Debt Moratoria and Macroeconomics[1]

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Abstract

Our study analyzes the impact of debt moratorium policies, possibly the oldest approach to addressing repayment problems. Using Colombian administrative data, we compare two groups of firms: those narrowly meeting moratorium criteria and those missing it. Our findings show that stressed firms accessing moratoria enjoy favorable loan conditions on subsequent borrowing: higher loan amounts, a higher probability of obtaining a new loan, and lower interest rates, which in turn drive increased investment and employment. We propose a quantitative general equilibrium model to assess short- and long-term implications, and find reduced liquidity concerns alongside heightened default risk. Importantly, our research underscores welfare benefits of interest forgiveness during debt suspension.

Keywords: Debt moratoria, default, regression discontinuity design
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"If *it is difficult for someone to repay a debt, postpone it until a time of ease. And if you waive it as an act of charity, it will be better for you, if only you knew.*" –Qur'an 2:280

1 Introduction

Deeply rooted in history, debt moratorium policies, which refer to the suspension of payments, have only recently gained significant attention.[1] These policies came to the forefront of economic debates at the onset of the 2020 pandemic crisis, with over 70 countries adopting them (for a summary, see Appendix A). Paradoxically, despite their historical lineage and sudden surge in implementation, their importance stands in stark contrast to the academic literature, which has focused primarily on alternative debt resolution practices.

To fill this gap, our study takes a comprehensive approach. Using a combination of theoretical, empirical, and quantitative methods, we delve into the intricacies of this longstanding but unexplored policy. We first establish the causal impact of the policy using administrative data and a regression discontinuity design (RDD). Typically, the local average treatment effects estimated with the RDD are abstracted from general equilibrium effects, limiting the ability to study the policy's long-term effects. To overcome these limitations, we also contribute by building a quantitative default model, matching the short-run evidence obtained from the data and subsequently studying the policy's general equilibrium and long-run effects.

By investigating the policy's effects on firms and banks and their ability to alleviate debt burdens, we contribute key insights and enhance the understanding of these policies within the context of contemporary debt management practices. This is particularly relevant as we navigate a world characterized by historically high debt levels in both the public and private sectors. These levels, already elevated before the COVID-19 pandemic, have only intensified since then.

On the empirical front, we use data from Colombia during 2018-2021 to separately evaluate the effects on stressed and non-stressed firms, which we define as those with and without days past due on their loans (i.e., days in arrears). For stressed firms, we exploit a discontinuity in the eligibility criterion according to how the Colombian regulation was enacted: eligible borrowers (firms) could not exceed 60 days past due on their loans as of the 29^{th} of February 2020. In essence, we argue that stressed borrowers just below and above this threshold are ex-ante similar (and comparable) across different types of loan

[1] To illustrate, if a firms original last day of payment was scheduled for Q1 2025, and they receive a 6-month moratorium, their new last day of payment would be in Q3 2025.

terms, and differ mainly in receiving treatment. For the case of non-stressed firms, we conduct a difference-in-difference (DID) estimation and purge demand shocks from the supply channel by controlling for the interaction between time and firm fixed effects.

While we explore the impact of the policy on a range of financial and real variables, our primary focus revolves around three key indicators: the amount of new loans, the associated interest rates, and default rates. These variables serve as the primary transmission mechanisms influencing critical aspects of firm output, such as investment and labor, with consequential macroeconomic effects. Further, we utilize these variables to discipline our quantitative model.

We recognize that a key challenge for causal inference is the fact that the policy responds directly to the episode of economic distress (in our case, the 2020 pandemic, which was an unprecedented global shock). In principle, the pandemic acts as a confounding factor that affects loans and corporate variables as well as the enactment of the policy. Fortunately, the rich borrower heterogeneity in the entire Colombian credit registry allows us to compare similar firm-bank-loan relationships with and without treatment. For stressed firms, the closeness to the regulatory threshold guarantees local exogeneity, while for non-stressed firms, the firm-time fixed effects strip out unobserved credit demand-driven factors.

We also rule out a potential anticipation of the policy: The regulation's cutoff date, announced on March 17, 2020, mandated that firms should not have 60 days past due on existing loans as of February 29, 2020. Importantly, this regulation cutoff date was established before the first reported COVID-19 case in Colombia, specifically on March 6, 2020. Notably, Colombia was among the earliest countries to implement moratorium measures in response to the COVID-19 shock, as illustrated in Figure A1 of Appendix A, not to mention that these policies did not exist prior to the COVID-19 shock. This timeline emphasizes that the policy was not influenced by any prior knowledge or anticipation of the COVID-19 pandemic, affirming the exogeneity of the policy introduction and its impact on the variables of interest in our study.

Our empirical findings for stressed firms indicate that the debt moratorium policy improved debtors' *new* loan conditions. Specifically, loan amounts (of new loans) increased by 16.4% (consistent with our theoretical predictions), the probability of obtaining a new loan increased by 1.04 percentage points (pp), while interest rates and the default probability decreased by 0.35 and 2.3 pp, respectively. Instead, for non-stressed firms, the policy tightened loan conditions albeit in lesser magnitude: loan amounts decreased by 0.15% (not statistically significant), the probability of obtaining a new loan dropped by 0.08 pp, while interest rates and the default probability increased by 0.005 pp and 0.002 pp, respectively. When mapping these loan-level results to the real sector (yearly firm balances), we find that stressed firms –with debt moratoria– see an increase in employment growth (1.8 pp), investment (0.05 pp), operating revenues (3.9 pp), and assets (1.7 pp), while for non-stressed firms we see a reduction in employment growth (-0.03 pp) and assets (-0.02 pp). Regarding the banking sector, it appears that while the policy imposed initial costs (due to delayed collections), the subsequent reduction in firm defaults and the preservation of loan values (facilitated by the accrual of interest during grace periods) likely resulted in a net benefit to the banking sector. This nuanced perspective highlights the complex interplay of costs and benefits associated with the policy and ultimately underscores the potential benefits for borrowers and lenders in this context.

While it may be intuitive that stressed firms fare better –both financially and economically– if they are provided relief when they need it most, it remains unclear how such policies impact the long-term economic outlook. To address this and make a final contribution, we incorporate a quantitative general equilibrium model of default. Our quantitative framework not only allows us to corroborate the local and short-run effects obtained in our empirical strategy but also enables us to examine the long-run, general equilibrium, and welfare consequences. We then utilize our model as a testing ground to explore and enhance the effectiveness of the policy. In particular, we delve into the optimal debt relief for existing loans. This exploration is particularly relevant due to the divergent approaches observed in different policy applications. For example, firms in Belgium did not accrue interest during moratoria, while they did in Colombia.

A brief context of the model is as follows: a representative firm can borrow two types of loans from banks: (i) a non-contingent (standard) loan, and (ii) a loan that includes provisions for suspending debt payments in response to liquidity shocks. Importantly, the pricing of both loans are endogenously determined. There are two types of aggregate shocks: liquidity shocks, which induce risk-averse behavior in banks that are otherwise risk-neutral, and total factor productivity (TFP) shocks, which impact firms modeled as in Mendoza and Yue (2012). We allow these shocks to be correlated, consistent with our empirical observations.

The primary trade-off firms face is related to the availability of the moratoria asset. On the one hand, this allows firms to secure low-cost financing, specifically during risk-off periods, thereby avoiding costly defaults. On the other hand, borrowing costs associated with the moratoria asset increase during normal times, as banks are reluctant to have their receivables delayed during adverse shocks. Consequently, firms actively manage their loan portfolios by balancing between non-contingent loans and those with moratoria provisions. To model the portfolio problem, we use ingredients from Hatchondo et al.

(2022). Further, we introduce a Nash-bargaining game between lenders and borrowers to restructure delinquent loans when borrowers fail to honor their repayment obligations.

We find that moratoria loans help reduce the number of firm defaults caused by liquidity shocks, leading to an increased overall welfare. However, these loans also contribute to a slightly higher frequency of defaults since borrowers opt for higher debt levels when they have access to the moratorium policy. Put differently, by alleviating liquidity concerns, these loans make borrowing more appealing, thereby increasing the risk of default. Moratorium loans also exacerbate the rise in interest rates (spreads) during normal times. This occurs for two main reasons: (i) lenders typically dislike payment suspensions caused by risk-premium shocks, unless these suspensions significantly reduce the likelihood of default, and (ii) payment suspensions resulting from financing shocks lead to increased debt levels while the firm grapples with these shocks.

Our research also reveals that merely postponing debt payments through moratoria loans provides limited relief as TFP shocks are persistent while the relief policy is short-lived. However, borrowers experience significant welfare gains when debt payment suspension is coupled with debt forgiveness, involving face-value haircuts. Namely, debt forgiveness reduces default risk, not only resulting in a reduction of the average spread but also mitigating the spread increase prompted by liquidity shocks. Intuitively, debt levels rise when moratoria loans defer loan payments, but they actually increase the lenders' expected debt recovery after a default. These findings provide valuable insights and recommendations for policymakers, contributing to the ongoing discourse on effective debt management and fostering financial stability.

In summary, our paper offers significant theoretical, empirical, and quantitative insights into this long-standing policy. Policy recommendations should be tailored with precision based on whether or not the borrower is under financial stress. The policy proves most effective "IF it is difficult for someone to repay a debt." On the contrary, providing it to non-stressed borrowers may, in fact, result in losses. Our quantitative model demonstrates that the policy yields the greatest benefit when combined with debt forgiveness. At the very least, the policy could be structured to include the forgiveness of interest accrued during the debt suspension.

Literature Review: Debt moratoria is one of the oldest practices to address debt repayment problems, but only a handful of research exists on their effectiveness. Earlier research has mainly examined the legislative process of enacting moratorium laws, mainly related to farm foreclosures following a drought (Woodruff, 1937, Alston, 1984). More recently, Dinerstein, Yannelis and Chen (2023) evaluated the effects of the 2020 student debt moratoria, which suspended payments for student loans in the United States. Within this broader context, there exists a substantial body of influential research examining the effectiveness of various debt forbearance measures, including: refinancing, restructuring, and modifications to loan terms such as interest rates, principal, and maturity. Notable among these are the works of: Mian, Rao and Sufi (2013), Mian and Sufi (2011), and Ganong and Noel (2020) which are all concentrated on the aspect of consumer debt. Nevertheless, none of these evaluate the effects of debt suspension.

On the quantitative side, our paper also contributes to the literature on state-contingent assets associated with long-term debt and default. Building upon the framework of Hatchondo et al. (2022), which quantitatively examines the suspension of sovereign debt payments using contingent convertible bonds triggered by changes in the EMBI spread, our quantitative model extends this framework by incorporating a production technology component. Additionally, our research aligns with studies such as Aguiar et al. (2019), Dvorkin et al. (2021), and Mihalache (2020), which delve deeply into the trade-offs between employing maturity extensions and debt forgiveness in the context of debt restructuring for the sovereign debt literature.

2 The Colombian Case

2.1 Matching Firm- and Bank-level data

We use administrative data from the Financial Superintendency (*Superintendencia Financiera de Colombia, Formato 341*) comprising the entire Colombian credit registry (at the loan level) from Q1-2018 to Q4-2021. The data (firm-bank pairs) contain over 4.4 million observations with information on all loans extended to corporates, such as interest rates, outstanding loan amounts, remaining maturity, value of the collateral for guaranteed loans, delinquency days (i.e., days past due), ex-ante probability of default, and ex-ante credit rating.[2] For clarity, while the loan data are reported quarterly, they trace the daily origination of new loans as well as non-performing days.

We merge these data with yearly firm-level balance sheet information from the EMIS (*Emerging Markets Information System*) database to include firm-specific variables such as asset size, liabilities, profits, operating revenue, investment, and equity. We obtain data on employment from CONFECAMARAS (*Colombian Confederation of Chambers of Commerce*), although only for a reduced subset of firms as per data availability. After merging these

[2] The origination of each credit is assigned with a rating qualification and a probability of default by the bank. The credit rating can take values from 1 (lowest rating) to 5 (highest rating), while the probability of default assigned by the bank varies between 0 to 100%. If necessary the bank can adjust both variables each quarter.

sources, which focuses mainly on stressed firms, we match 50,152 *existing* loans (which originated before Q4-2019) provided by 37 financial entities (mostly private banks) to 23,932 firms. Given that our unit of measurement consists of new loans disbursed from bank j to firm i in quarter t, we observe close to 100,000 new loans.

The empirical analysis aims to estimate the effect of the debt moratoria on two main dimensions: new loans conditions and firm performance. In terms of the former, we use loan data for each firm-bank pair and trace any new credit disbursed after the policy (during Q1-2020 to Q4-2021). That is, for each new loan we employ the information at the quarter of origination. In terms of the latter, we employ information from firm balance sheets during 2020-2021 related to: (i) operating revenues, (ii) employment, (iii) plant and equipment purchases (investment), (iv) total assets, (v) total liabilities, (vi) operating profits, and (v) equity.

2.2 Financial Alleviation Measures in Colombia

In March 2020, the Financial Superintendency enacted a set of emergency measures to mitigate the effects of the COVID-19 Pandemic. Among them was the payment relief measure (*grace periods*) to performing debtors with less than or equal to 60 days past due on their credit as of February 29th. While set to end on June 30th of 2020, the program was extended until August 31st of 2021.[3] More recently, the Financial Superintendency has been discussing the possibility of relaunching the program as of September 2023.[4]

During grace periods, which could last up to 120 days, banks could not increase interest on loans nor charge interest-on-interests. Also, loan ratings had to be temporarily frozen, and the number of days past due had to be reset. This framework allows us to rule out the potential anticipation of the policy. On the one hand, the regulation cutoff date applied to *existing* loans, meaning that most eligible loans originated before 2020. On the other hand, the first reported COVID-19 case in Colombia came after the policy, on March 6th. Still, one could argue that Colombian firms could have extrapolated similar measures being undertaken in other parts of the world. Fortunately, Colombia was among the earliest countries to implement moratorium measures in response to the COVID-19 shock, as illustrated in Figure A1 of Appendix A. This timeline, for over 70 countries, underscores that the policy was not influenced by any prior knowledge or anticipation of the COVID-

[3]See regulation CE007 and CE014 (March 17th and 31st) of the Financial Superintendency. While regulation CE007 initially installed a criteria of 30 days past due, regulation CE014 extended the criteria to 60 days.

[4]Media posts on this announcement can be read at the following link.

19 pandemic, affirming the exogeneity of the policy introduction and its impact on the variables of interest.

2.3 Identification

We separately evaluate the effects on stressed and non-stressed firms, which we define as those with and without days past due on their loans. For stressed firms we exploit an RDD approach while for non-stressed firms we conduct a DID estimation.

2.3.1 Stressed Firms

For stressed firms (defaulting firms), we exploit the discontinuity in the eligibility criterion according to how the Colombian regulation was enacted: eligible borrowers could not exceed 60 past due days on their *existing* loan as of the 29^{th} of February 2020.[5] Hence, borrowers within the close vicinity of the threshold are ex-ante similar (and comparable) across various types of financial variables and mainly differ in receiving treatment.

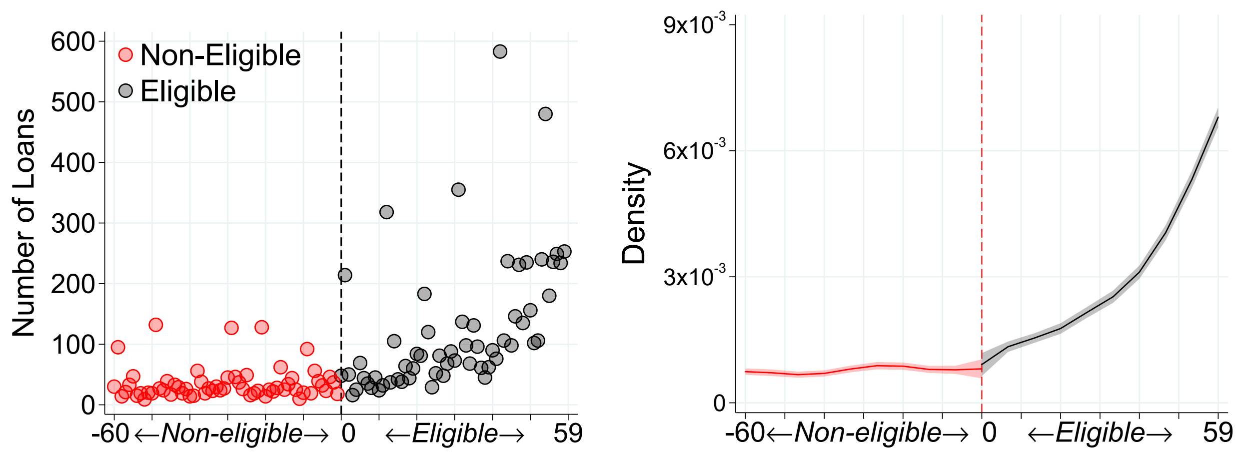
The distribution of eligible and non-eligible loans is plotted in Figure 1. Panel (a) shows the frequency (histogram) of corporate loans for a given number of delinquency days (our running variable, centered at zero henceforth). That is, eligible loans lie on the positive support of the x-axis, and non-eligible loans lie on the negative support. To clarify, -1 and 0 on the x-axis refer to observations with 61 and 60 days of delinquency on their loans as of February 29^{th}, respectively. Likewise, $+59$ refers to loans with only one day of delinquency as of February 29^{th}. Thus, the increased number of loans towards the right end of the figure is not surprising: it simply depicts a greater number of loans with fewer delinquency days, as is common in most loan balances. To exemplify, note that firms' delinquency records drop out as they are paid (i.e., not every loan that starts with one delinquency day will remain in delinquency until default). Therefore, it is typical to observe a higher number of loans that have a few days of delinquencies in their accounts. This behavior is also clearly observed in Figure B2 (Appendix B) , which plots the same chart but covers the pre-treatment period of 2019Q2. The visuals are equivalent if we use 2019Q3 or 2019Q4.

