaths by municipality and week. We also control for the mobility restrictions, which vary across industries. The main specification of our model includes time-fixed effects, which control for the epidemiological and economic shocks that homogeneously affected credit across municipalities and banks. We also control for firm-bank fixed effects, which account for the bank-firms pairs' observed and unobserved time-invariant characteristics. To further purge supply shocks from the demand channel, our most restrictive specification controls for the interaction between time and bank fixed effects. Our results indicate that neither the local outbreaks nor the mobility restrictions significantly affected credit. The coefficients are economically small and are precisely estimated.

We then assess the role of bank supply shocks in the contraction of credit. We base our analysis on the empirical strategy of Khwaja and Mian (2008), which tracks the credit decisions of the same firm with differently exposed banks. In this setting, given that 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 the elderly population, population density, and urban density. In sum, our time-invariant measure of bank exposure is defined as the banks' average predicted deposit changes, 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 the 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 contribute to an average credit reduction of at least 5.2%. For robustness, we estimate alternative specifications, varying the fixed effects structure, including municipal fixed effects, and using a discrete credit measure as an 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 non-significant gradient coefficients. Overall, our results confirm that the pandemic highly affected the credit market through a heterogeneous effect on banks' liquidity. We further test the role of bank supply shocks with a Amiti and Weinstein (2018) decomposition. Consistent with our previous findings, results indicate that most of the variation in credit growth during the pandemic is driven by the supply shocks.

In the last section, we assess heterogeneous effects based on the firm's balance sheet

information, including size, age, and various liquidity measures based on the corporate registry, such as the current ratio (current assets / current liabilities), acid test, and debt-to-equity ratio. Results indicate that most of the bank supply shocks are passed on to firms that are small, young, and have relatively low liquidity.

Our contribution is threefold. First, we add to the empirical literature that disentangles and quantifies the relative importance of supply and demand factors within the financial sector (Amiti and Weinstein, 2018; Huber, 2018; Alfaro et al., 2021; Cherry et al., 2021; Altavilla et al., 2022). Overall, our results indicate that, in this context, bank supply shocks account for most corporate credit contraction during the pandemic. 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 spread and find important negative demand-driven effects. A potential explanation is that in the United States deposits increased in the hardest-hit regions, which in turn led the more exposed banks to increase loans (Dursun-de Neef and Schandlbauer, 2022; Levine et al., 2021). 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, partly explaining the variation in bank liquidity and corporate credit.

Second, our paper also contributes to the literature on the heterogeneous effects of liquidity shocks (Holmstrom and Tirole, 1997; Siriwardane, 2019; Chodorow-Reich et al., 2021; Berger et al., 2021; Fahlenbrach et al., 2021). Specifically, we use triple-difference models to test whether the impact of the bank supply shock varies based on firm characteristics, such as firm size, age, and liquidity. Consistent with previous studies, we show that small, young firms with low liquidity are particularly vulnerable in this context.

Third, the paper contributes to the growing literature on the mechanisms through which

the Covid-19 pandemic affected the economy, particularly in developing countries (Brodeur et al., 2020; Barua, 2021; Chetty et al., 2020; Fernandes, 2020; Maliszewska et al., 2020; Ozili and Arun, 2023; del Rio-Chanona et al., 2020; Psacharopoulos et al., 2021; Yeyati et al., 2021a; Jordà et al., 2022). Specifically, we provide new evidence on the leading role of bank-supply shocks in the corporate credit channel.

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.

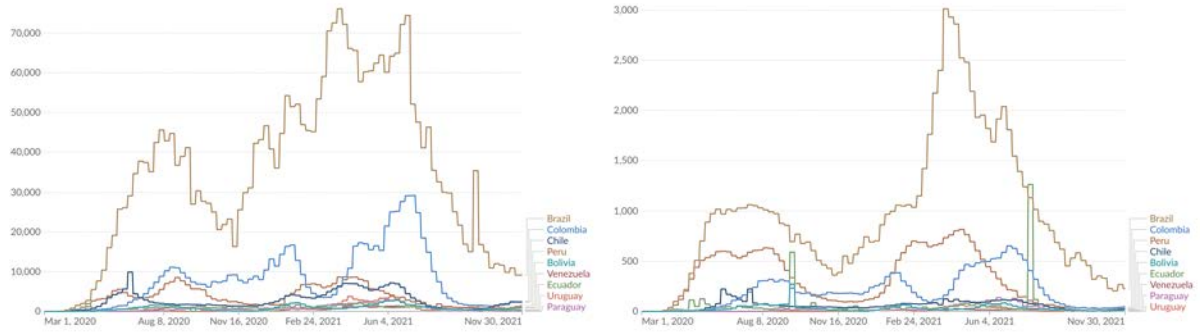
2 Pandemic and Credit in Colombia

The Covid-19 pandemic has been one of the deadliest and most disruptive events in recent 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). While it did not specifically center (nor originate) in the financial sector, as was the case of the 2008-09 world crisis, the pandemic did affect the credit market. On the one hand, the economic 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; Haddad et al., 2021). On the other hand, consumption fell, and precautionary savings increased, which translated into a large influx and recomposition of bank liabilities (Dursun-de Neef and Schandlbauer, 2022; Levine et al., 2021). While credit increased during the first months of the pandemic, 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 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 three weeks later, 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, the 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 reopen gradually. 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, Colombia ranked (almost always) second in the region with the most cases and third in the region with the most deaths.