Notably, the policy was announced weeks after the triggering cutoff date to prevent any potential "manipulation" of the running variable. To formally test for this, panel (b) statistically evaluates if there are bunching of observations around the cutoff value (zero-valued vertical line), as proposed by McCrary, 2008. Intuitively, the test separately

[5] To measure delinquency days at the cutoff date of the policy we use end of Q1-2020 data (March 31^{st}) and subtract thirty days to correct for the difference with the actual cutoff date (February 29^{th}).

estimates the density of the running variable (i.e., *existing* loan's past due days) on either side of the cutoff point and provides a Wald estimate in which the null corresponds to the non-existence of a discontinuity at the threshold. The resulting p-value, of 0.819, indicates a lack of manipulation of the running variable.

Figure 1: Eligible and Non-Eligible Loans



(a) Treatment Distribution (b) McCrary's Test

Panel (a) shows the histogram of eligible versus non-eligible corporate loans along the running variable which we center at zero around the cutoff date, 29^{th} of February 2020. Namely, all non-eligible loans (red) are to the left of the cutoff. Panel (b) statistically evaluates if there is a bunching of observations around the cutoff value (McCrary, 2008). The p-value (0.8195) does not reject the null, indicating a lack of manipulation of the running variable.

Next we proceed to formulate the RDD empirical strategy focusing on the the impact of treatment (i.e. receiving a moratoria on *existent* debt) on new lending conditions.[6] We note that there was imperfect compliance among eligible borrowers, meaning that for reasons such as lack of information or costs associated with a time-consuming process, some eligible firms were not compliant with the government policy. For this reason, we correct treatment compliance with a fuzzy instrumental variables *Regression Discontinuity Design* (**RDD**) specification (see Imbens and Lemieux, 2008).

Formally, let X_{ij} be our assignment variable representing the difference between the 60 days cutoff rule and the number of past-due days (as of February 29th, 2020) of firm's "j" *existing* loan with bank "i". Moreover, let $\tilde{D}_{ij}$ be an indicator variable denoting the debt moratoria eligibility of that loan. Given the regulatory conditions of the policy, We know

[6]An equivalent approach is conducted for the RDD estimates on firm-level outcomes related to performance, the only difference being that the variables in the analysis are firm-specific and not firm-bank specific.

that $\tilde{D}_{ij}$ is determined by the the assignment variable X_{ij}, as follows:

$$\tilde{D}_{ij} = \mathbf{1}\left\{X_{ij} \geq 0\right\} \tag{1}$$

To clarify, treatment assignment D_{ij} takes the value of one if the *existing* loan received the policy at some point during 2020 and zero otherwise.

Notice that in a *sharp* setting with full compliance, the treatment assignment is always deterministically determined by the running variable. However, in our case, there is some degree of *fuzziness*, in the sense that our eligibility rule does not perfectly predict treatment (i.e., $D_{ij} \neq \tilde{D}_{ij}$). This is a common case in the RDD literature, where there is still a large and discontinuous jump in the probability of being treated (captured by X_{ij} crossing the threshold), but is does not jump from zero to unity, as in the case of a *sharp* design.[7] In order to correct for the imperfect treatment compliance in our RD design, we employ the standard fuzzy two-stage approach based on the following local non-parametric linear regressions:

$$1^{st} \text{ stage:} \qquad \arg\min_{\boldsymbol{\theta}} \sum_{ij=1}^{I\times J} \left[D_{ij} - \theta_0 + \theta_1 \tilde{D}_{ij} + \theta_2 X_{ij} + \theta_3 X_{ij} \times \tilde{D}_{ij}\right]^2 K\left(\frac{X_{ij}}{h}\right) \tag{2}$$

$$2^{nd} \text{ stage:} \qquad \arg\min_{\boldsymbol{\delta}} \sum_{ij=1}^{I\times J} \left(Loan_{ij} - \delta_0 + \delta_1 \hat{D}_{ij} + \delta_2 X_{ij} + \delta_3 X_{ij} \times \hat{D}_{ij}\right)^2 K\left(\frac{X_{ij}}{h}\right) \tag{3}$$

where $Loan_{ij}$ denotes the several outcomes related to the conditions of new loans that were disbursed after the policy. Our baseline specification controls for bank, quarter of origination and firm's two-digit industry code.[8] The term $K(\cdot)$ denotes a triangular kernel with optimal bandwidth "h" as described in Calonico, Cattaneo and Titiunik (2014). We include the term $\hat{D}_{ij} \times X_{ij}$ to allow for different specifications of how the running variable affects the outcome, at either side of the cutoff.

Intuitively, in the first stage (equation 2) we estimate the predicted probability of treatment, –intent-to-treat–, and use it to instrument compliant observations in the second stage (equation 3). Consequently, the fuzzy RDD estimand can be formulated as:

$$\delta_1 = \frac{\lim_{x\downarrow 0} \mathbb{E}[Loan_{ij}|X_{ij} = x] - \lim_{x\uparrow 0} \mathbb{E}[Loan_{ij}|X_{ij} = x]}{\lim_{x\downarrow 0} \mathbb{E}[D_{ij}|X_{ij} = x] - \lim_{x\uparrow 0} \mathbb{E}[D_{ij}|X_{ij} = x]} \tag{4}$$

[7]In Appendix C we further characterize and illustrate the *fuzziness* induced by imperfect compliance in our RD design.

[8]For the outcome variables of loan amount and interest rate, we also control for the outstanding balance previous to the policy and the interest rate of the *existing* loan at the end of 2020Q1, respectively. This improves the precision of the RDD estimates although our results are robust to excluding these controls.

which represents the ratio between the jump in the outcome variable and the share of compliant observations (those that are triggered by the rule and receive treatment).

2.3.2 Non-stressed Firms

For non-stressed (non-defaulting) firms, we compare only across eligible borrowers, with and without treatment, and employ a difference-in-difference (DID) regression model. This strategy ensures that variation is explained by differences in the moratorium policy rather than by unobserved factors that are bank-firm specific but constant across time or time-varying but common across bank-firm pairs (in Section 3.3 we provide evidence of the parallel trends assumption). However, we acknowledge that our DID identification is not as clean as the previous RDD for stressed firms, as our estimates could capture unobserved firm-specific and time-varying confounding factors driven by self-selection. In other words, since, in this case, all non-stressed firms were eligible, they could choose to participate –or not– in the program. With this caveat in mind, we estimate the following DID model:

$$Loan_{ij,t+1} = \alpha_{j,it} + \gamma D_{ij} + \underbrace{\beta D_{ij} \times T_t}_{\substack{\text{new loans originated} \\ \text{on or after 2020Q1}}} + \underbrace{\sum_{\tau=1}^{q} \phi_{-\tau} D_{ij} \times T_{t+\tau}}_{\substack{\text{new loans originated} \\ \text{on or before 2019Q4}}} + \epsilon_{ij,t} \tag{5}$$

where the $Loan_{ij,t}$ variable again denotes the various outcomes capturing new loan conditions in quarter "t", and D_{ij} is a treatment indicator for *existent* loans that received moratoria. The term $\alpha_{i,jt}$ includes bank and firm-time fixed effects, with the latter specifically controlling for unobserved demand-driven factors. Finally, T_t is a time dummy switched on for $2020Q1 \leq t \leq 2021Q4$, while $T_{t+\tau}$ denotes quarterly time dummies before the policy took place (i.e., $t \leq 2019Q4$). Our coefficient of interest is "β", which captures the effect of debt moratoria on new loans (those that originated after the policy between 2020-2021).[9]

A key assumption is that in the absence of treatment, the difference between treatment and control groups remains constant (i.e., parallel trends assumption). We test for this in Section 3.3.4 for existing loans (2018-2019) under the null $H_0 : \phi_{-\tau} = 0$, for $\tau = 1, 2, ..., 5$, that is, up to five quarters before treatment.

[9] By definition, non-stressed firms have a zero number of delinquency days on their *existing* loans, and hence were eligible to receiving debt moratoria at the time of the policy cutoff date.

3 Results

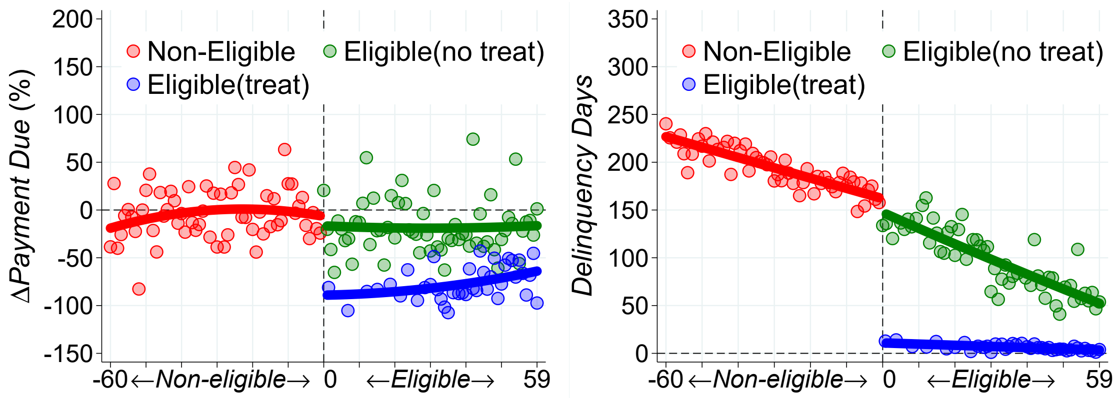
While we investigate the impact of the policy on a variety of financial and real variables, our central emphasis pertains to three key indicators: the amount of new loans, and the corresponding interest and default rates. These variables play a pivotal role as transmission mechanisms, affecting firm output, including investment and labor, thereby potentially inducing macroeconomic effects. Moreover, we use these variables to discipline our quantitative model.

3.1 Loan Conditions

3.1.1 Stressed Firms

As an initial step, we corroborate that the policy had the intended effect on *existing loans*, regarding the (i) suspension of debt repayments and (ii) reset of delinquency days. In other words, we first test whether our data on eligible and treated loans match the characteristics of the policy enforcement during grace periods. Figure 2 shows: (a) the change in payments due and (b) delinquency days. As expected, we observe a large and negative discontinuous jump in debt repayment and delinquency days for loans close and above the cutoff, when comparing eligible treated and non-eligible loans (panels in left column).

Figure 2: Debt Moratoria on Existent Loans



(a) Change in Payment Due

(b) Delinquency Days

The figure shows, for existing loans, the effect of the debt moratoria policy on eligible treated (blue-dots), non-eligible (red-dots), and eligible non-treated (green-dots) loans. Panel (a) shows the enforcement of the policy on debt repayment, where ΔPayment denotes the growth rate relative to Q1-2020. Panel (b) shows the enforcement of the policy on past due days. For treated loans, we use information at the quarter of treatment (i.e., 2020Q2-2020Q4); for non-treated eligible and non-eligible loans, we use data at the end of Q2-2020. Each dot represents the mean of the outcome variable within a bin of the running variable. The number of bins and specific location are determined using a quantile-spaced mimicking variance approach (see Cattaneo, Idrobo and Titiunik (2019)).

Specifically, eligible treated loans reduce their debt payments, while their delinquency days are reset. This confirms exactly what the policy intended. On the other hand, notice that the discontinuity disappears when comparing eligible non-treated loans with non-eligible loans (panels in the right column), which further suggests that the effects are in fact attributable to treatment and not solely on the eligibility status.

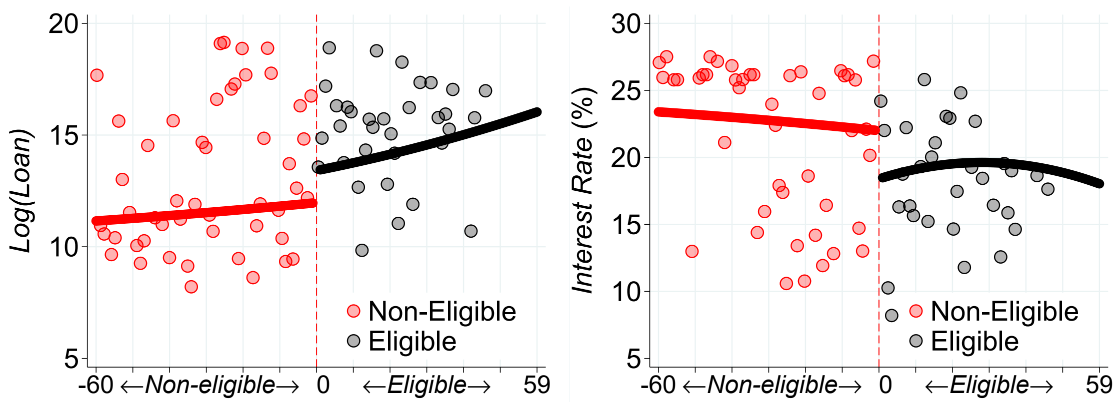
In particular, we find that (see Supplementary Material B) during the quarter of treatment: (i) loan payments were reduced by approximately 90%,[10] and (ii) days past due decreased, on average, by 108 days showing not only a successful reset of days past due

[10]There are two reasons why we do not observe an exact reduction of 100%. The first is that existing loans received benefits at some point during the quarter, while we can only observe the quarterly sum of payments (in some cases, we only observe payments in the quarter before the policy). Second, some companies did not wait until the end of the suspension period. They paid their dues earlier.

buts also an increase in delinquency days for non-treated loans that barely missed the eligibility cutoff.[11]

We next present our results on *new loan conditions* (i.e., for a given firm, loans that originated after the policy). For stressed firms, we present fuzzy RDD estimates as specified by equation (4). Our main findings indicate that stressed firms receiving moratoria on their *existent* debts increased the likelihood of receiving a new loan (extensive margin), while the new credit is of higher amount (intensive margin) and has lower cost relative to stressed firms not receiving debt moratoria. Graphically, the effects are shown in Figure 3, resulting from a discontinuous jump at the cutoff point: positive for loan amounts in panel (a) and negative for loan interest rates in panel (b).

Figure 3: Loan amount and interest rates for eligible and non-eligible observations



(a) Log(Loan) (b) Interest rate

The figure shows the impact of the policy on loan conditions along the running variable. Panel (a) shows the loan amount (in logs of COP). Panel (b) shows the interest rate. We employ data on new loans at the quarter of origination during 2020Q1-2021Q4. Each dot represents the mean of the outcome variable within a bin of the running variable. The number of bins and specific location are determined using a quantile-spaced mimicking variance approach (see Cattaneo, Idrobo and Titiunik (2019)).

More formally, Table 1 reports our benchmark fuzzy RDD results. In general, we find that the debt moratorium policy alleviated the debtors' new loan conditions. Specifically, the policy on stressed firms increased the new loan amount by 16.44%, which is in line

[11]To understand why the latter is true, lets compare the delinquency days of an existent loan with 60 and 61 days past due on February 28th, 2020. Assume the former receive a moratoria on Q2-2020. For the treated loan the reset in delinquency days implies that at the end of Q2-2020 the past due days is greater or equal to zero but lower than 60 days. If we assume that the ineligible loan is delinquent at the end of Q2-2020, then its past due days at least 90 days but no more than 181 days. Therefore, the reduction in delinquency days for the loan receiving a moratoria relative to the ineligible loan is always within the interval $[-181, -30]$ which is consistent with the magnitude of our estimate.

with our theoretical predictions. As a reminder, our model accounts for the fact that firms demand larger loans when moratoria is in effect.

Table 1 also shows that the policy increased the probability of obtaining a new loan by 1.04 pp, and lowered interest rates by 0.35 percentage points (pp). One factor contributing to this decline is banks' expectation of a reduced likelihood of default. This is in line with Ganong and Noel (2020), who show that maturity extensions for household debt obligations, which reduce payments in the short term, significantly reduce default rates. In our data, the ex-ante probability of default is assessed by each bank at the origination of the loan (in column 7, we observe a 1.17 pp decrease). When we examine the ex-post outcomes, we find that stressed firms that received the policy defaulted 2.32 pp less frequently compared to their counterparts who barely missed qualifying for the policy. This confirms that banks' ex-ante assessments were indeed accurate. Our quantitative model also provides the following intuition for this outcome: moratorium policy reliefs firms and mitigates concerns of default triggered by adverse shocks. By mitigating liquidity concerns, moratoria makes indebtedness more attractive. However, our quantitative model predicts that this increase in debt, while reducing the likelihood of default in the short run, will lead to slightly higher default risk in the long run unless future moratorium policies are accompanied by debt forgiveness.

Finally, the policy also increased loan maturity by 5.59 years and improved the loan rating by approximately four categories. However, it also increased the amount of loan collateral requirements by 1.1 pp.[12]

3.1.2 Non-stressed Firms

We next evaluate the effects of debt moratorium policies for non-stressed firms (i.e., with no days past due on their *existing* loans). Since our RDD identification no longer applies (all firms are eligible for treatment), we carry out a difference-in-difference loan-level estimation, as exemplified by equation (5).

Our results, reported in Table 2, for non-stressed point towards tighter loan conditions (albeit much lesser in magnitude). Namely, for *non-stressed* firms, receiving moratoria on their *existing* loans reduced the probability of acquiring a new loan by -0.078 pp, while conditional on obtaining a new credit, the amount was reduced by 0.15% (not statistically significant), the interest rate increased rate by 0.005 pp, and the ex-ante and ex-post probability of default raised by 0.001 pp and 0.003 pp, respectively. Notice that only our estimates for interest rate and ex-post default probability are statistically significant. These

[12] For comparability purposes, in Appendix D we show summary loan statistics for stressed firms (Table D1) and non-stressed firms (Table D2).