Figure 1: Covid in Colombia and Latin America

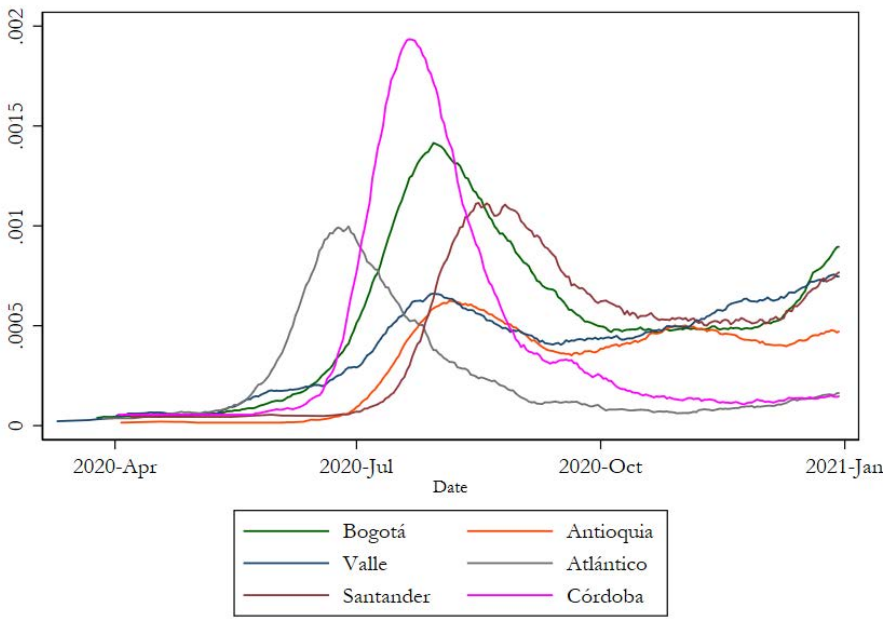


Notes: Daily new confirmed Covid cases (left panel) and deaths (right panel).
Source: WHO COVID-19 Dashboard.

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 depart-

ments such as *Santander*, *Norte de Santander*, and *Antioquia*, exhibited their initial effects only until August (Figure 2). There is also variation in the disease intensity, with some departments peaking at 0.0005 deaths per thousand per week while others reach 0.002. We exploit this spatial and temporal variation to identify the effect of local outbreaks on credit.

Figure 2: Covid Deaths by Department



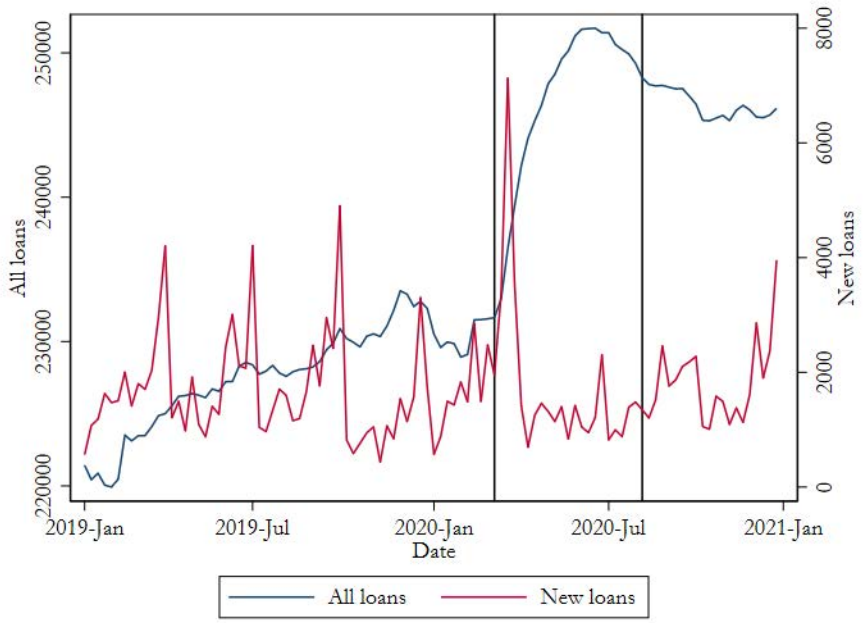
Notes: Each line represents the 1-month moving average of the weekly number of Covid-related deaths per thousand people in the ten most populated departments in Colombia.

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 four 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 and 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 began 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



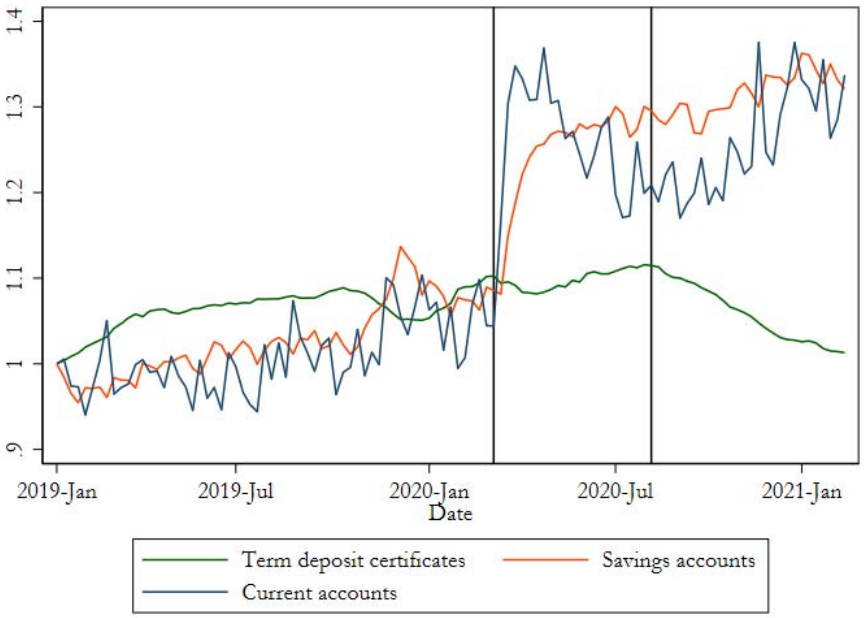
Notes: The volume of corporate credit is expressed in COP billions (10^9) per week. The two vertical lines represent the beginning and the end of the strict lockdown policy.