Table 1: RD Benchmark results: new loans

	Intensive	Extensive	Interest	Maturity	Collateral	Rating	Default Prob.	
	Log(Loan)	$\mathbb{1}\{\text{loan}\}$					Ex-ante	Ex-post
Fuzzy-RD	16.44***	1.04*	-0.35***	5.59*	1.10***	4.07*	-1.17*	-2.32***
	(4.8)	(0.6)	(0.1)	(2.9)	(0.6)	(2.2)	(0.7)	(0.8)
	First Stage							
D_{ij}	0.19***	0.15*	0.34***	0.15***	0.20***	0.16***	0.16***	0.14***
	(0.0)	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Observations	35,072	70,764	35,072	35,072	35,072	35,072	35,072	68,901
BW (in days)	15.3	13.0	7.5	11.9	13.3	19.9	20.5	17.8

Authors' calculations. Table shows the estimates for the effect of the debt moratoria on new loan conditions for stressed firms. Estimates in the first row correspond to Fuzzy RD coefficient δ_1 in equation (4). The second row shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (2). The last row report the bandwidth (BW) in days used to compute the local RD estimate. We employ data on new loan conditions during 2020Q1-2021Q4. Robust Bias-corrected standard errors in parentheses, *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. To capture the intensive margin for new loans, we use the amount (in logs of COP) at the quarter of origination. The extensive margin of new loans is captured by a dummy taking the value of one in the quarter of origination. Maturity is denoted in number of years, collateral is expressed as percentages of the loan amount, credit rating is a categorical variable from 1-5 where 5 is the highest rating, ex-ante default represents the expected default probability assigned to the loan by the bank, and ex-post default is a dummy variable that takes the value of one if the loan has more than thirty days of delinquency at the end of each quarter. The interest rate, maturity, collateral, rating of new loans, and ex-ante default are measured only at the quarter of origination of the loan. All columns control for bank, quarter, and two-digit industry code fixed effects. For the intensive margin (first column) and the interest rate (third column), we control for the balance of the existing loan and its interest rate at the end of Q1-2020, respectively.

results are also consistent with our models predictions and highlight banks unwillingness to supply loans when resources are scarce. However, we argue that the small magnitudes (arguably economically insignificant) stem from the fact that non-stressed firms are less vulnerable to shocks, and consequently react less to a given subsidy. An interpretation of this finding is that future policies could target only vulnerable firms to maximize social welfare, as firms in our DID setting were not considered stressed.[13]

3.1.3 Financial Sector

We now highlight a few points about the potential impact of the policy on banks. The costs of the policy appear to be imposed on banks ex-ante. By forcing banks to delay the collection of their claims during the suspension periods and not subsidizing these costs, it can be argued that banks have borne the toll of the policy. This may be particularly relevant as the debt moratoria was applied during a period when lenders would value cash more.

Our analysis leads us to infer that banks may not necessarily be worse off with the introduction of the policy, and in fact, may even be better off. The ex-ante "Default Prob" column of Table 1 shows that stressed firms that received the policy defaulted 2.3 pp

[13]An example of this approach is currently practiced by banks in the EU: following the success of debt moratoria, banks now offer payment holidays to agents experiencing hardship (see HM Government, 2022).

Table 2: DID Benchmark results: new loans

	Intensive	Extensive	Interest	Maturity	Collateral	Rating	Default Prob.	
	Log(Loan)	$\mathbb{1}\{\text{loan}\}$					Ex-ante	Ex-post
DID	-0.149	-0.078***	0.005*	-0.109	-0.046	-0.010	0.001	0.002***
	(0.092)	(0.008)	(0.003)	(0.089)	(0.032)	(0.006)	(0.001)	(0.000)
Observations	263,304	379,577	267,415	272,872	263,304	272,872	272,868	809,435
$\bar{R}^2$	0.426	0.183	0.376	0.173	0.029	0.573	0.679	0.145

Authors' calculations. Table shows the estimates for the effect of the debt moratoria on new loan conditions for non-stressed firms. Estimates correspond to DID coefficient β in equation (5). Standard errors in parentheses, *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. We employ data on new loan conditions during 2018Q4-2021Q4. To capture the intensive margin for new loans, we use the amount (in logs of COP) at the quarter of origination. The extensive margin of new loans is captured by a dummy taking the value of one in the quarter of origination. Maturity is denoted in number of years, collateral is expressed as percentages of the loan amount, credit rating is a categorical variable from 1-5 where 5 is the highest rating, ex-ante default represents the expected default probability assigned to the loan by the bank, and ex-post default is a dummy variable that takes the value of one if the loan has more than thirty days of delinquency at the end of each quarter. The interest rate, maturity, collateral, rating of new loans, and ex-ante default are measured only at the quarter of origination of the loan. All columns control for bank and firm-quarter fixed effects.

less than their counterparts who narrowly missed qualifying for the policy. This is also consistent with our findings in the quantitative section, as the policy almost completely eliminates liquidity-driven defaults.

In the Colombian context, loan interests continue to accrue during the suspension period. Consequently, banks were not compelled to accept a reduction in the value of their claims. Instead, they ended up receiving more than they would have without the policy because firms that narrowly missed the program's eligibility experienced a higher rate of default. In sum, we argue that while the policy did impose upfront costs on banks in terms of delayed claim collections, the subsequent reduction in defaults and the associated preservation of loan values may have led to a net benefit for the banking sector.

3.2 Real Sector (Firm-Balances)

We next evaluate whether the effects on new loan conditions translate into end-of-year firm balances. To do so, we control for firm-sector and firm-size fixed effects. Our firm-level dependent variables consist of: employment, investment rate, operational revenue, liabilities, assets, profits, and equity. All variables, except investment rate, are expressed in percentages symmetric growth rate changes.

3.2.1 Stressed Firms

For stressed firms, we see an increase in the investment rate (0.05 pp) as well as in the growth of: employment (1.8 pp), operating revenues (3.8 pp), total assets (1.7 pp), total liabilities (1.95 pp), profits (2.5 pp), and equity (0.85 pp). These results are presented in Table 3 (to illustrate, some of these are also presented in Figure 4). The rationale behind

Table 3: RD benchmark results: firm level outcomes

	ΔEmp.	Inv.rate	ΔOp. Rev.	Δ Assets	ΔLiab.	ΔProfit	ΔEquity
Fuzzy-RD	1.83***	0.05**	3.87***	1.70**	1.95***	2.54***	0.85*
	(0.7)	(0.0)	(0.8)	(0.8)	(0.7)	(0.8)	(0.5)
	First Stage						
D_{ij}	0.21***	0.22***	0.35***	0.16***	0.19***	0.19***	0.15***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.1)	(0.0)
Observations	15,379	11,386	31,786	30,887	30,660	29,762	30,887
BW (in days)	28.9	9.7	7.0	12.8	9.0	9.4	14.8

Authors' calculations. Table shows the estimates for the effect of the debt moratoria on firm-level variables for stressed firms. Estimates in the first row correspond to the Fuzzy RD coefficient δ_1 in equation (4). The second row shows the first stage estimates for the probability of treatment (D_{ij}) described in equation (2). Robust Bias-corrected standard errors clustered at the firm's province in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. The last row report the Bandwidth (BW) in days used to compute the local RD estimate. We use employment and balance sheet data for firms during 2020-2021. ΔEmp., ΔOp. Rev., ΔAssets and ΔLiab. denote yearly symmetric growth rates of the number of employees, operating revenues, total assets, and liabilities, respectively. Inv.rate represents the investment rate computed as the ratio of new purchases of buildings, plants, and equipment to total assets lagged one year. ΔProfit, ΔEquity are computed as the yearly change in gross profits and equity relative to the operating revenues and total assets lagged one year, respectively. All columns control for bank and two-digit industry codes' fixed effects.

these positive macroeconomic outcomes can be attributed to two key mechanisms in our quantitative model. First, the policy effectively averts defaults that would have otherwise resulted in efficiency losses for employment and output. Second, there is a noteworthy impact via the interest rate channel. With working capital, loans become more affordable for firms that had limited access to the policy, and can therefore allocate resources more efficiently.

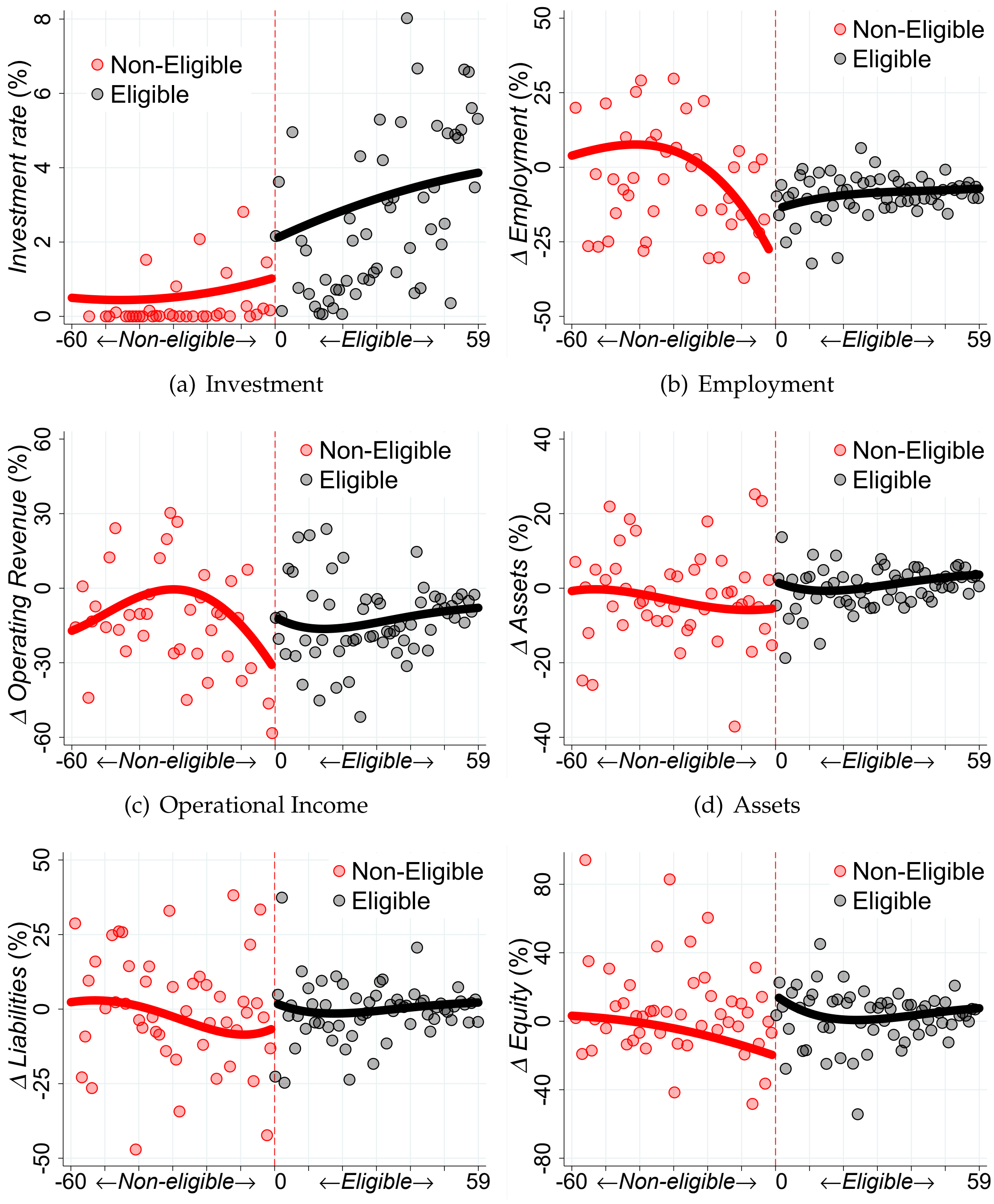
3.2.2 Non-stressed Firms

For non-stressed firms, as shown in Table 4, we do not find significant results except for a slight decrease in growth of: employment (0.026 pp) assets (0.016 pp) and liabilities (0.027 pp), which confirms that non-defaulting firms are much less vulnerable. That is, even if we find small effects on their loan conditions, these are not significantly translated into their end-of-year balances. This is intuitive as our findings on loan conditions for stressed firms are not *economically* meaningful.

3.3 Robustness checks

For expositional purposes, we present robustness checks focusing on our two main variables of interest: loan amounts and interest rates. Robustness for all other variables, yielding similar results, can be made available upon request. For stressed firms, we conduct exercises with placebo cutoffs and falsification tests (Section 3.3.1), we test for bal-

Figure 4: Firm-level outcomes for eligible and non-eligible firms



(a) Investment

(b) Employment

(c) Operational Income

(d) Assets

(e) Liabilities

(f) Equity

The figure shows the impact of the policy on firm-level outcomes along the running variable. Panel (a) shows the investment rate. Panel (b), (c), (d), (e), and (f) show the growth rate of employment, operating revenue, total assets, total liabilities, and equity. We use employment and balance sheet data for firms during 2020-2021. Each dot represents the mean of the outcome variable within a bin of the running variable. The number of bins and specific location are determined using a quantile-spaced mimicking variance approach (see Cattaneo, Idrobo and Titiunik (2019)).

Table 4: DID benchmark results: firm level outcomes

	ΔEmp.	Inv. rate	ΔOp. Rev.	Δ Assets	ΔLiab.	ΔProfit	ΔEquity
DID	-0.026*	0.022	0.013	-0.016***	-0.027**	-0.001	0.647
	(0.015)	(0.047)	(0.016)	(0.003)	(0.010)	(0.005)	(0.450)
Observations	131,431	76,044	204,954	206,437	208,564	196,029	202,815
$\bar{R}^2$	6.7	0.2	1.5	2.7	1.0	3.3	0.0

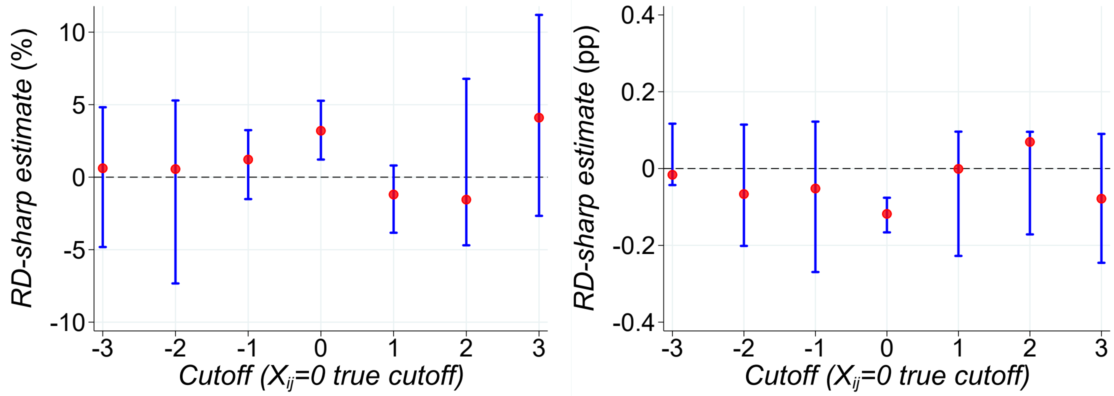
Authors' calculations. Table shows the estimates for the effect of the debt moratoria on firm-level variables for non-stressed firms. Estimates correspond to the DID coefficient β in equation (5). Standard errors clustered at the firm's province in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. We use employment and balance sheet data for firms during 2015-2021. ΔEmp., ΔOp. Rev., ΔAssets and ΔLiab. denote yearly symmetric growth rates of the number of employees, operating revenues, total assets, and liabilities, respectively. Inv.rate represents the investment rate computed as the ratio of new purchases of buildings, plants, and equipment to total assets lagged one year. ΔProfits, ΔEquity are computed as the yearly change in gross profits and equity relative to the operating revenues and total assets lagged one year, respectively. All columns control for bank-year and two-digit industry code fixed effects.

anced covariates (Section 3.3.2), and we check the robustness of our results to alternative specifications (Section 3.3.3). In turn, for non-stressed firms, we present evidence of the (DID) parallel trends assumption (Section: 3.3.4).

3.3.1 Placebo Cutoffs and Falsification Tests

We begin our robustness checks by evaluating arbitrary cutoff points different from the one triggering treatment. In principle, a significant placebo cutoff could indicate either: (i) a concurrent policy, potentially contaminating our results, or (ii) systematic differences among eligible and non-eligible borrowers –even far from the discontinuity point–. In Figure 5, we evaluate placebo cutoffs for days before and after the actual cutoff $X_{ij} = 0$. As expected, none of these different cutoffs are statistically significant for both loan amounts (panel a) and interest rates (panel b). Further, in Table 5, we present a falsification test in which we regress the treatment status (D_{ij}) on banks' and firms' balance sheet information. For the entire sample (column 1), treatment is partially explained by bank variables such as collateral and maturity and firm variables such as profits (in some bandwidths also, assets, liabilities, and equity). However, when restricting the sample to smaller bandwidths (within the vicinity of the triggering threshold), treatment becomes uncoupled from these factors. With a 20-day bandwidth (column 5), the treatment assignment is no further explained by either bank or firm variables. The only explanatory power is driven by the running variable, which, by the characteristics of our design, increases as observations get closer to the cutoff (BW=0). This exogenous variation around the cutoff is precisely what our empirical strategy exploits for the case of stressed firms.

Figure 5: Placebo cutoffs



(a) Log(Loan)

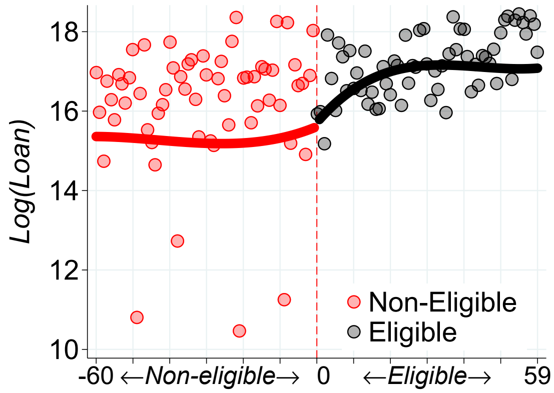
(b) Interest Rate

The figure shows the sharp RD estimates for (a) the size of new loans and (b) the loan interest rate at the quarter of origination using alternative placebo cutoffs. We employ data on new loans at the quarter of origination during 2020q1-2021q4. Each placebo cutoff denotes the closest possible value (from the true cutoff) for the running variable. The red dots and vertical blue lines capture the point estimates and 95% robust confidence intervals, respectively. To compute RD estimates for positive (negative) placebo cutoffs, we restrict the sample to only eligible (non-eligible) loans to avoid potential "*contamination*" coming from eligibility to the debt moratorium policy (see Cattaneo, Idrobo and Titiunik (2019)).