Total bank deposits also increased at the beginning of the pandemic and stayed at high levels throughout the year. This resulted from 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 relatively slow growth during the first months of the pandemic and fell afterward, ending 2021 almost 7 pp below pre-pandemic levels (Figure 4).

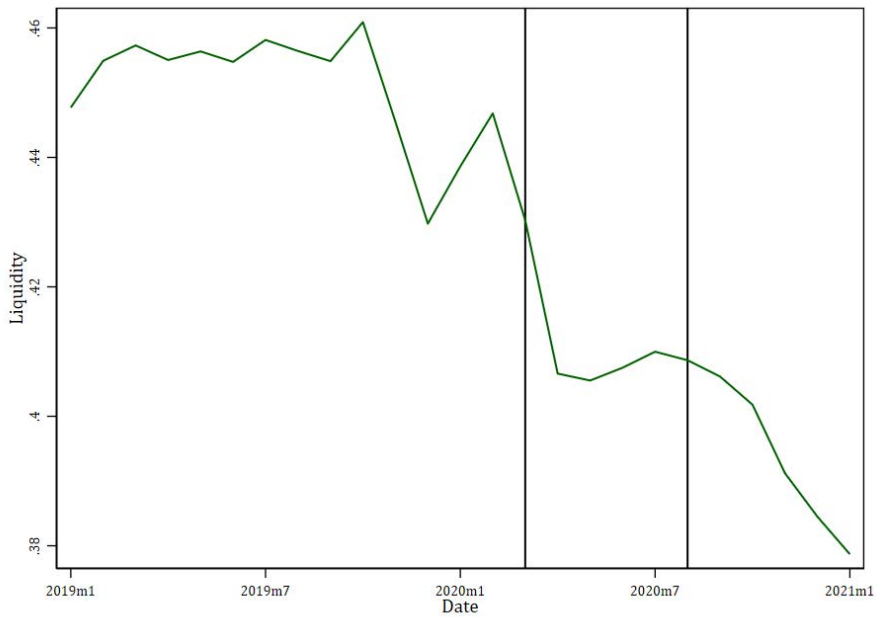
The restructuring of bank liabilities prompted by the pandemic may have exerted a notable impact on credit supply, especially within financial institutions with heightened exposure to the crisis. We delve into this rationale in Section 4.2, positing that the increase of liquid assets amplifies the maturity mismatch between banks' assets and liabilities. This not only accentuates liquidity risks (as depicted in Figure 5) but also introduces complications in meeting financial regulations. Liquid assets, subject to higher reserve requirements and, under the prevailing BASEL-3 standards, contributing to the deterioration of the net stable funding ratio (NSFR), further compound these challenges.

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.

Figure 5: Banks liquidity



Notes: Bank liquidity is the ratio of liquid (savings and current accounts) assets to Total bank deposits. The two vertical lines represent the beginning and the end of the strict lockdown policy.

3 Data and Empirical Strategy

3.1 Data

Our analysis is based on the administrative credit records from the Financial Regulator, the *Superintendencia Financiera de Colombia* - SFC. The dataset contains the entire registry of individual corporate credits 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.[1] Out of 22,420 firms that reported to SS between 2000 and 2020, we were able to match 15,398,

[1]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 ten employees. When a firm operates in multiple cities, we use the headquarters location.

which account for 64,7% of the total corporate assets. We measure the volume of new credits (i.e., new disbursements or new loans) by firm and bank, at a weekly frequency, 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 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 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. The SFC also provides bank deposit data. 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 square kilometer, is calculated using the urban population from the 2018 Population Census and the area of urban land computed from the official 2018 cartography from DANE. Alternative municipal characteristics, such as population density and the share of the elderly population in 2018, are also calculated 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 corporate registry to measure total assets and age, and to 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 the value of 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.

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.

3.2 Empirical Strategy

3.2.1 Demand factors

We begin our analysis on the demand-driven effects of the pandemic on credit by exploiting the geographic variation of the disease spread and the sector-specific mobility restrictions using the following difference-in-differences model:

$$Credit_{i,b,t} = \beta Covid_{m,t} + \gamma lockdown_{s,t} + \delta_t + \phi_{i,b} + \epsilon_{i,b,t} \tag{1}$$

where $Credit_{i,b,t}$ 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. $Covid_{m,t}$ 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. $lockdown_{s,t}$ 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 ($\phi_{i,b}$). 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-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 outbreaks and the lockdown policy. Businesses can be directly affected by the virus or mobility restrictions or indirectly through cuts and disruptions in the supply chain and abrupt changes in consumer behavior. Note that demand shocks could be correlated with the bank supply shocks. To fully isolate them from bank-supply shocks, we estimate the model including the interaction between banks and time fixed effects ($\phi_{b,t}$).

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 5th 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:

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

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. Regressions control for time and bank-municipal fixed effects and errors are clustered at the municipal level.

A potential limitation is that the staggered treatment nature of this specification could lead to biased estimates (Goodman-Bacon, 2021).[2] We address this concern by using 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 the same firm with differently exposed banks. In this setting, given the heterogeneous geographic distribution of deposits and pandemic vulnerability, we exploit the fact that some banks were more exposed to the pandemic than others. The differential exposure could, in turn, translate into a heterogeneous bank supply shock.[3] We are interested in this mechanism, given the high correlation between banks' deposits and credit in Colombia. We estimate the relationship between different types of deposits and total credit volume at the bank and

[2] In fact, the two-way fixed effect estimator is the weighted sum of different 2×2 treatment effects, and the presence of negative weights can lead to biased results.

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

week level in 2019, the year before the pandemic began. The coefficients are positive and significant in all cases, with 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 the pandemic vulnerability. The first step in making 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 the share of the the elderly population, population density, and urban density. To select the best predictor, we regress the local intensity of the disease spread (measured by cases and deaths rates) 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 robust negative and significant effect 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.[4] 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).

The main advantage of using this bank exposure measure, based on pandemic vulnerability, 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 shocks and the bank supply shocks are mostly independent.

Finally, we estimate the heterogeneous effects of the pandemic by bank exposure. Specifically, we interact the exposure measure with a post-term that takes the value one in the third week of March. Since we want to identify changes in the 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:

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

$$Credit_{i,b,t} = \theta Exposure_b \times post_t + \beta Covid_{m,t} + \gamma lockdown_{s,t} + \delta_t + \phi_{i,b} + \epsilon_{i,b,t} \quad (3)$$

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

We complement our analysis with an alternative, time-varying measure of bank exposure. We interact the share of deposits in each municipality in 2019 and the local intensity of the disease spread, measured by the weekly infection rate by municipality. Additionally, we estimate the direct impact of banks' liquidity, expressed as the ratio of liquid assets (savings and current accounts) to total bank deposits, on credit. While both measures reflect the extent to which some banks are more vulnerable than others to the pandemic, they are less exogenous than the bank exposure measure based on pandemic vulnerability.

For additional robustness, we estimate alternative specifications, varying the fixed effects structure, including municipal fixed effects, and using a discrete credit measure as an 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 shocks.

As an alternative strategy to assess the role of supply shocks, we decompose banks' credit growth following Amiti and Weinstein (2018). Credit growth can be expressed in terms of aggregate, demand, and supply shocks, as presented in Equation 4:

$$D_{b,t} = (\bar{a_t} + \bar{b_t})1_b + \phi_{t-1}a_t + b_t \tag{4}$$

Where D_{bt} is the weekly change in log volume of new credits of bank b. The first term on the right hand side is the the sum of the median firm and bank shocks ($(\bar{A}_t + \bar{B}_t)1_B$), reflecting any aggregate shocks affecting lending pairs identically. The second term ($\phi_{t-1}A_t$) is the firm shock, computed as the weighted sum of firms shocks.[5] The third term (B_t) is the bank shock. We measure the relative importance of each of these terms with their contribution to the R^2 in OLS estimations of Equation 4.

Finally, we study some of the mechanisms behind our main results by assessing the heterogeneous effects of the pandemic on corporate credit by firm characteristics. In total, we use eight 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 the value one if the firm is above the median of the respective measure, and zero otherwise.

4 Results

4.1 Demand factors

The first set of estimates, based on Equation 1 with continuous measures of Covid cases and deaths by municipality, indicate that neither the local outbreaks nor the mobility restrictions impact corporate credit. As 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 virus prevalence with Covid cases, column 3 with deaths, and column 5 with both. Results are fairly similar when we use separate firm and bank fixed

[5] ϕ_t is a matrix reflecting the firm-bank lending network in each period.

effects (columns 2, 4, and 6). Likewise, we find small and non-significant coefficients for the sector-specific mobility restrictions in all estimations.

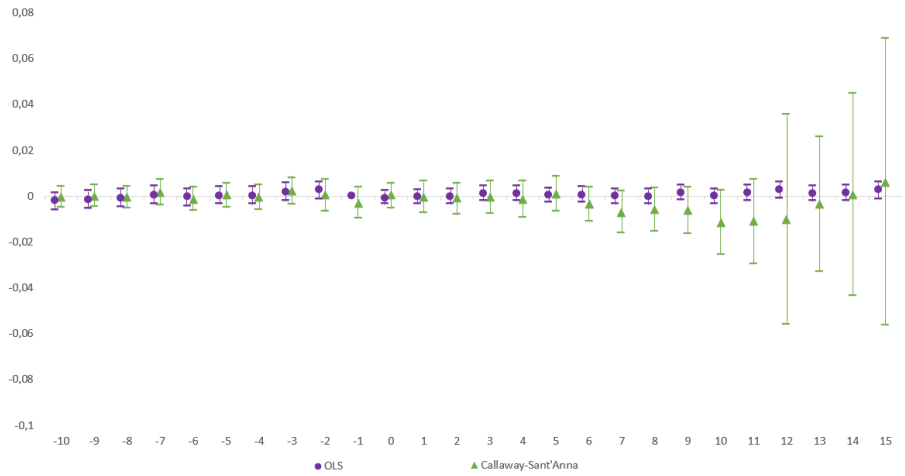
Results are overall similar with OLS and Callaway and Sant'Anna (2020) event study specifications. The estimated effects are economically small and non-significant in all periods, indicating that credit is overall unaffected by the local spread of the disease. Moreover, the null coefficients in the pre-treatment period show no relevant differences in credit before the pandemic hit, confirming that the parallel trends assumption holds (Figure 6).