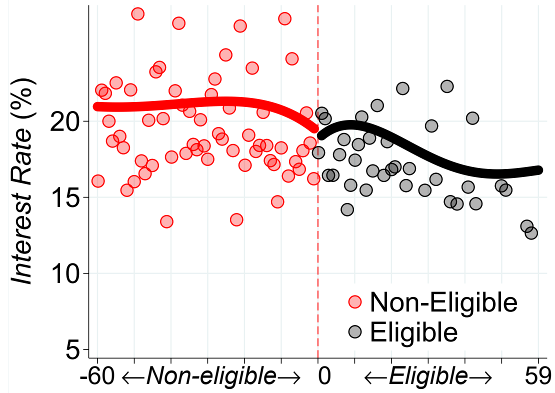
3.3.2 Checking for Balanced Covariates

One crucial element in our RDD identification strategy is that loans in treatment and control groups should be almost identical in everything except receiving treatment. A leading marker, one that rules out precise sorting (i.e., manipulation or self-selection around the cutoff), commonly known as the McCrary Test, was previously presented in Figure 1 (panel b). In addition to this test, in Appendix E.1, we present a "donut-hole" test, which re-estimates our benchmark results but excludes observations in the immediate neighborhood of the cutoff. Intuitively, the test checks for additional "bunching" of observations around the cutoff that the McCrary test might have potentially missed. As shown, we find similar results when excluding 1, 2, and 3 days before and after the actual cutoff. To complement this analysis, we present a visual inspection of whether loan amount, interest rates, and firm-level variables such as investment, employment, operation income, and total assets carried systematic differences *before* the debt moratorium policy took place (i.e., existing loans, previous to the policy, $t < 2020$). If this were the case, then our results would reflect pre-existing differences rather than a causal relationship due to the policy. As shown in Figure 6, the conditions on existing loans are equally balanced across the running variable for the quarter before the policy (2019Q4).

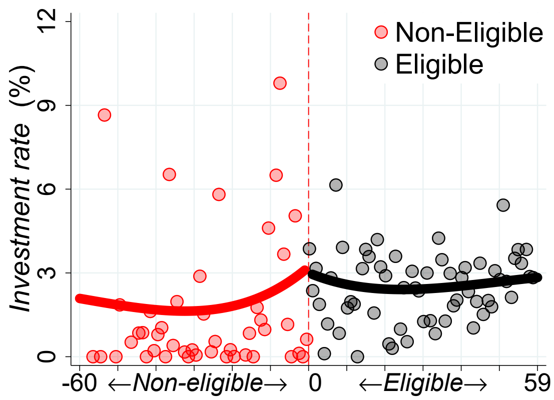
Figure 6: Testing for pre-existing differences: Stressed Firms



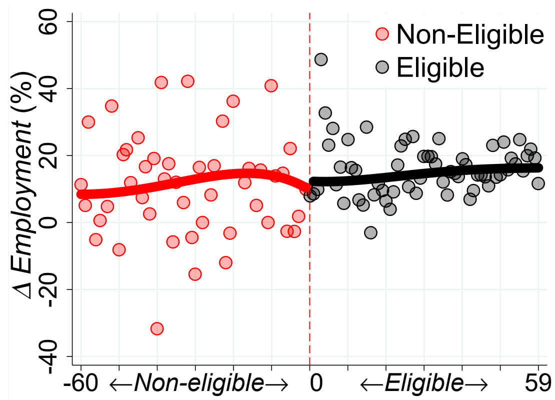
(a) Log(Loan)



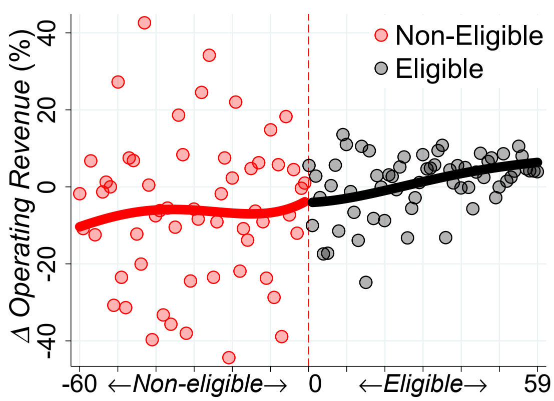
(b) Interest Rate



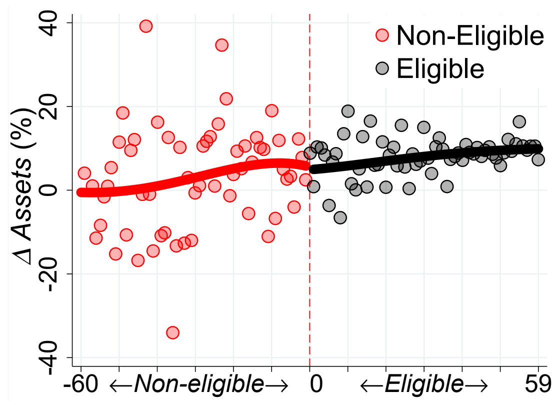
(c) Investment



(d) Employment



(e) Operational Revenue



(f) Assets

The figure examines pre-existing differences along the running variable before the implementation of the policy. We employ loan and balance sheet data for firms at the end of 2019. Panel (a) shows the outstanding loan (in logs of COP), and panel (b) the interest rate. Panel (c) shows the investment rate, while panels (d), (e), and (f) show the growth rate of employment, operating income, and total assets, respectively. Each dot represents the mean of the outcome within a bin of the running variable. The number of bins and specific location are determined using a quantile-spaced mimicking variance approach (see Cattaneo, Idrobo and Titiunik (2019)).

Table 5: Falsification test: (Un)-Predictability of Treatment

	Entire sample	BW=80	BW=60	BW=40	BW=20
Loan variables					
Loan	0.000	0.000	-0.000	0.009	0.030
	(0.001)	(0.001)	(0.001)	(0.006)	(0.022)
Collateral	0.000**	0.002***	0.001**	-0.006	-0.015
	(0.000)	(0.001)	(0.000)	(0.008)	(0.017)
Maturity	0.007***	0.003*	-0.006**	-0.005	0.001
	(0.001)	(0.002)	(0.003)	(0.005)	(0.008)
Running Var X_{ij}	0.001***	0.003***	0.009***	0.012***	0.014***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Total Assets	0.007	0.012***	0.022***	0.022***	0.004
	(0.007)	(0.003)	(0.002)	(0.003)	(0.017)
Total liabilities	-0.001	-0.001***	-0.002***	-0.002***	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
Equity	-0.007	-0.012***	-0.022***	-0.022***	-0.005
	(0.007)	(0.003)	(0.002)	(0.004)	(0.017)
Profits	-0.000**	-0.000	-0.000	0.001	0.013
	(0.000)	(0.000)	(0.001)	(0.005)	(0.020)
Constant	0.552***	0.430***	0.335***	0.286***	0.213***
	(0.007)	(0.015)	(0.016)	(0.020)	(0.033)
Observations	15,904	8,458	2,494	968	316
R-squared	8.10	5.26	22.10	21.93	12.98
F-test all	23.29	33.14	128.85	73.17	5.42
pvalue all	0.00	0.00	0.00	0.00	0.00

Each column reports a linear regression with the treatment dummy $D_{ij,t}$ as the dependent variable and with different bandwidth choices (entire sample, 80, 60, 40, and 20 days). Heteroskedasticity-robust standard errors in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. All columns control for bank and year fixed effects.

In Table E3 of Appendix E.2, we conduct a formal analysis of all the relevant loan and firm-level variables, which include loan characteristics such as loan outstanding balance, interest rates, collateral requirements, maturity periods, credit ratings, ex-ante default probabilities, ex-post default probabilities, delinquency days, as well as broader firm-level indicators like investment rates, changes in employment, changes in operating revenue, changes in assets, changes in liabilities, and changes in profits. As shown, these results provide evidence of equally balanced distributions across the running variable before the treatment was enacted.

3.3.3 Alternative Specifications

As an additional robustness tests, We also check how our results differ with two changes (see Supplementary Material C). First, we restrict our analysis to firms with a single *existing* loan relationship prior the debt moratorium policy to isolate the effect of firms with multiple loans some eligible for treatment. Our results not only remain but are, in most cases, relatively stronger and point to the importance of the moratoria for stressed-firms with single bank relationships.

Lastly, we control for firms' credit risk on *existing* loans to absorb any effect of the debt moratoria coming from the "artificial" boost in credit ratings to firms receiving suspension of payments. our results show that controlling by this channel strengthens the increase in the size of new loans and the drop in the interest rate on stressed treated firms while, at the same time, absorbs completely the effect on ex-ante firm's default and credit rating, which are now not significant. The latter is consistent with a stronger improvement in end-of-year employment, investment rate, and operating revenues for treated stressed firms when we control for this potentially confounding channel.

3.3.4 Parallel Trends Assumption

To ensure the internal validity of our estimates for the case of non-stressed firms, we next test for the parallel trends assumption. Intuitively, in periods before intervention, the difference between treatment and control loans must be constant over time. In our context, pre-treatment observations correspond to *existing* loans, as opposed to newly disbursed loans after treatment (as in our benchmark case).

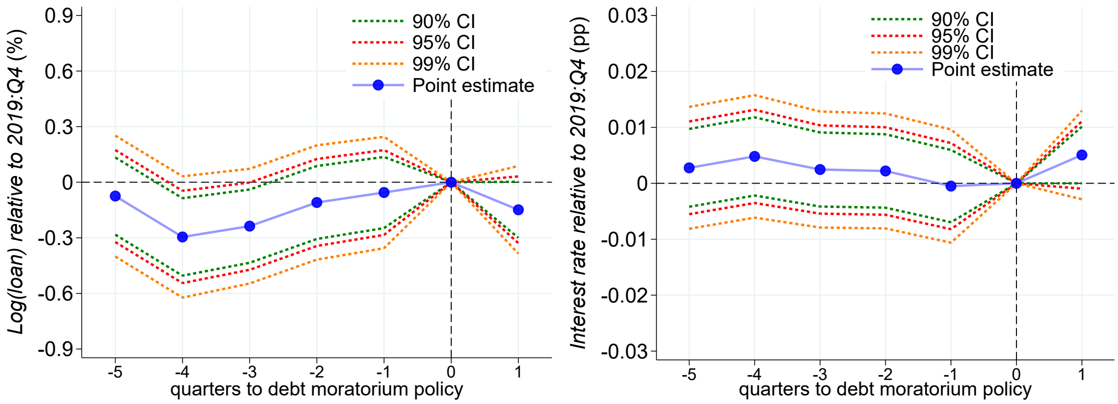
In Figure 7, we present results that test for this assumption, as exemplified by equation (5). As shown, the effect on loan amount (panel a) and interest rates (panel b) before the policy is not statistically significant. Formally, we do not reject the null that interaction coefficients associated with pre-treatment time dummies are equal to zero. On the other hand, for the period after treatment, results match our benchmark results (see Table 2).[14]

4 A Quantitative Exploration

Through our empirical approach, we have estimated the immediate and local effects of debt moratorium policies, shedding light on their short-term effects. While we have causally established that stressed firms fare better, both financially and economically, when provided relief when they need it most, the long-term impact of such policies on the economic outlook remains unclear. Given the widespread implementation of these policies in the aftermath of the pandemic, it is necessary to properly price these moratorium loans as the re-introduction of this policy will not be unanticipated anymore along with

[14] In Supplementary Material D we also show evidence of the parallel trends assumption for other loan-level variables (i.e., collateral requirements, loan maturity, credit rating, and default probability) and firm-level variables (i.e., investment, employment, liabilities, assets, profits, equity, and operating revenue.)

Figure 7: Parallel trends assumption for non-stressed firms



(a) Log(Loan)

(b) Interest Rate

The figure plots the point estimates and confidence intervals for the lead (ϕ_{-1},..,ϕ_{-5}) and contemporaneous (β) coefficients of equation (5). We employ data on new loans at the origination quarter during 2018Q4-2021Q4. Panel (a) shows the dynamic estimates for new loans (in logs of COP). Panel (b) shows the results for the interest rate of new loans.

standard loans. Besides, given the success of moratoria policies following the COVID-19, banks now offer payment holidays for individuals going through hardship (see HM Government (2022)).

To address this gap, we extend our analysis to a quantitative framework. This expanded framework enables us to explore not only the long-term and general equilibrium effects but also the broader welfare implications associated with debt moratorium policies. In addition, this approach provides a basis for exploring potential policy amendments.

This section provides a brief overview of a quantitative default model that illustrates the potential macroeconomic impact of introducing the debt moratorium policy. Two crucial modeling choices underpinning our findings are emphasized: a portfolio problem involving standard loans and moratorium loans, and the specification of the production technology.

We incorporate an additional defaultable asset class, which incorporates grace periods during adverse shocks on payments. This class is referred to as a moratorium asset. This inclusion allows us to propose potential amendments to the policy for future reference. If one were to consider this shock as a one-time event, or if such a moratorium policy were never to be introduced again, our analysis would have focused solely on counterfactual policies without the need for a portfolio problem. However, as this program is anticipated to be relaunched in Colombia as well, see footnote 4, and given that this longstanding policy might resurface in response to future shocks as a toolkit to policymakers, it is both plausible and prudent to engage in a portfolio problem to explore alternative, welfareenhancing moratorium policies. Alternatively, one can drop the endogenous pricing of moratorium loans but focus on the one-time introduction of a moratorium policy in a heterogeneous agent model and study the dynamics as in Guler et al., 2024 where they study the effect of moratorium policies on the household's mortgage. Our contribution on the modeling side is instead to properly price these assets and study the long-run dynamics.

To solve the portfolio problem, we rely on ingredients from Hatchondo et al. (2022). We adopt the standard production economy model originally proposed by Mendoza and Yue (2012). A salient ingredient of the framework of Mendoza and Yue (2012) is that firms require working capital financing to pay for a subset of imported inputs, which are imperfect substitutes for domestic or other inputs. As a result, default generates an efficiency loss in production and results in an endogenous decline in output. We extend the production framework of Mendoza and Yue (2012) by allowing the rate on working capital loans to be a function of default risk, and this will also define how we link the consumer's borrowing conditions to the real economy. Lastly, we introduce a Nash-bargaining game between the borrower and the lender in the event of a default.[15]

In particular, we study an equilibrium default model in which a representative firm obtains loans from banks in two different categories: (i) non-contingent (standard) long-term loans: These loans are conventional and do not contain any special conditions. They follow the typical repayment structure. (ii) Moratorium loans: These loans have a unique feature - the possibility of suspending debt payments when the economy experiences liquidity shocks, which triggers an increase in bank risk aversion. Apart from this suspension feature, these loans are identical to standard loans. The interest rates for both standard and moratorium loans are determined in the model as endogenous variables. Two types of aggregate shocks affect the economy. Liquidity shocks: These shocks make otherwise risk-neutral banks risk-averse. These shocks are associated with changes in banks' risk aversion. Total factor productivity (TFP) shocks: These shocks affect firms' productivity levels. Importantly, these two types of shocks are modeled to be correlated, reflecting the observed empirical relationship between them. During liquidity shocks, al-

[15]The rationale is that the introduction of a new asset with grace period clauses may alter the renegotiation dynamics particularly when default likelihoods are high as these are the periods in which grace periods are triggered. By setting out, ex-ante, a pre-defined path for each restructuring, such contracts would dramatically change the renegotiation and restructuring process. The outside options for all parties will be very different. Because of this, it is unclear that haircut numbers calculated based on non-moratoria restructurings and used in the calibration would apply to a world where most debt was in moratoria loans. To address this concern, we incorporate a Nash-bargaining game between lenders and borrowers into the analysis. Intriguingly, it turns out that our outcomes remain equivalent even when we remove the Nash-bargaining game structure, assuming either zero recovery or a constant recovery upon the borrower's re-entry into the credit markets. This insight underlines the robustness of our results under different assumptions.

though payments on moratorium loans are suspended, they continue to accrue interest during the suspension period. There are no idiosyncratic shocks in the economy.

To tighten the connection between the reduced part of the paper and the calibrated macro analysis, we utilize Colombian administrative data where possible. We begin by introducing a COVID-type shock to estimate the model's initial short-term dynamics and align it with its empirical counterpart. Subsequently, we use the model's general equilibrium structure to estimate the long-run effects.

The main trade-off that firms face with the availability of moratorium assets is that they provide the following covariance: The firm can borrow cheaply with a moratorium asset precisely during risk-off episodes and avoid costly defaults. However, the cost of borrowing with a moratorium asset increases in normal times because banks do not like their claims to be delayed during adverse shocks. Thus, firms actively manage their portfolio between standard (non-contingent) loans and moratorium loans.

After tightening the link between our empirical results and the quantitative model, we investigate the effects of an unanticipated announcement that permits firms to borrow new loans with payment suspensions. This analysis allows us to explore the implications of such a policy on various economic variables. In particular, we examine the effects on new loan amounts and interest rates, providing insights into the borrowing behavior of firms in response to the announcement. Additionally, we assess the impact on real variables such as employment, income, and overall welfare, enabling us to gauge the broader economic consequences of the policy. Furthermore, we complement our analysis by considering an amendment to the policy. Specifically, we explore the scenario where payments during suspensions do not accrue interest rates, or a portion of the loan is forgiven, or firms still pay a fraction of their loans during suspensions. By investigating this alternative approach, we aim to quantify the potential gains from such a modified moratorium policy.

Our research indicates that the benefits of the moratorium policy are significantly higher when payments do not accrue interest during suspensions. Similarly, the highest welfare gains are obtained when firms do not pay any fraction of their loans during suspensions. The intuition is as follows. TFP shocks are persistent, while the duration of the moratorium policy, which is triggered by a liquidity shock, is typically short-lived. Thus, debt suspension provides limited relief. With debt forgiveness, it provides the right covariance: both the probability of default and spreads are reduced in both the short and long run. This finding underscores the importance of carefully designing and implementing policies to maximize their positive impact on the welfare of firms and the economy as a whole. In what follows, we provide a succinct description of the key elements of the model and relegate the rest of the exposition and details of the quantitative application, including the quantitative model, calibration, and numerical algorithm, to Appendix F purely due to space constraints of the journal.