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.

Figure 6: Event Study Estimates of Local Outbreaks



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.

We run multiple robustness check to this model. First, we use a discrete measure of credit as outcome (Appendix Table A4). Second, we replicate the model replacing firm fixed-effects with municipality fixed-effects (Appendix Table A5). Third, we interact the local outbreaks measures with the mobility restrictions, allowing for the pandemic impact to vary depending on these restrictions (Appendix Table A6). Fourth, we drop the 1% of the firms that had more credit before the pandemic to discard the possibility that our results are driven by outliers (Appendix Table A7). Fifth, we control for government programs designed to preserve employment and firm liquidity (Appendix Table A8).[6] Finally, we discard possible auto-correlation and volatility problems in the weekly data by estimating the model with monthly data (Appendix Table A9). In all cases, results are unchanged.

In the last set of regressions, we fully purge bank supply shocks by including the inter-

[6]Using administrative records, we identify the firms that were recipients of employment subsidies ($PAEF$) and firm liquidity (debt moratorium -PAD). For each program, we create a dummy variable that takes the value one for firms that received it

action between time and bank fixed effects. Results are presented in Appendix Table A10. Odd (even) columns include firm (municipal) fixed effects. Overall, the results are similar to those reported in Tables 2 and A5, which implies that the correlation between the local demand shocks and bank supply shocks is small.

We posit several potential explanations for the negligible impact of demand-driven factors, in contrast to findings observed in advanced economies (Beck and Keil, 2021; Norden et al., 2021; Çolak and Öztekin, 2021; Altavilla et al., 2022). First, the Colombian banking sector exhibits high concentration, where the top-3 banks have a combined market share of more than 50% across most major lending and deposit categories.[7] This considerable market power may curtail the influence of demand-driven effects. Second, our results, anchored by time and municipality fixed effects, specifically address local demand, diverging from aggregated country-level responses to the crisis. More notably, the restructuring of banking deposits in Colombia significantly deviated from patterns observed in other countries. For instance, in the United States, deposits surged in regions hardest hit by the pandemic, prompting more exposed banks to increase loans (Dursun-de Neef and Schandlbauer, 2022; Levine et al., 2021). In contrast, Colombia experienced growth in liquid assets, accompanied by a decline in term deposits. Furthermore, a distinct and noteworthy negative relationship exists between municipality pandemic vulnerability and deposits in Colombia.

4.2 Supply factors

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

[7] See the World Bank and IMF Financial Sector Assessment Program (FSAP) of 2021.

be explained by the 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 demand and supply shocks simultaneously has little effect on the first set of estimated coefficients confirms that the correlation between these shocks is not affecting our main results. It also validates that our bank exposure measure is largely exogenous from the actual disease spread.

In addition to this, we estimate two alternative measures for the supply shock. The first one is a direct measure of bank exposure, based on the interaction between baseline deposits deposit distribution and weekly rates of contagion (Appendix Tables A17). The second one is bank liquidity (Appendix Table A18). In both cases, we find economically and statistically significant effects for the supply shocks.

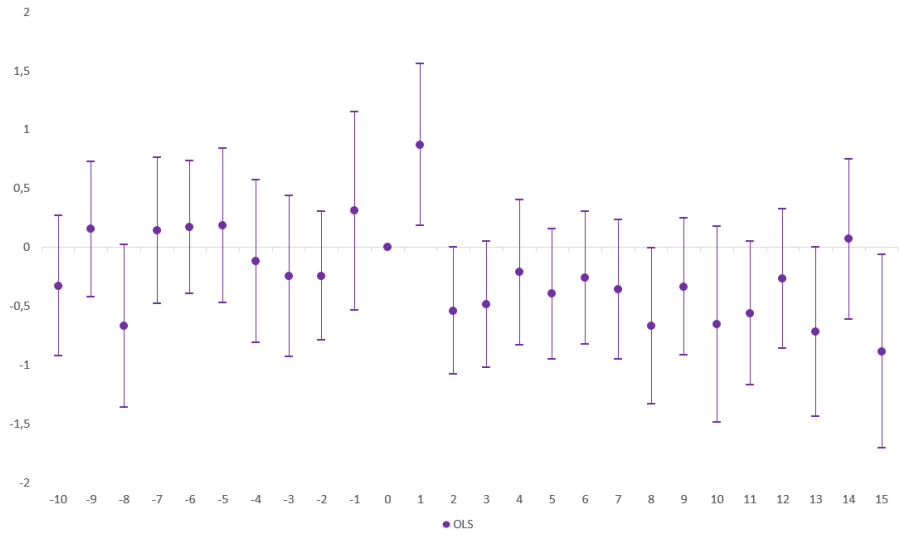
We observe the dynamic effect of bank supply shocks with an event study specification in which we interact the exposure variable with a set of time dummy variables. Since all units are treated simultaneously in the third week of March, we only estimate the OLS version of the model. Results are presented in Figure 7. We observe a short surge in credit in the first week, followed by a negative and significant effect that extends for approximately four months.

Table 3: Bank Supply Shocks

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000325		-0.000317
		(0.000225)		(0.000315)
New Deaths/inhab.			-0.00647	-0.000330
			(0.00592)	(0.00826)
Lockdown	0.000370	0.000376	0.000377	0.000376
	(0.000527)	(0.000527)	(0.000527)	(0.000527)
Exposure*Post	-0.159***	-0.157***	-0.159***	-0.157***
	(0.0403)	(0.0403)	(0.0403)	(0.0403)
Observations	1,948,128	1,948,128	1,948,128	1,948,128
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.

Figure 7: Event Study Estimates of Local Outbreaks



Notes: Lines represent the point estimates and 95% confidence bands from the OLS estimator. All models control for time and bank-municipal fixed effects, and errors are clustered at the municipal level.

As for the demand factors, our main findings are robust to alternative specifications.

These include regressions with discrete credit outcomes (Appendix Table A11, municipal fixed effects (Appendix Table A12), and heterogeneous impact of local outbreaks depending on mobility restrictions (Appendix Table A13). We also drop outlier firms (Appendix Table A14), control for government programs (Appendix Table A15), and use monthly data (Appendix Table A16).

To further disentangle the effect of bank supply shocks, we control for 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 slightly larger than in the main specification, with an estimated coefficient of -0.152. These results again confirm that the correlation between the local shocks and the bank supply shock is negligible.

Table 4: Bank Supply Shocks (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.

We next drop the municipalities most affected by the pandemic as an alternative way to account for local demand shocks. The new samples include 90% and 75% of the mu-

nicipalities 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. These results are consistent with the fact that the local demand effects of the pandemic are negligible in municipalities 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 smaller and less liquid firms 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.

We also 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

A19). The triple interaction term reflects the bank supply shock gradient along the Covid accumulated cases distribution. 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 shocks are independent of the bank supply shock.

Finally, we use an Amiti and Weinstein (2018) decomposition of credit growth during our study period. We test the relative importance of firm and bank shocks by regressing Equation 4, and measuring their individual contribution to the R^2 in Table 6. While bank shocks account for approximately 92% of the variability in credit growth during this period, the aggregate and firm shocks only account for 0.1% and 1.6%, respectively. Results are fairly similar when we compute credit growth using percentage growth instead of log chance and also using monthly data (Appendix Table A20). Overall, our findings consistently show that bank supply shocks account for most of the credit variation during the pandemic period.

Table 6: Amiti & Weinstein decomposition

	(1)	(2)	(3)	(4)
Common shock	0.947***			1.000
	(0.0602)			(0)
Bank shock		0.956***		1.000
		(0.000561)		(0)
Firm shock			0.450***	1.000
			(0.00693)	(0)
Observations	252,225	252,255	252,255	252,255
R-squared	0.001	0.920	0.016	1

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Each column corresponds to a separate regression of Equation 4.

4.3 Heterogeneous effects by firms' characteristics

In the last set of results, we assess the heterogeneous effects of demand and supply factors by firm characteristics. We observe firms' characteristics in 2019, before the pandemic began, using eight indicators reflecting firms' size, age, and liquidity: total assets, number of workers, age, current ratio, acid test, debt-to-equity ratio, financial debt ratio, and no days-past-due (moratorium) payment. For ease of interpretation, we multiply the 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, presented in brackets, are computed with a linear test.

Results are presented in Table 7. 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 the 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 demand side, the estimated effects remain small and insignificant in most cases. However, there are two dimensions with some heterogeneity across firms. On the 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 has a negative and significant effect on younger firms.[8]

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

Table 7: 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

We assess the role of demand and supply shocks in the credit market during large economic downturns by using granular firm-bank administrative data from Colombia in the context of the Covid-19 pandemic. We begin our analysis by evaluating the demand-driven effects of the pandemic on credit. Our results robustly discard the presence of demand-driven effects, as neither the local outbreaks nor the mobility restrictions significantly impact corporate credit.

We then evaluate the role of 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 outbreaks 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. Additionally, the impact of the bank supply shock remains constant across varying levels of local pandemic intensity. We confirm the dominant role of bank supply shocks with an Amiti and Weinstein (2018) decomposition, in which bank shocks account for most of the variability in credit growth.

In the paper's final section, we estimate the heterogeneous effects, finding that most of the impact of the supply shocks are driven by small, young firms with relatively low liquidity. In summary, our study provides nuanced insights into the intricate dynamics of the credit market during economic downturns, offering a focused understanding of the differential impacts experienced by various segments of the corporate sector.

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6 Appendix

Table A1: Municipal Characteristics Predicting Local Intensity of Covid Cases and Deaths

	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: Demand 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: Demand 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: Table 3 interaccion newcases*lockdown (demand)

	(1)	(2)	(3)	(4)
New Cases/inhab.	-0.000359			-0.000365
	(0.000236)			(0.000236)
New Deaths/inhab.		-0.00549		0.000256
		(0.00726)		(0.00813)
Lockdown	0.000201	0.000266	0.000166	0.000203
	(0.000504)	(0.000540)	(0.000533)	(0.000540)
New Cases*Lockdown	-0.0000492			-0.0000520
	(0.000398)			(0.000406)
Observations	2,053,181	2,053,181	2,053,181	2,053,181
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.