Households. Households choose consumption and labor supply to maximize a standard time-separable utility function. Households make the borrowing decision on behalf of the firms. In the event of a loan default, households engage in a Nash-bargaining game with banks. This negotiation process is aimed at determining the recovery rate for the amount that has become delinquent. This step reflects the households' interaction with banks in order to reach an agreement on how much of the delinquent sum needs to be repaid.

Final Goods Producers. Firms in this sector produce using labor and intermediate goods, as well as a time-invariant capital stock. They combine domestically produced inputs and imported inputs into a single final good.

Intermediate Goods Producers. Intermediate good-producing firms rent labor services from households to produce the domestic inputs used in the production of final goods.

Lenders. Banks are risk-neutral during normal times and become risk-averse during risk-off episodes. This transition follows an estimated Markov process. If a firm chooses to declare default, banks go into a Nash-bargaining process with firms over the recovery rate on the loan.

5 Quantitative Results

This section presents our results. We first calibrate our baseline model to Colombia's aggregate moments and then introduce a moratoria loan. Using our model, we match the short-run empirical estimates obtained in Section 3.1.1 to demonstrate that our model is closely aligned with our estimates. Having established the consistency of our model with its empirical counterpart, we then use it to study alternative policy amendments.

Table 6 compares the data moments from Colombian data with the one obtained from the model. The model features plausible moments and matches both the debt statistics as well as the business cycle moments reasonably well. Briefly, the model generates a loan-to-income ratio of 15.5 percent, which corresponds to the median loan-to-income ratio of all Colombian firms in our administrative data. The model can also match the median credit spreads. It is not immediately possible to compute the bankruptcy rate in our data. Therefore, we instead aim to match the non-performing loans (NFL) ratio, which is around 3.5 percent in the data. We leave the details of the calibration targets and sources to Appendix F.7 and proceed to analyze the impact of moratorium loans.

Table 6: Long-run effects of introducing moratorium loans.

	Data	Benchmark	Moratoria
Mean standard loan/income (%)	15.7	15.5	4.0
Mean moratorium loan/income (%)	*n.a.*	*n.a.*	14.2
Mean r_s (%)	5.7	5.7	6.5
Mean moratorium r_s (%)	*n.a.*	*n.a.*	7.6
Share of NPL	3.5	3.7	3.9
Recovery rate (%)	33	31.2	29.2
Duration	5.0	5.0	4.8
Duration moratorium	*n.a.*	*n.a.*	5.2
σ_{r_s}	2.2	2.4	2.8
σ_{r_s} moratorium	*n.a.*	*n.a.*	2.9
Labor decline during defaults (%)	18.1	14.4	14.3
Labor decline during high-risk-premium (%)	3.6	2.8	3.2
Probability high-risk-premium starts (%)	15.0	15.0	15.0
Lower income during high-risk-premium (%)	4.0	4	4.5
Δ r_s with high-risk-premium shock	3	3	3.8
Fraction of defaults triggered by liquidity (%)	*n.a.*	10.1	0.8
$\sigma(c)/\sigma(y)$	0.87	0.95	0.93
$\rho(c,y)$	0.92	0.99	0.99

The standard deviation of x is denoted by $\sigma(x)$. Moments are computed using detrended series. Trends are computed using the Hodrick-Prescott filter with a smoothing parameter of 100. Moments for the simulations correspond to the mean value of each moment in 500 simulation samples, with each sample including 5 years without a default episode. Simulation samples start at least five years after a default. Default episodes are excluded to improve comparability with the data. Consumption and income are expressed in logs. Default frequencies and the probability that a high-risk-premium episode starts are computed using all simulation periods. For moratorium debt, the yield (and spread), debt duration, and debt stock are computed using expected payments, thus incorporating uncertainty about the timing of payments.

5.1 The effects of moratorium debt

To assess the impact of moratorium debt, we conduct a comparative analysis using long-run statistical moments and impulse response function (IRF) evaluations. In particular, we compare simulation results in the benchmark economy without the presence of moratorium loans with the ones obtained when we introduce the policy for households to borrow both standard loans and moratorium loans. We assume suspended payments earn the risk-free rate ($r_m = r$) and thus the nominal haircut from triggering the contingency clause in moratorium loans is equal to zero. We assume moratoria payments decay at the same rate as the payments of standard non-contingent loans ($\delta_m = \delta$).[16] By comparing the results between these two scenarios, we can assess the dynamic response of the

[16]When we assume that moratorium loan payments decline at the same rate as standard loan payments, it implies that moratorium loans have a longer duration than non-contingent loans, as we anticipate postponing the payments for moratorium loans. This phenomenon is illustrated in Figure F6. This extended loan duration could exacerbate the inefficiencies arising from the firm's lack of commitment to future borrowing (Hatchondo and Martinez, 2009). To ensure that our findings are not significantly influenced by the assumed duration of moratorium loans, we conduct experiments with varying durations and ascertain that equivalent outcomes are observed. For instance, altering δ_m in a way that aligns the durations of moratorium loans and standard loans does not notably impact our results. This indicates that the higher default probability associated with moratorium loans (as shown in Table 6 under *share of NPL* row) is not merely a consequence of assuming longer debt durations. Further details on this matter are available in footnote 18.

economy between the baseline scenario (without moratorium loans) and an alternative scenario where moratorium loans are introduced. By observing how key economic variables react over time to various shocks or policy changes, we can gain insights into how the presence of moratorium loans influences the short- to medium-term dynamics of the economy.

Table 6 displays the results of the baseline model in the second column. The long-run moments of the model incorporating moratorium loans are presented in the third column, while the IRF analysis is illustrated in Figure 10.[17] Figure 10 provides a visual comparison of the two simulations, starting from the transition point between the baseline economy and the economy with moratorium loans. The plots depict the relative deviation of variables from their simulated counterparts in the baseline economy, except for the "Moratoria/y" chart.

Both Figure 10 and Table 6 depict a result that aligns with the concerns expressed by critics of moratorium loans: the frequency of defaults increases, as indicated by the "share of NPL" in the table, leading to higher spreads. This effect arises from the contribution of moratorium loans to an elevation in the overall debt level. Notably, households are inclined to borrow more with moratorium loans due to the absence of concerns related to rollover risks, as presented by risk-premium shocks.[18]

Examining Figure 10, one observes that the standard loan-to-income ratio experiences a decline of approximately 75 percent within five years, while moratorium loans to income reach their long-run averages within the same time frame. This adjustment occurs gradually due to the long-term nature of debt.

[17]To compare the two scenarios, we conduct simulations using simulated economies. The simulations commence with a pool of 100,000 observations. All these observations commence with a debt level of zero and are characterized by an ergodic income distribution. To initiate the analysis, we simulate the trajectories of two separate economies. For each of these economies, We apply the decision rules established for the baseline economy until they reach a steady state. This steady state point is marked by consistent average debt levels, default rates, and bond spreads. This approach allows us to establish a stable basis for comparison between the two scenarios. Next, in one of the simulated economies, we continue using the decision rules of the baseline economy. In the other simulated economy, we switch to using the decision rules of the economy with moratorium loans. We continue the simulation until the averages of the variables reach their steady-state levels in the economy with moratorium loans (see Önder (2023*a*).

[18]We have conducted simulations where the household is not permitted to buy back debt in the moratorium economy. Remarkably, the results remain almost identical, signifying that buybacks (potentially prompted by shifts in lenders' valuation of sovereign debt) do not significantly impact the simulations. Furthermore, when we simulate an economy solely reliant on moratorium debt (as opposed to a combination of moratorium and non-contingent debt), similar outcomes are observed, albeit with slightly higher debt levels (20.1), spreads (6.8), and default probabilities (4.0). This modest discrepancy could potentially be attributed to the extended duration of moratorium loans, exacerbating the inherent time inconsistency problem with long-term debt (Hatchondo, Martinez and Sosa Padilla (2016), Aguiar and Amador (2019)). For further discussion on the effects of the duration of moratorium loans, see footnote 16.

The level of consumption (excluding defaults) initially increases by around 0.06 percent in response to the change to the economy with moratorium loans. However, consumption follows an inverted U-shaped pattern. After 20 years, consumption reaches a new level slightly below 0.1 percent lower than its baseline level.

The inverted U-shape in consumption is primarily influenced by the sovereign's consumption front-loading profile. As moratorium loans gradually increase toward their new steady-state level, debt dilution begins to take its toll. This leads to slightly lower prices for standard loans and an increase in default realizations within the economy with moratorium loans. The impact is also reflected in the average spread of standard loans, which rises, increasing the cost of rolling over moratorium loans and subsequently resulting in decreased consumption levels.

The economy with moratorium loans attains a lower consumption volatility profile during the transition (Table 6). Net revenue from issuance chart measures how much revenue the sovereign generate from total debt issuance (both standard loan and moratorium loans) and is $-(q(b', b'_m, y, p)\,[b' - b(1-\delta)] + q_m(b', b'_m, y, p)\,[b'_m - b_m(1-\delta_m)] - \kappa b - \kappa b_m)$. This also explains the inverted U-shape in consumption. It is important to note that net revenue issuance is always negative for both economies. To ensure accurate interpretation, we multiply it by minus one. Otherwise, it appears in the graph as if the long-run net revenue issuance is greater in the economy with moratorium loans while it is actually lower.

The macroeconomic variables of labor and output exhibit a consistent pattern, closely mirroring the trends observed in the default chart initially, and then the spread chart. Specifically, both output and labor experience an initial surge. This initial uptick is primarily attributed to the fact that in an economy with moratorium loans, defaults are initially circumvented. Consequently, this economy avoids the sharp declines in both output and labor that typically accompany defaults. The underlying intuition behind this decline in output and labor can be traced back to insights articulated by Mendoza and Yue (2012). Their work sheds light on the mechanisms driving this phenomenon. In this model, final goods producers make decisions regarding their input choices. These inputs consist of a combination of imported and domestic components, and they are not perfect substitutes; they are aggregated using an Armington aggregator. Additionally, there are different varieties of imported inputs, which are also not perfect substitutes, and these are aggregated using a Dixit-Stiglitz aggregator. Importantly, some of these imported input varieties necessitate foreign working capital financing, while the production of domestic inputs relies on domestic labor. In this framework, the concept of "strategic default" leads to an efficiency loss. This is because final goods producers are unable to continue using the imported input varieties that require credit. Instead, they must find alternative imported inputs and domestic inputs to replace them. Additionally, there is a labor reallocation from the final goods sector to the sector responsible for producing domestic inputs. The consequences of this strategic default include disruptions in the production process due to the unavailability of certain imported inputs that require credit. Furthermore, the shift of labor away from the final goods sector can affect overall productivity and efficiency in the economy. These effects contribute to the efficiency loss observed in this model. In the long run, both labor and net output are smaller than in an economy without the moratorium loan. This is partly because working capital loans are a function of interest rates. As spreads rise, the cost of working capital rises, generating very similar dynamics in labor and output as described above.

The welfare implications of the analysis are noteworthy. The introduction of moratoria loans increases welfare, as is picked up by the initial observation. In the steady state, it then slides into the negative territory, which becomes more pronounced over the course of a few years during the transition period. In the long run, the welfare losses amount to approximately 0.2 percent. In Section 5.3, we delve further into the factors contributing to the gains and losses, providing a more comprehensive understanding of their implications.

5.2 Event Analysis

Assessing whether our quantitative model aligns with empirical estimates is a complex endeavor, and we must exercise caution when drawing comparisons. There are inherent challenges in bridging micro-estimates with a general equilibrium macro model (see Önder et al. (2023)). Several nuances need consideration. Here are three key points to keep in mind. (*i*) *Empirical Strategy vs. Model Assumptions:* In our empirical approach, we aim to discern the impact of the moratorium policy on corporate lending. To do so, we use localized methods, control variables, and fixed effects (e.g., firm-time fixed effects) to account for credit demand. In contrast, the quantitative model doesn't control for demand; it seeks to model it. Some effects are the result of the firm's demand for credit. (*ii*) *Partial Equilibrium vs. General Equilibrium:* Empirical estimates are interpreted as partial equilibrium effects on loans. The quantitative model operates in a general equilibrium framework where changes in the endogenous components (e.g., rates of return) and loans can affect aggregate outcomes. (*iii*) *Comparing Access to Policy*: Empirical analysis measures the incremental effect of having access to the policy relative to firms that could not access it. The model incorporates these dynamics but abstracts from some of the aggregate effects by using firms that barely missed the policy as controls. Given these disparities, the objective now is to explore how our model's implications align with empirical observations. This will be done through an event study analysis conducted during the COVID-19 crisis in Colombia. With this analysis, where we assume that the government makes an unanticipated announcement such that firms can now access to moratoria loans that were never available before, we address some of these disparities. The timeline is as follows:

The economy operates according to the dynamics of the baseline model up to 2020, and starting in 2020 the economy transitions to the moratoria economy. Throughout this transition, both the baseline and the economy with moratoria loans in the model will face identical TFP and liquidity shocks as their empirical counterparts.[19]

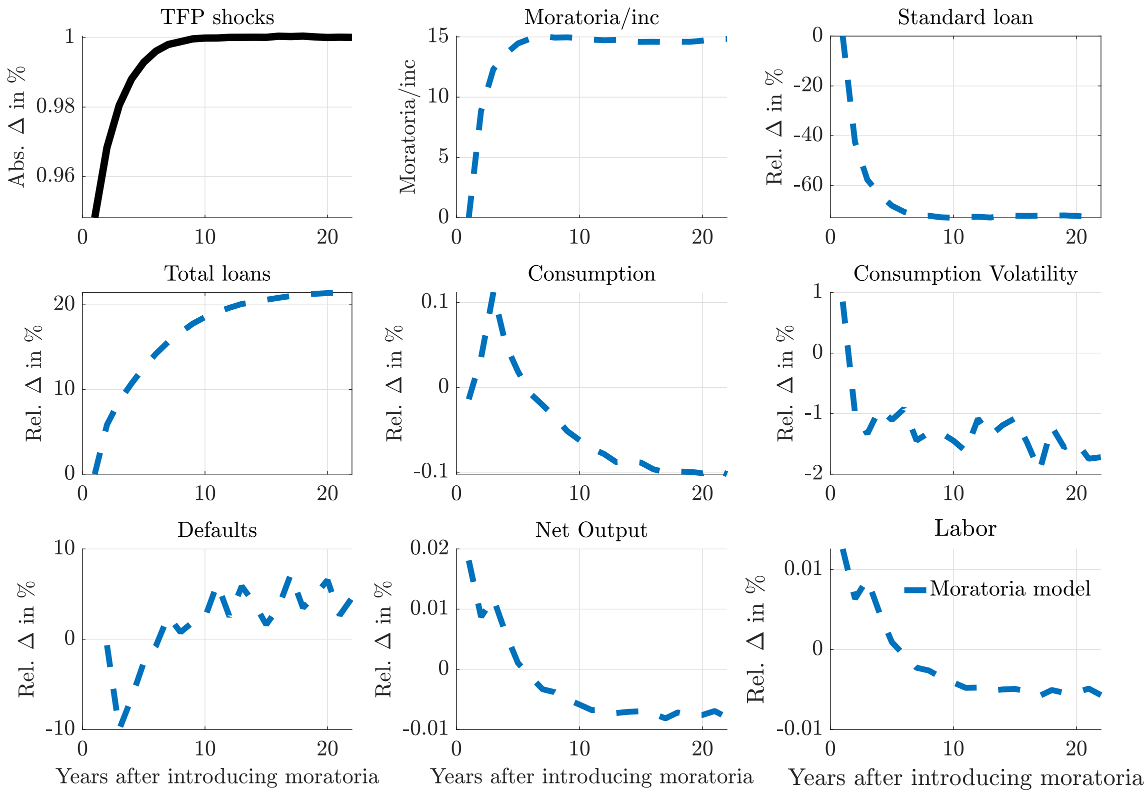
This event study analysis aims to bridge the gap between the theoretical model and the empirical findings outlined in Section 3. By comparing how the model predicts outcomes during the COVID-19 crisis, we seek to establish a tighter link between the model's assumptions and the real-world estimates we have derived.

Results from this analysis are provided in Figure 8. The upper left chart shows the fed TFP shocks and the initial state corresponds to a liquidity shock (in our case, the COVID-19 shock) with which moratoria is triggered. The plots depict the relative deviation of variables from their simulated counterparts in the baseline economy, except for the "Moratoria/income" chart. The model generates some stark similarities to the one we observed in our empirical analysis. To start with, our empirical estimates in Section 3.1.1 point to an average of 16.4% increase in loan amounts extended to the firms who barely have accessed the policy, while we obtain a 10% increase in the short-term and 20% increase in the long-run for Total Loans chart. Similarly, we have documented that firms who have barely accessed the moratoria loans defaulted 2.3% less often than their counterparts. Our default model also resonates with this finding quite well in the short run. As an outcome of fewer defaults, interest rate spreads are also lower in the short term for firms in an economy with moratoria loans. Turning to macroeconomic variables, our model does a good job picking up the directions of the macroeconomic variables. In particular, our model predicts an immediate increase in the output, driven by an increase in profits and a jump in labor, which are also consistent with our estimates provided in Section 3.2.1.

Based on our analysis, we can reasonably conclude that our quantitative model offers a reasonably accurate description of the primary empirical estimates. This alignment

[19]We follow the methodology provided in Önder and Sunel (2021) for this event analysis. Please refer to it for the technical details.

Figure 8: Impulse response functions of introducing moratoria loans during a liquidity shock



Effects of introducing moratoria loans along with standard loans on debt, default, consumption (including default episodes), labor and output changes.

between the model and empirical findings suggests that the model's assumptions and mechanisms capture essential aspects of the real-world dynamics we have studied. Moreover, in the upcoming subsection, we delve into a welfare analysis. This aspect of our investigation cannot be directly assessed through our empirical strategy.

5.3 Welfare Implications

In this section, we compute state-dependent welfare gains in terms of percentage changes in compensating consumption variations that would leave a household indifferent between staying in the baseline economy or switching to the economy with moratorium loans. We measure consumption-equivalent welfare gains denoted by η as,

$$\mathbb{E}_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} u\left(c_\tau^{baseline}[1+\eta] | b_{m,t}, b_t, s_t\right) = \mathbb{E}_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} u\left(c_\tau^{moratoria} | b_{m,t}, b_t, s_t\right), \tag{6}$$

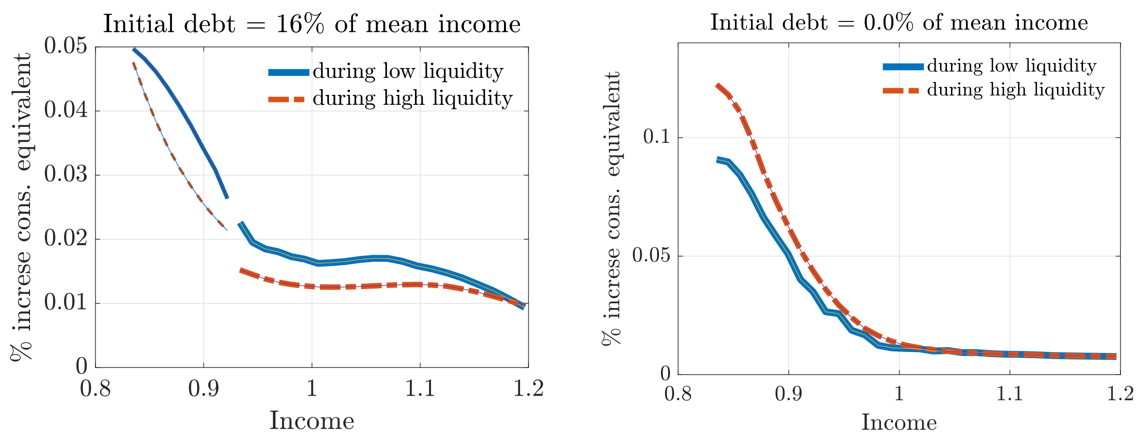
in which the consumption streams $\{c_{\tau}^{baseline}\}_{\tau=t}^{\infty}$ and $\{c_{\tau}^{moratoria}\}_{\tau=t}^{\infty}$ are attained in the baseline economy and the economy with moratorium loans, respectively. The welfare gain measure denoted as η is computed under the condition of initial non-contingent loan b_t, moratorium loans $b_{m,t}$, and the exogenous state of the world $s_t = \epsilon_t, p_t$, where ϵ_t represents the TFP and p_t signifies the liquidity shock. This welfare gain measure is derived from equilibrium value functions, encompassing the CRRA (Constant Relative Risk Aversion) form for household preferences:

$$\eta(b_{m,t}, b_t, s_t) = \left(\frac{V^{baseline}(b_{m,t}, b_t, s_t)}{V^{moratoria}(b_{m,t}, b_t, s_t)} \right)^{\frac{1}{1-\sigma}} - 1. \tag{7}$$

In this equation, $V^{baseline}(b_t, s_t)$ and $V^{moratoria}(b_{m,t}, b_t, s_t)$ refer to value functions evaluated for the given combinations of moratorium loans $b_{m,t}$, non-contingent debt b_t, and state variables $s_t = \epsilon_t, p_t$. The positive values of η indicate that transitioning to an economy with moratorium loans is preferable. This measure serves as an indicator of the extent to which the introduction of moratorium loans leads to improvements in welfare.

Figure 9 shows that introducing a moratoria increases welfare. The initial consumption increase triggered by the household's willingness to sustain higher levels of indebtedness with moratorium loans, as well as the decline in initial default incidences, account for the bulk of these welfare gains. In addition, as expected by proponents of moratoria and illustrated in Table 6, debt moratoria improves consumption smoothing. However, in the standard default model, the effect of lowering consumption volatility on welfare is small. Despite small and negative welfare changes observed during the transition from the baseline economy to the economy with moratorium loans, as shown in the bottom panel of Figure 10, the magnitude of welfare losses becomes more pronounced after a few years, eventually reaching -0.2 percent after 20 years. Figure 11 provides a deeper understanding of the heterogeneity in welfare changes present within the ergodic distribution of the economy featuring moratorium loans. The left chart depicts the distribution of welfare changes during the initial implementation of moratorium loans. The average of this distribution corresponds to the initial data point in the welfare plot shown in the lower panel of Figure 10. Conversely, the right chart illustrates the welfare distribution in the steady state. The average of this distribution corresponds to the final data point in the welfare plot depicted in the lower panel of Figure 10. Both charts in the figure reveal considerable heterogeneity in the welfare changes, and the following important observations stand out. An important observation to highlight is that when the policy was initially introduced, all observations in the distribution experienced positive welfare

Figure 9: Welfare gains from introducing loan moratorium.



The panel plots welfare gains measured in consumption-equivalent terms from the introduction of debt moratorium. The initial debt portfolio at the time of inception entails no moratorium ($b_m = 0$) and a stock of defaultable debt that equals the long-run average debt-to-mean-annual-income ratio of the baseline economy. The right panel plots welfare gains when the stock of defaultable debt equals to zero.

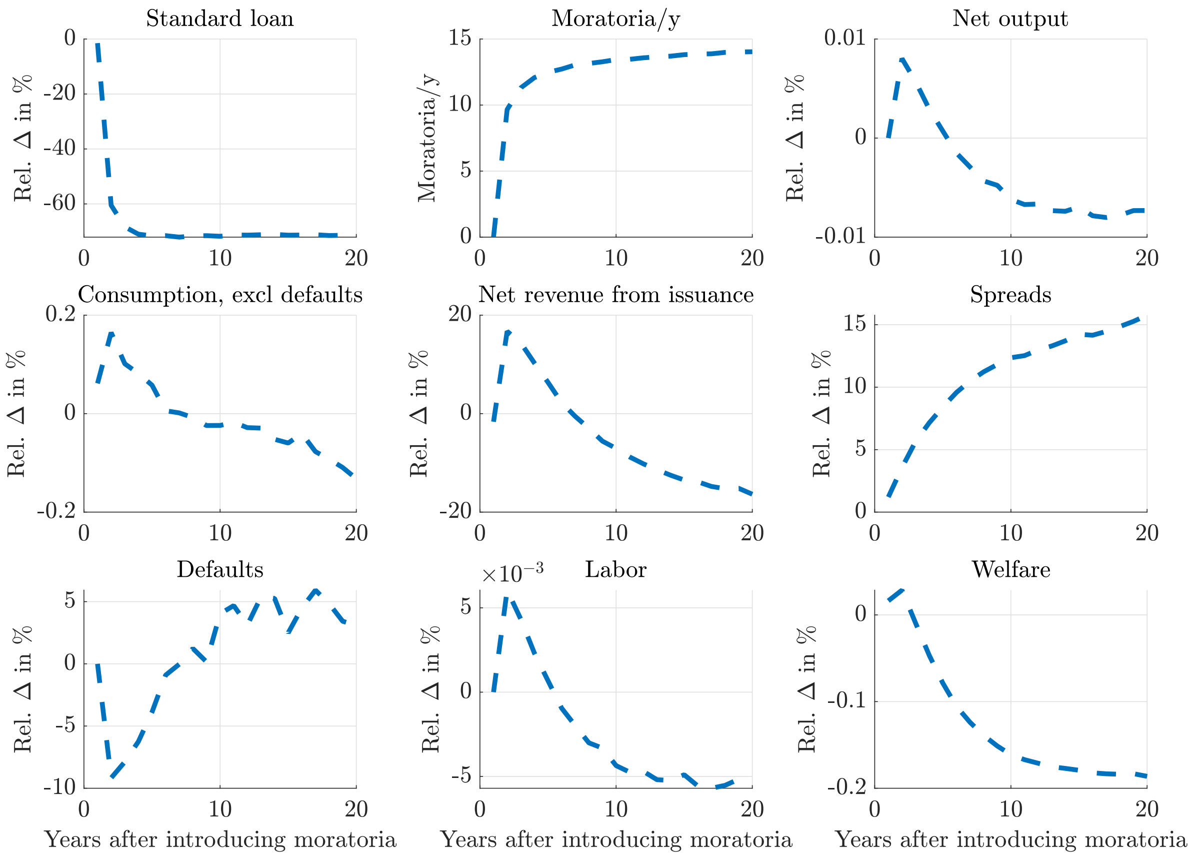
gains. However, as time progressed, a notable shift occurred in the distribution of welfare changes, with most observations moving into the negative range. This shift signifies that, over time, the overall welfare impact of the policy has become less favorable. In the next section, we will propose an amendment of the policy with which welfare gains remain in the positive territory in the long run as well.

6 Improving the policy

Our baseline analysis assumes that the debt moratorium policy suspends all debt payments without implying any debt relief on the principal level ($r_m = r$). However, it is important to note that debt moratorium policies can vary significantly in their design and implications, as evidenced by different approaches taken globally.

As highlighted in our introduction, Colombia allowed interest to accrue during the moratorium period, which corresponds to our baseline scenario ($r_m = r$), while Belgium did not. In light of these variations, our analysis in this section aims to explore the optimal policy to complement debt moratoriums. Specifically, we delve into the question of what constitutes the optimal level of debt relief that can be offered to borrowers in conjunction with the moratorium. This exploration allows us to consider how different policy designs might be more effective in addressing the unique economic challenges borrowers face during times of financial stress.

Figure 10: Impulse response functions of introducing moratoria loans.



Effects of introducing moratoria loans along with standard loans on debt, default, consumption (excluding default episodes), spread, labor, output and welfare changes. Net revenue from issuance is defined as $-(q \times (b' - (1-\delta)b) - \delta b - q_a \times a' + a)$ whereas revenue from total debt issuance is defined as $q \times (b' - (1-\delta)b) + q_a \times a'$.

We show in the left panel of Figure 12 that households do not prefer less debt relief as welfare gains are lower if the policy suspends only a fraction of debt payments.[20]

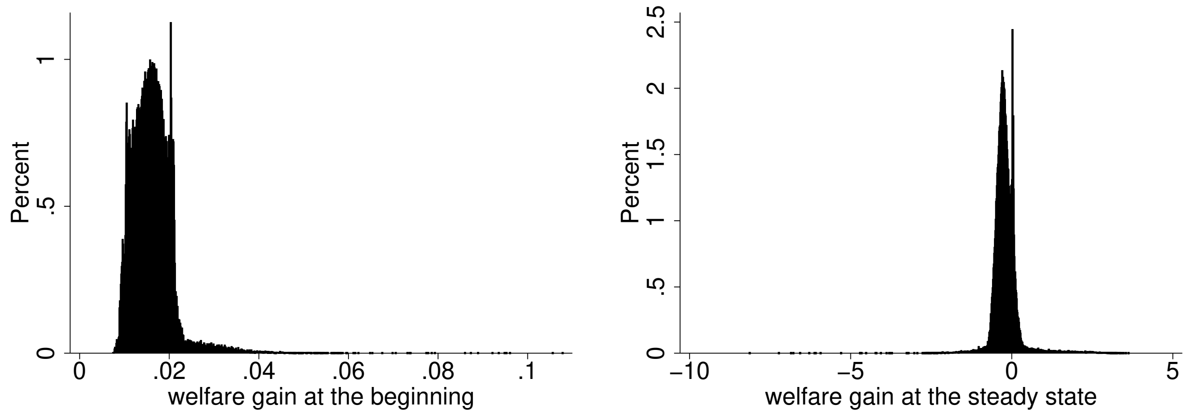
The right panel of Figure 12 shows that households would benefit from a policy that provides additional debt relief: The optimal rate of growth of suspended moratorium payments (r_m) is negative, implying that it is optimal for the policy to entail haircuts following adverse global shocks. Without haircuts, recall that the moratorium loans feature higher default probability, picked up by higher spreads. With haircuts, however, moratorium loans feature significantly lower default probability, lower spreads, a lower spread in-

[20] Let θ denote the fraction of coupons paid during the moratorium payment suspension. The next-period stock of moratorium loans is given by

$$b'_m = [1 - \mathcal{I}(p)]\, b_m(1-\delta_m) + \mathcal{I}(p) b_m[\theta(1-\delta) + (1-\theta)e^{r_m}] + i_m.$$

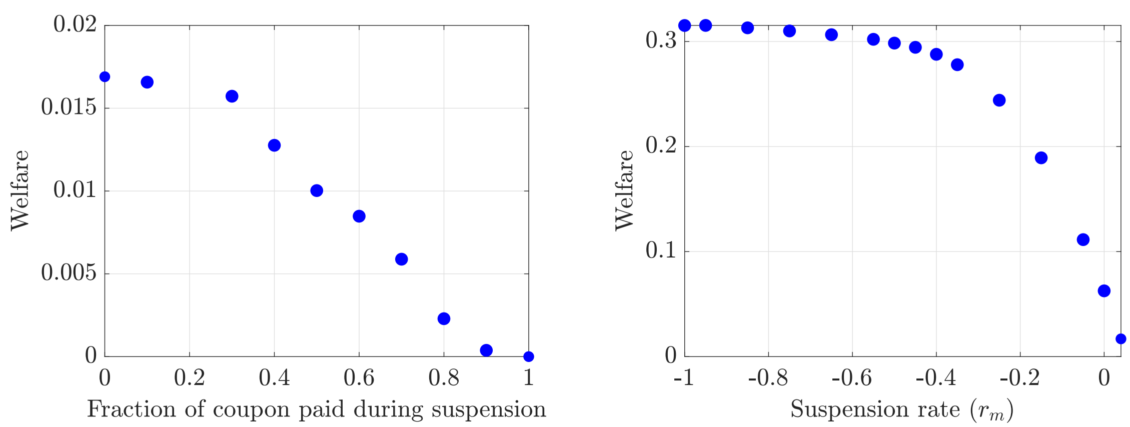
Note that $\theta = 1$ makes the debt non-contingent, and $\theta = 0$ corresponds to the case where all moratoria payments are suspended.

Figure 11: Distribution of welfare changes at the moment of the introduction of moratorium loans and in the long run with long-term debt.



The left panel shows the distribution of welfare changes at the time of the switch, and the right panel shows the distribution of of welfare changes across steady states.

Figure 12: Optimal moratorium debt relief.



The left panel shows the average welfare gains for a given fraction of coupons paid during suspensions, and the right panel shows the average welfare gains for a given suspension rate r_m.

crease triggered by risk-premium shocks, and improved consumption smoothing picked up by lower consumption volatility.

The outcomes observed for debt forgiveness are in line with findings from other state-contingent debt instruments. These instruments similarly reduce default probabilities and facilitate higher levels of indebtedness, achieved by diminishing debt levels following adverse shocks. This consistency in results across various state-contingent debt approaches highlights the effectiveness of such instruments in mitigating default risks and

Table 7: Debt-forgiveness with moratoria loans.

	Bmark	$r_m = r$	$r_m = 0.0$	$r_m = -0.35$	$r_m = -1$
Mean standard loan/income (%)	15.5	4.0	3.9	3.1	5.1
Mean morator. loan/income (%)	*n.a.*	14.2	15.7	20.7	19.8
Mean r_s (%)	5.7	6.5	6.4	4.9	3.9
Mean moratorium r_s (%)	*n.a.*	7.6	8.3	12.9	19.0
Share of NPL	3.7	3.9	3.9	3.3	2.9
Recovery rate (%)	31.2	29.2	29.5	34.1	36.9
$\sigma(c)/\sigma(y)$	0.99	0.97	0.92	0.93	0.93
$\sigma(r_s)$	2.4	2.8	1.22	1.16	1.13
$\Delta\ r_s$ with shock	3.0	3.8	3.6	1.9	1.0
$\Delta\ r_s$ moratorium with shock	*n.a.*	3.7	3.6	2.7	2.0

The first column reports the baseline result without the moratorium loan and the second column $r_m = r$ reports the results when the moratorium loan has no haircuts. Columns $r_m = 0$, $r_m = 0 - 0.35$, and $r_m = -0.95$ report the results with different values of the haircut during moratoria on the moratorium loan alone. The yield (and spread), debt duration, and debt stock are computed using expected payments, thus incorporating uncertainty about the timing of payments.

promoting increased indebtedness in the aftermath of unfavorable economic shocks (Önder (2023*b*)).