Table A7: Bank Demand Shocks (Without big firms)

	(1)	(2)	(3)	(4)
New Cases/inhab.	-0.000368*			-0.000369
	(-1.69)			(-1.22)
New Deaths/inhab.		-0.00711		0.0000341
		(-1.24)		(0.00)
Lockdown	0.000173	0.000174	0.000166	0.000173
	(0.34)	(0.34)	(0.33)	(0.34)
Observations	2,053,181	2,053,181	2,053,181	2,053,181
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.

Table A8: Bank Demand Shocks (Control for government subsidies)

	(1)	(2)	(3)	(4)
New Cases/inhab.	-0.000317*			-0.000358
	(0.000186)			(0.000259)
New Deaths/inhab.		-0.00536		0.00160
		(0.00492)		(0.00685)
Lockdown	0.000116	0.000120	0.000120	0.000119
	(0.000415)	(0.000415)	(0.000415)	(0.000415)
Paef*Post paef	-0.0000598	-0.0000673	-0.0000699	-0.0000593
	(0.000388)	(0.000388)	(0.000388)	(0.000388)
Subsidio*Post subsidio	-0.00176 ***	-0.00177***	-0.00176 ***	-0.00177 ***
	(0.000374)	(0.000374)	(0.000374)	(0.000374)
Observations	2,563,392	2,563,392	2,563,392	2,563,392
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.

Table A9: Bank demand Shocks (Monthly)

	(1)	(2)	(3)	(4)
New Cases/inhab.	-0.000437*		-0.000330	
	(0.000237)		(0.000381)	
New Deaths/inhab.		-0.0113*	-0.00409	
		(0.00630)	(0.0102)	
Lockdown	0.00377*	0.00383*	0.00382*	0.00383*
	(0.00215)	(0.00215)	(0.00215)	(0.00215)
Observations	486,456	486,456	486,456	486,456
R-squared	0.098	0.098	0.098	0.098
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 A10: Demand 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 A11: 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 A12: 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 A13: Table 3 interacción newcases*lockdown

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New Cases/inhab.		-0.000320		-0.000312	-0.000307		-0.000309		-0.000307
		(0.000224)		(0.000313)	(0.000317)		(0.000245)		(0.000317)
New Deaths/inhab.			-0.00636	-0.000315	-5.46e-05			-0.00435	-5.46e-05
			(0.00589)	(0.00823)	(0.00842)			(0.00750)	(0.00842)
Lockdown	0.000343	0.000349	0.000350	0.000349	0.000384	0.000343	0.000384	0.000465	0.000384
	(0.000524)	(0.000524)	(0.000524)	(0.000524)	(0.00561)	(0.000524)	(0.000562)	(0.000552)	(0.000561)
Exposure*Post	-0.156***	-0.155***	-0.156***	-0.155***	-0.155***	-0.156***	-0.155***	-0.156***	-0.155 ***
	(0.0402)	(0.0402)	(0.0401)	(0.0402)	(0.0402)	(0.0402)	(0.0402)	(0.0402)	(0.0402)
New Cases*Lockdown					-6.08e-05		-6.14e05		-6.08e-5
					(0.000422)		(0.000412)		(0.000422)
Observations	1,956,674	1,956,674	1,956,674	1,956,674	1,956,674	1,956,674	1,956,674	1,956,674	1,956,674
R-squared	0.023	0.023	0.023	0.023	0.023	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.

Table A14: Bank Supply Shocks (Without big firms)

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000320		-0.000312
		(0.000224)		(0.000313)
New Deaths/inhab.			-0.00636	-0.000315
			(0.00589)	(0.00823)
Lockdown	0.000343	0.000349	0.000350	0.000349
	(0.000524)	(0.000524)	(0.000524)	(0.000524)
Exposure*Post	-0.156***	-0.155***	-0.156***	-0.155***
	(0.0402)	(0.0402)	(0.0401)	(0.0402)
Observations	1,956,674	1,956,674	1,956,674	1,956,674
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.

Table A15: Bank Supply Shocks (Control for government subsidies)

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000315		-0.000307
		(0.000224)		(0.000313)
New Deaths/inhab.			-0.00627	-0.000316
			(0.00590)	(0.00822)
Lockdown	0.000468	0.000476	0.000477	0.000476
	(0.000513)	(0.000513)	(0.000514)	(0.000513)
Exposure*Post	-0.160***	-0.158***	-0.160***	-0.159***
	(0.0400)	(0.0401)	(0.0400)	(0.0401)
Paef*Post paef	-0.00114**	-0.00112**	-0.00113**	-0.00112***
	(0.000527)	(0.000528)	(0.000527)	(0.000528)
Subsidio*Post subsidio	-0.00139**	-0.00139**	-0.00139**	-0.00139***
	(0.000539)	(0.000539)	(0.000539)	(0.000539)
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.

Table A16: Bank supply Shocks (Monthly)

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000427*		-0.000235
		(0.000243)		(0.000390)
New Deaths/inhab.			-0.0125*	-0.00733
			(0.00649)	(0.0105)
Lockdown	0.00459**	0.00464**	0.00464**	0.00465**
	(0.00220)	(0.00220)	(0.00220)	(0.00220)
Exposure*Post	-0.696***	-0.687***	-0.696***	-0.691***
	(0.174)	(0.174)	(0.174)	(0.174)
Observations	451,854	451,854	451,854	451,854
R-squared	0.096	0.096	0.096	0.096
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 A17: Bank Supply Shocks (direct exposure)

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000326		-0.00233
		(0.000225)		(0.000704)
New Deaths/inhab.			-0.00647	-0.233
			(0.00592)	(0.185)
Lockdown	0.000365	0.000372	0.000373	-0.0493***
	(0.000527)	(0.000527)	(0.000527)	(0.0116)
Direct exposure*Post	-0.192***	-0.190***	-0.192***	-4.123***
	(0.0496)	(0.0496)	(0.0496)	(2.144)
Observations	1,948,128	1,948,128	1,948,128	32,571
R-squared	0.023	0.023	0.023	0.865
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.