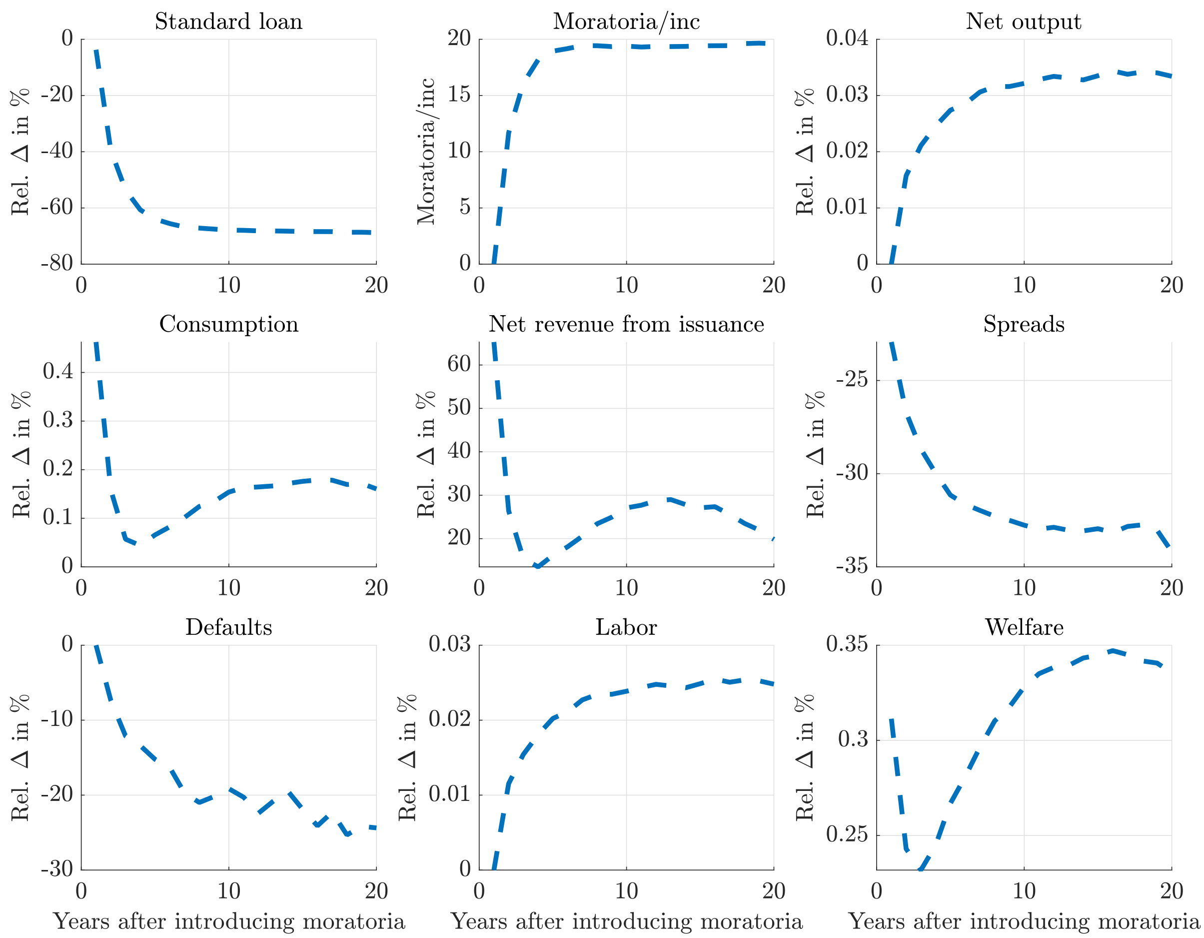
Our intuition is similar to Hatchondo et al. (2022). Moratorium loans that solely trigger a suspension of payments lead to an escalation in the overall debt level. This occurs due to the automatic rollover of suspended payments, which effectively increases the total debt burden. Consequently, this heightened level of debt results in a higher default probability and elevated spreads. These effects can be detrimental to the household's capacity to borrow for the purpose of consumption smoothing.

Conversely, when moratorium loans are designed with debt relief, they have the opposite effect. These assets work to reduce the level of debt, subsequently lowering the default probability and decreasing spreads. This, in turn, enhances the household's ability to borrow for the purpose of consumption smoothing. In essence, the presence of debt relief on moratorium loans serves as a mechanism to alleviate the adverse consequences associated with high debt levels and increased default risks.

The right panel of Figure 12 shows that welfare gains from increasing haircuts level off after sufficient debt relief is provided. This occurs because, as illustrated in Table 7, if moratorium loans provide too much debt relief (haircuts are too high), the household can always compensate by borrowing fewer moratorium loans and more non-contingent bonds.[21] In Figure 13, we revisit the analysis previously presented in Section 5.1, but with a crucial modification: we consider the optimal haircut rate of $r_m = -0.95$. This specific haircut rate was determined through the analysis showcased in the right panel

[21]Note, however, that the household's ability to compensate for excessive debt relief in moratorium loans is not perfect in the model. Moratoria loans and non-contingent bonds have different durations, and committing to higher haircuts implies a commitment to a shorter expected duration. Longer durations imply stronger ex-post incentives to dilute the value of bonds held by lenders.

Figure 13: Impulse response functions of introducing moratoria loans with optimal haircut.



Effects of introducing moratoria loans along with standard loans on debt, default, consumption (excluding default episodes), spread, labor, output and welfare changes under optimal haircut. Net revenue from issuance is defined as $-(q \times (b' - (1-\delta)b) - \delta b - q_a \times a' + a)$ whereas revenue from total debt issuance is defined as $q \times (b' - (1-\delta)b) + q_a \times a'$.

of Figure 12. The impulse response functions (IRFs) resulting from this analysis differ significantly from those in Figure 10. Several indicators exhibit positive changes both in the short and long term. Output and labor show permanent increases. This reflects a reduced default risk and lower borrowing costs for working capital, as evidenced by the decline in spreads. Welfare consistently remains in positive territory. This is attributed to two critical factors: (i) an immediate and sustained reduction in defaults and (ii) a front-loaded in consumption that maintains a higher level over the long run.

These findings underscore the positive outcomes associated with the optimal haircut rate. The reduction in default risk, cost savings in borrowing for working capital, and improved consumption patterns collectively contribute to enhanced economic well-being, making this a valuable policy consideration.

7 Conclusion

Our study presents a thorough examination of the effects of implementing a debt moratorium policy, which is historically one of the oldest policy proposals to address repayment challenges during periods of economic distress. By combining theoretical predictions with empirical and quantitative analysis, we aim to shed light on the effects of this policy across several dimensions.

Theoretical predictions, based on the concepts of demand and supply elasticities, suggest that firms not experiencing financial stress will face higher loan interest rates, while stressed firms will observe an increase in their loan amounts. To empirically test these predictions, we use administrative data from Colombia and, for the case of stressed firms, employ a regression discontinuity design. We argue that by comparing loans that barely qualified for the policy with those that barely missed it, we can accurately assess the causal effects of the policy. For non-stressed firms, we conduct a difference-in-difference estimation and control for bank and firm-time fixed effects.

We find that stressed firms accessing moratoria experience more favorable loan conditions on subsequent borrowing, characterized by higher loan amounts, a higher probability of obtaining an new loan, and lower interest rates. In contrast, for non-stressed firms, the policy tightened loan conditions, albeit to a lesser magnitude. In addition to examining the impact on loan rates and amounts, our analysis also examines how real variables such as investment and labor are affected by the debt moratorium policy. Our findings indicate that stressed firms benefiting from the debt moratoria, experience positive changes in various key indicators such as employment, investment, operating revenues, and assets. For non-stressed firms, we see a slight reduction in employment and assets. Lastly, we construct a quantitative default model to gain insights into the long-run gains and losses associated with debt moratorium policies in a general equilibrium framework. In particular, our results indicate that the moratorium policy is welfare improving, and gains become more substantial when the policy includes forgiveness of interest accumulation during suspension episodes.

Through our comprehensive approach, which combines theoretical, empirical, and quantitative analysis, we aim to provide a comprehensive assessment of the effects of debt moratorium policies and provide valuable insights for policymakers involved in designing and implementing such policies.

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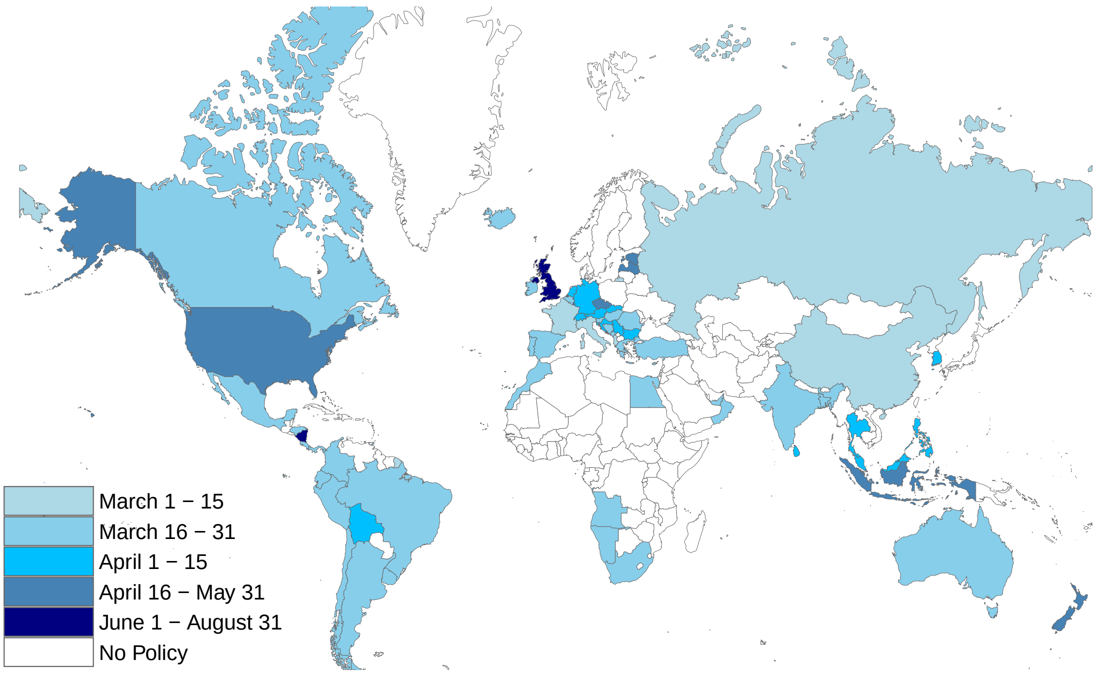
Online Appendix

Appendix A Moratoria measures in other countries

Figure A1: Moratorium Policies (COVID-19)



The figure displays the nations that have implemented a form of moratorium policy after the start of the COVID-19 pandemic. For details on the implementation for each colored country, please refer to the working paper version of the manuscript.

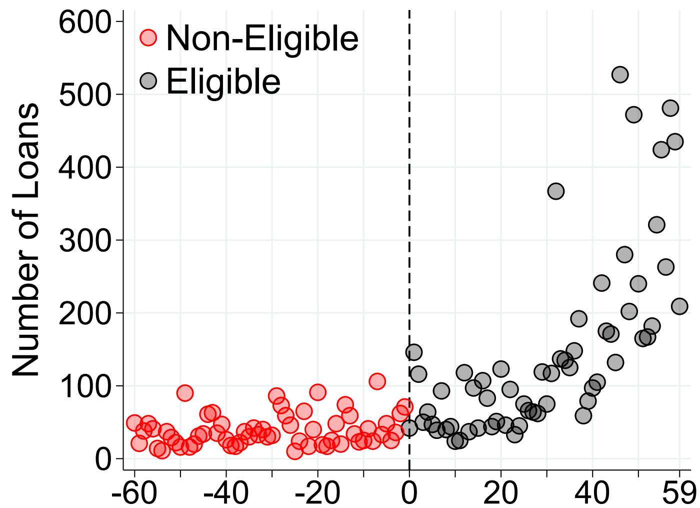
Appendix B Pre-treatment Distribution of Loans along the running variable

In Figure 1, we observe an increase in the number of loans towards the right end of the figure, indicating a greater number of loans with fewer delinquency days. This is a common pattern because delinquency records drop out as loans are paid off, leading to a higher number of loan accounts with fewer delinquency days. The notation "+59" refers to loans with only 1 day of delinquency.

To support this explanation, Figure B2 presents data from a pre-treatment period, as if the policy had been enacted in 2019Q2. Notably, this chart displays a remarkably similar pattern to that of Figure 1. The consistency of this pattern holds if we use data from 2019Q3 or 2019Q4 as well.

These observations reinforce the notion that the increase in loans with fewer delinquency days is a natural outcome of loan payment dynamics.

Figure B2: Pre-treatment distribution of loans along the running variable

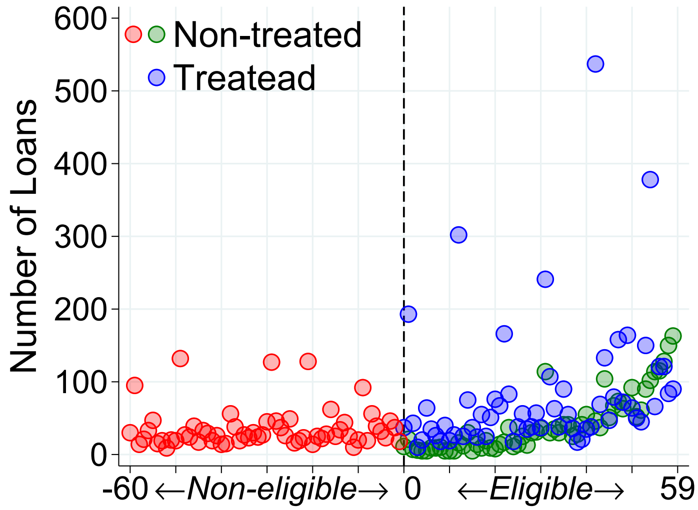


The figure displays the number of corporate loans along a placebo running variable computed with pre-treatment information on delinquency days. Red dots are loans with more than 60 days of delinquency by the end of 2019Q2. Black dots represent loans with less than 60 days of delinquency by the end of 2019Q2.

Appendix C Fuzzy RDD characterization

In this section we characterize the *fuzzyness* in our RDD design. As explained in Section 2.3, for reasons such as lack of information or costs associated with a time consuming process, some eligible firms decided not to take part in the government policy. Figure C3 clearly depicts this, by showing eligible borrowers (positive support of the running variable) that either received (blue dots) or did not receive the policy (green dots).

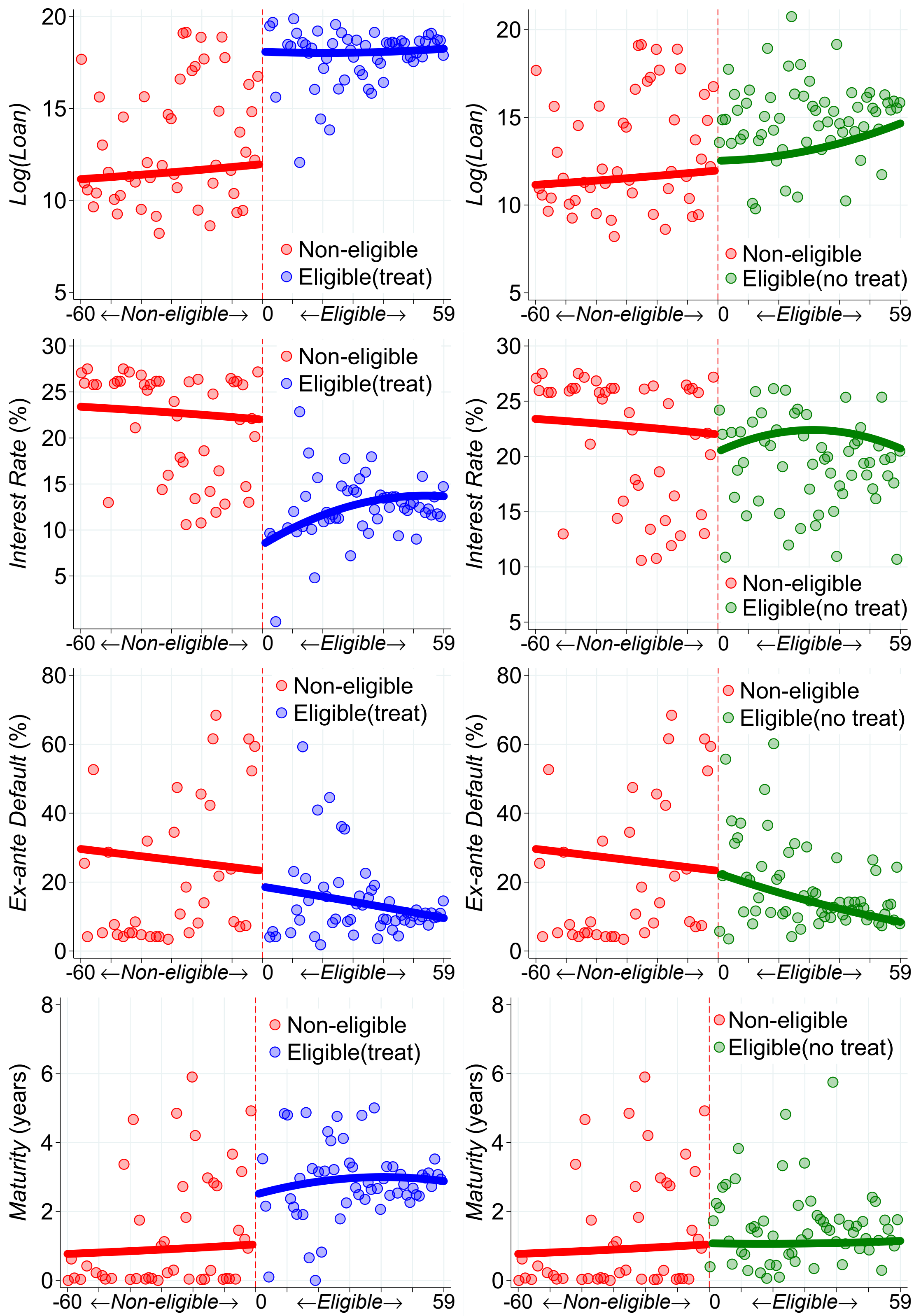
Figure C3: Treated and non-Treated Loans



The figure displays the number of corporate loans along the running variable. Non-eligible loans (red) are to the left of the cutoff. Eligible loans (right of the cutoff) are either treated (blue) or non-treated (green) by the debt moratorium policy.