Table A18: Bank Supply Shocks (bank liquidity)

	(1)	(2)	(3)	(4)
New Cases/inhab.		-0.000135		0.000128
		(0.000174)		(0.000284)
New Deaths/inhab.			-0.00726	-0.0101
			(0.00476)	(0.00784)
Lockdown	0.00197	0.00199	0.0200	0.00199
	(0.00146)	(0.00146)	(0.00146)	(0.00146)
Bank liquidity	0.0424***	0.0424***	0.0423***	0.0423***
	(0.00960)	(0.00960)	(0.00960)	(0.00960)
Observations	456,198	456,198	456,198	456,198
R-squared	0.083	0.083	0.083	0.083
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.

Table A19: 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	-0.192 ***	-0.190 ***	-0.192 ***	-0.190 ***
	(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	✓	✓	✓	✓

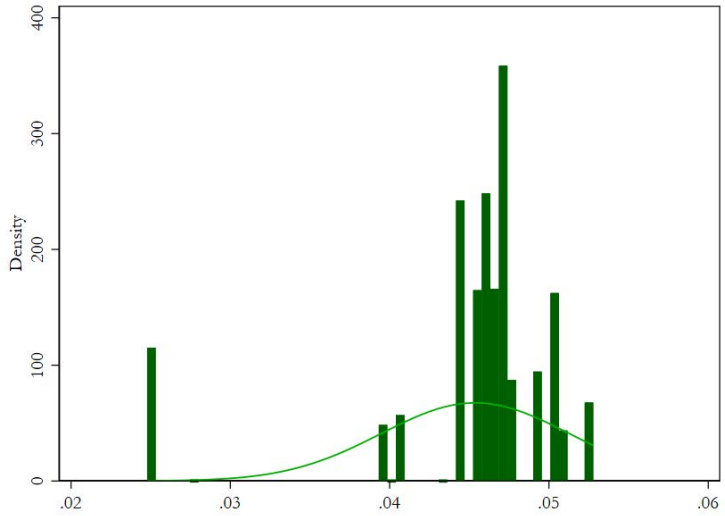
Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Standard errors clustered at the municipal level in parenthesis. Post is a dummy that is switched on after the third week of March (when the lockdown measures were announced). Bank exposure denotes the average expected change in deposits 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.

Table A20: Amiti & Weistein decomposition (alternative specifications)

	Percentage growth				**Monthly log-change**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Common shock	-6.503**			1.000	-8.432***			1.000
	(2.602)			(0)	(1.377)			(0)
Bank shock		0.969***		1.000		0.936***		1.000
		(0.00105)		(0)		(0.000572)		(0)
Firm shock			0.881***	1.0000			0.658***	1.000
			(0.00397)	(0)			(0.00305)	(0)
Observations	252,225	252,225	252,225	252,225	560,303	560,303	560,303	560,303
R-squared	0.001	0.781	0.171	1.000	0.001	0.827	0.077	1.000

Notes: Significance levels shown below *p<0.10, ** p<0.05, ***p<0.01. Each column corresponds to a separate regression of Equation 4.

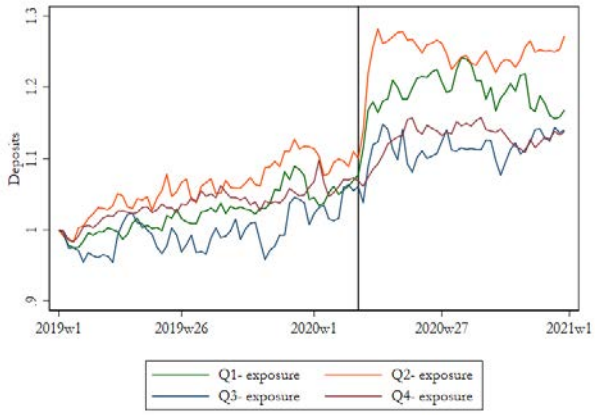
Figure A1: Bank Exposure



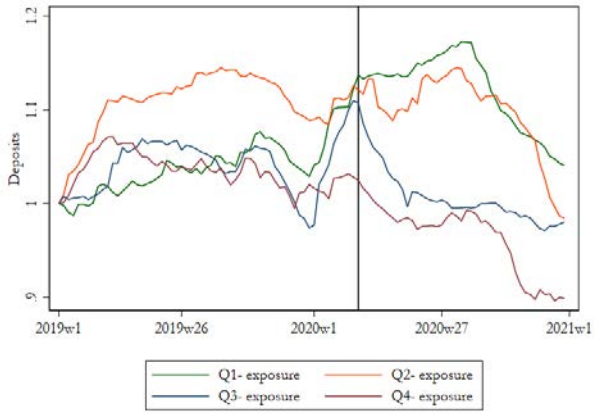
Notes: Bank exposure denotes the average expected change in total deposits during the pandemic, weighted by the respective share of deposits in each municipality during 2019.

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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