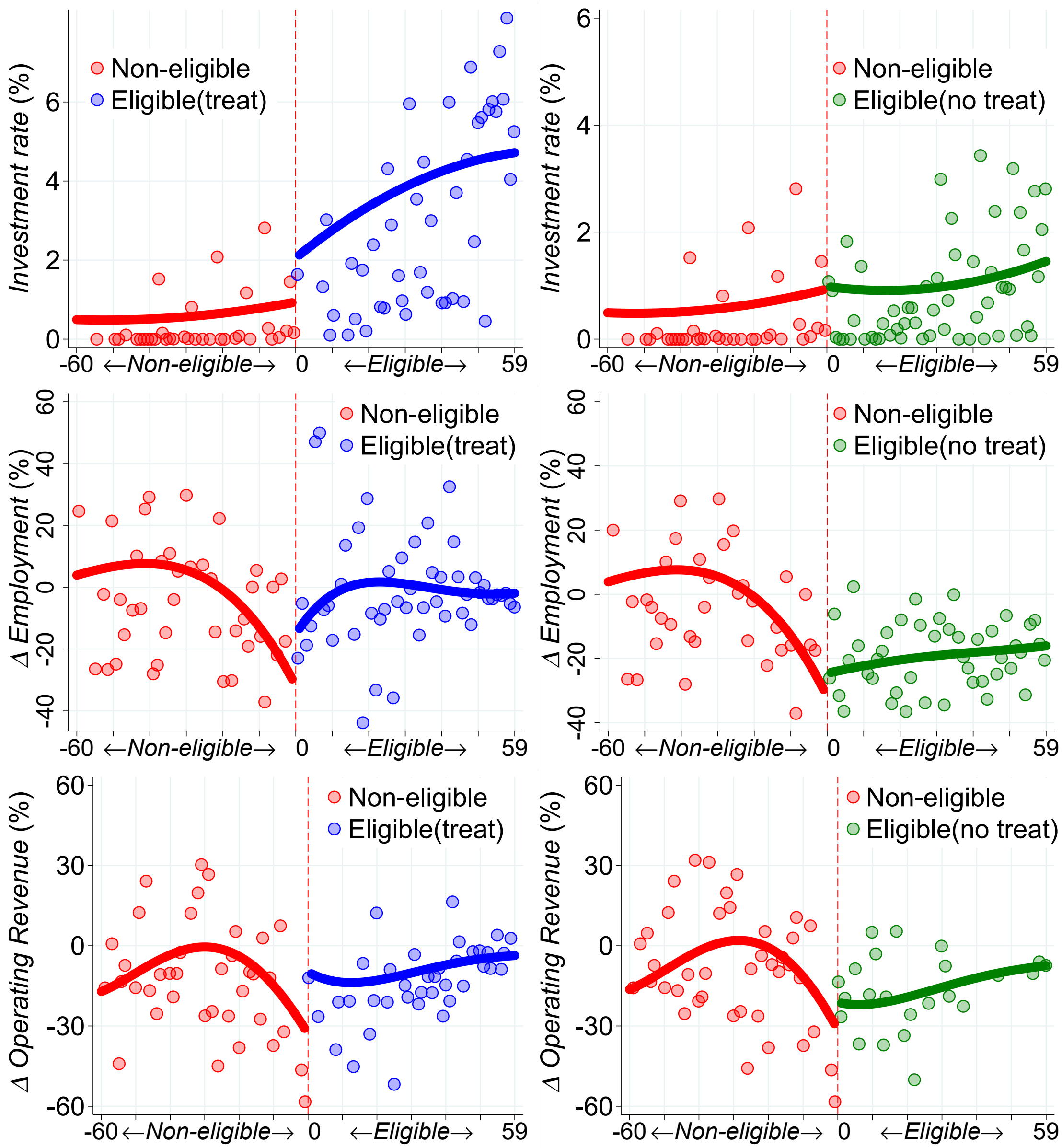
If, for some reason, these "untreated but eligible" loans showed a significant effect after the policy, then the validity of the design would be compromised, since the effects would not be attributable to receiving treatment, but rather, on being eligible. In Figure C4 we split the eligible sample into eligible treated (left panels) and eligible non-treated (right panels). As shown, the discontinuous jump at the cutoff is only significant for those eligible loans that in fact received treatment. This result applies to all variables considered: loan amount (row 1), interest rates (row 2), probability of default (row 3), and maturity (row 4). Similarly, in Figure C5 we present results for firm-level variables: Investment (first row), employment growth (second row), and operating revenues (third row).

Figure C4: New Loans Conditions: Eligible Treated and Non-Treated vs Non-Eligible.



The figure shows the effect of the policy on eligible treated loans (left panels) and eligible non-treated loans (right panels). Outcome variables correspond to new loan amount (first row), interest rate (second row), ex-ante default (third row), and maturity (fourth row). We employ data on new loans at the quarter of origination during 2020Q1-2021Q4. The number of bins and specific location are determined using a quantile-spaced mimicking variance approach (see Cattaneo, Idrobo and Titiunik (2019)).

Figure C5: Firm Level Outcomes: Eligible Treated and Non-Treated vs Non-Eligible.



The figure shows the effect of the policy on firms with eligible treated loans (left panels) and eligible non-treated loans (right panels). The outcome variables correspond to the investment rate (first row), employment growth (second row), and growth of operating revenues (third row). We employ balance sheet data for firms during 2020-2021. Each dot represents the mean of the outcome variable within a bin of the running variable. The number of bins and specific location are determined using a quantile-spaced mimicking variance approach (see Cattaneo, Idrobo and Titiunik (2019)).

Appendix D Summary Statistics

Table D1: Loan and firm level outcomes: Stressed

	Non-Eligible						Eligible Treated						Eligible Non-Treated					
	Mean	S.D	P^{25}	P^{50}	P^{75}	N_{obs}	Mean	S.D	P^{25}	P^{50}	P^{75}	N_{obs}	Mean	S.D	P^{25}	P^{50}	P^{75}	N_{obs}
Loan	88	661	0.01	0.04	0.24	710	615	1395	42	175	501	14,140	412	1383	0.16	20	182	20,222
$\mathbb{1}\{\text{Loan}\}$	0.19	0.40	0	0	0	911	0.22	0.41	0	0	0	34,462	0.28	0.45	0	0	1	35,391
Interest	0.23	0.08	0.26	0.26	0.26	705	0.12	0.07	0.07	0.10	0.16	14,084	0.18	0.09	0.09	0.23	0.26	20,129
Maturity	0.70	1.98	0.08	0.08	0.08	710	2.56	2.25	0.66	2.41	3.46	14,140	1.18	1.78	0.08	0.10	2.00	20,222
Collateral	0.26	1.22	0.00	0.00	0.00	710	0.39	0.82	0.00	0.22	0.47	14,031	0.27	0.86	0.00	0.00	0.25	20,001
Rating	3.50	1.57	2.00	4.00	5.00	710	4.74	0.64	5.00	5.00	5.00	14,140	4.75	0.60	5.00	5.00	5.00	20,222
Ex-ante default	0.38	0.44	0.04	0.05	1.00	710	0.07	0.15	0.02	0.04	0.04	14,140	0.07	0.13	0.04	0.04	0.04	20,222
Ex-post default	0.34	0.47	0.00	0.00	1.00	966	0.03	0.18	0.00	0.00	0.00	33,331	0.07	0.25	0.00	0.00	0.00	34,604
Past due days	51.49	135.50	0.00	17.00	50.00	966	5.67	27.06	0.00	0.00	1.00	33,331	8.23	25.85	0.00	0.00	7.00	34,604
ΔEmp.	-0.22	0.52	-0.33	-0.09	-0.01	552	-0.04	0.43	-0.12	-0.04	0.00	8,057	-0.12	0.41	-0.17	-0.05	0.00	6,353
Inv.rate	0.01	0.03	0.00	0.00	0.00	942	0.03	0.07	0.00	0.00	0.02	6,723	0.02	0.06	0.00	0.00	0.02	3,374
ΔOp.Rev	-0.17	0.98	-0.71	-0.09	0.35	1,784	-0.01	0.67	-0.30	0.03	0.31	19,261	-0.02	0.80	-0.32	0.04	0.32	10,795
ΔLiab.	-0.05	0.37	-0.10	-0.00	0.05	1,863	0.05	0.30	-0.05	0.03	0.16	19,464	0.05	0.34	-0.05	0.03	0.18	11,014
ΔAssets	-0.04	0.60	-0.14	0.00	0.10	1,843	0.03	0.50	-0.13	0.03	0.21	19,319	0.02	0.59	-0.18	0.02	0.26	10,936
ΔProfits	0.02	0.41	-0.15	0.00	0.12	1,672	0.03	0.29	-0.08	0.00	0.10	18,183	0.04	0.33	-0.07	0.00	0.11	9,926
ΔEquity	-0.01	0.24	-0.06	0.00	0.04	1,863	0.04	0.19	-0.01	0.02	0.08	19,464	0.05	0.23	-0.02	0.03	0.10	11,014

Authors' calculations. The Table presents the summary statistics for stressed firms. For loan level variables, we consider only information on new loans originated during 2020Q1-2021Q4. Loan amount (in millions of COP) represents the value of the new loan at the quarter of origination, $\mathbb{1}\{\text{Loan}\}$ (extensive margin) represents a dummy taking the value of one in the quarter of origination of the loan. Maturity is denoted in number of years, collateral is expressed as a percentage of the loan amount, credit rating is a categorical variable from 1-5 where 5 is the highest rating, ex-ante default represents the expected default probability assigned to the loan by the bank, and ex-post default is a dummy variable that takes the value of one if the loan has more than thirty days of delinquency at the end of the quarter. The interest rate, maturity, collateral, rating of new loans, and ex-ante default are measured at the quarter of origination. For firm-level variables, we use employment and balance sheet data from 2020 to 2021. ΔEmp., ΔOp. Rev., ΔAssets and ΔLiab. denote yearly symmetric growth rates of the number of employees, operating revenues, total assets, and liabilities, respectively. Inv.rate represents the investment rate computed as the ratio of new purchases of buildings, plants, and equipment to total assets lagged one year. ΔProfit, ΔEquity are computed as the yearly change in gross profits and equity relative to the operating revenues and total assets lagged one year, respectively.

Table D2: Loan and firm level outcomes: Non Stressed

	Eligible Treated						Eligible Non-Treated					
	Mean	S.D	P^{25}	P^{50}	P^{75}	N_{obs}	Mean	S.D	P^{25}	P^{50}	P^{75}	N_{obs}
Loan	735	1823	50	190	561	41,631	905	2441	13	118	510	70,074
$\mathbb{1}\{\text{Loan}\}$	0.21	0.41	0	0	0	203,907	0.26	0.44	0	0	1	282,803
Interest	0.11	0.07	0.07	0.09	0.14	42,069	0.12	0.08	0.06	0.09	0.18	72,541
Maturity	2.24	2.06	1.00	2.00	3.00	42,268	1.71	1.89	0.25	1.00	3.00	72,996
Collateral	0.37	0.72	0.00	0.17	0.50	41,631	0.34	0.78	0.00	0.00	0.50	70,074
Rating	4.91	0.36	5.00	5.00	5.00	42,268	4.95	0.30	5.00	5.00	5.00	72,996
Ex-ante default	0.04	0.07	0.02	0.04	0.04	42,268	0.04	0.06	0.02	0.04	0.04	72,994
Ex-post default	0.00	0.07	0.00	0.00	0.00	202,161	0.00	0.05	0.00	0.00	0.00	280,912
Delinq days	1.64	9.78	0.00	0.00	0.00	42,268	1.01	7.01	0.00	0.00	0.00	72,996
ΔEmp	-0.06	0.28	-0.11	-0.03	0.00	12,189	0.07	0.33	-0.12	-0.04	0.00	21,656
Inv.rate	0.06	1.92	0.00	0.00	0.02	10,695	0.03	0.20	0.00	0.00	0.02	15,143
ΔOp.Rev.	0.03	0.63	-0.23	0.06	0.32	32,743	0.02	1.69	-0.22	0.06	0.31	46,847
ΔLiab.	0.07	0.29	-0.04	0.05	0.19	33,079	0.08	0.32	-0.04	0.05	0.20	47,502
ΔAssets	0.05	0.50	-0.14	0.04	0.26	32,845	0.05	0.58	-0.18	0.04	0.31	47,259
ΔProfits	0.06	0.34	-0.06	0.00	0.11	30,799	0.06	0.38	-0.06	0.00	0.11	43,891
ΔEquity	0.06	0.19	-0.00	0.03	0.10	33,079	0.07	0.22	-0.00	0.04	0.12	47,502

Authors' calculations. The Table presents the summary statistics for non-stressed firms. For loan level variables, we consider only information on new loans originated during 2020Q1-2021Q4. Loan amount (in millions of COP) represents the value of the new loan at the quarter of origination, $\mathbb{1}\{\text{Loan}\}$ (extensive margin) represents a dummy taking the value of one in the quarter of origination. Maturity is denoted in number of years, collateral is expressed as a percentage of the loan amount, credit rating is a categorical variable from 1-5 where 5 is the highest rating, ex-ante default represents the expected default probability assigned to the loan by the bank, and ex-post default is a dummy variable that takes the value of one if the loan has more than thirty days of delinquency at the end of the quarter. The interest rate, maturity, collateral, rating of new loans, and ex-ante default are measured at the quarter of origination. For firm-level variables, we use employment and balance sheet data from 2020 to 2021. ΔEmp., ΔOp. Rev., ΔAssets and ΔLiab. denote yearly symmetric growth rates of the number of employees, operating revenues, total assets, and liabilities, respectively. Inv.rate represents the investment rate computed as the ratio of new purchases of buildings, plants, and equipment to total assets lagged one year. ΔProfit, ΔEquity are computed as the yearly change in gross profits and equity relative to the operating revenues and total assets lagged one year, respectively.

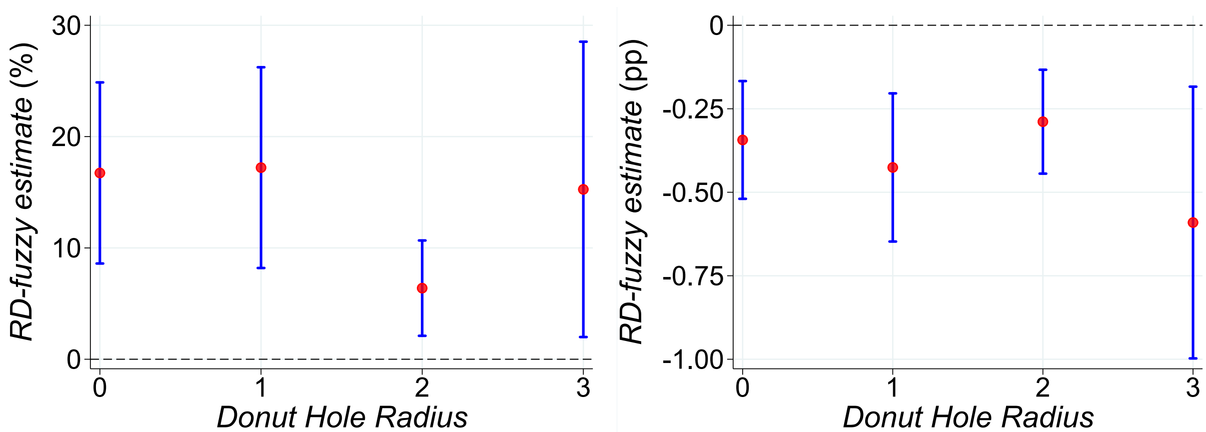
Appendix E Additional Robustness Checks

Appendix E.1 Donut-Hole Test

In this exercise we evaluate the sensitivity of our benchmark results, when excluding observations in the close vicinity of the cutoff-point (1, 2, and 3 days before/after the actual cutoff, $X_{ij} = 0$). These observations are, in principle very informative, with similar values of the running variable. The test, however, checks for additional "bunching" of observations around the cutoff that the McCrary test (see Figure 1) might have potentially missed.

Figure E6 shows similar results when excluding 1, 2, and 3 days before/after the actual cutoff, suggesting a lack of "bunching" of observations –at and close to– the cutoff-point.

Figure E6: Donut-Hole Sensitivity Test



(a) Log(Loan) (b) Interest Rate

The figure shows the Donut-hole sensitivity test, excluding 1, 2, and 3 days before/after the cutoff. We employ data on new loans at the quarter of origination during 2020Q1-2021Q4. Panel (a) corresponds to the effect on the amount of the new loan (in logs of COP). Panel (b) shows the estimates on the interest rate for new loans. The zero-value radius (no holes) corresponds to our benchmark results.

Appendix E.2 Pre-existing differences: Stressed-Firms

In this section we evaluate whether loan and firm-level variables carried systematic differences before the debt moratorium policy took place. Table E3 presents Sharp RDD estimates, as exemplified in equation (2) for the quarter before the policy was enacted (2019Q4). As shown, all these variables are equally balanced across the running variable.

Table E3: Testing for pre-existing differences prior to the debt moratorium policy

Variable	RD Estimator	Robust Inference		Bandwidth (in days)	Observations
		p-value	95% Conf. Int.		
Log(Loan)	0.13	0.39	[-0.14, 0.36]	33.59	48,017
Interest	-0.00	0.78	[-0.01, 0.01]	40.73	47,202
Collateral	0.03	0.85	[-0.19, 0.24]	32.09	47,903
Maturity	0.07	0.59	[-0.58, 1.01]	27.38	39,884
Rating	-0.02	0.95	[-0.24, 0.25]	16.97	47,476
Ex-ante default	0.00	0.78	[-0.07, 0.05]	24.18	48,256
Ex-post default	-0.06	0.16	[-0.19, 0.03]	15.28	47,476
Past due days	4.51	0.34	[-5.31, 15.29]	54.19	48,256
Inv rate	-0.00	0.88	[-0.05, 0.06]	29.92	4,949
ΔOp Rev	0.22	0.29	[-0.26, 0.87]	21.83	6,519
ΔEmp	-0.19	0.32	[-0.58, 0.19]	42.62	16,745
ΔAssets	-0.07	0.36	[-0.26, 0.10]	48.89	17,001
ΔLiab	-0.03	0.66	[-0.31, 0.19]	39.12	16,875
ΔProfits	-0.02	0.81	[-0.19, 0.15]	56.85	15,215
ΔEquity	-0.09	0.10	[-0.22, 0.02]	55.96	17,001

Authors' calculations. The Table presents the Sharp RD estimates in equation (4) for loan and firm-level variables before the debt moratorium policy was implemented. Confidence intervals (column 4) and p-values (column 3) are computed using robust bias-corrected standard errors. Loan level variables are measured at the end of Q4-2019. Loan amount (in logs of COP) represents the outstanding debt balance of the loan, maturity is denoted in number of years, collateral is expressed as a percentage of the outstanding loan, credit rating is a categorical variable ranging from 1-5 where 5 is the highest rating, ex-ante default represents the expected default probability assigned to the loan by the bank, ex-post default is a dummy variable that takes the value of one if the loan has more than thirty days of delinquency at the end of the quarter, and past due days are the end of the quarter number of days the loan was delinquent. For firm-level variables, we use employment and balance sheet data for 2019. ΔEmp., ΔOp. Rev., ΔAssets and ΔLiab. denote yearly symmetric growth rates of the number of employees, operating revenues, total assets, and liabilities, respectively. The inv.rate represents the investment rate computed as the ratio of new purchases of buildings, plants, and equipment to total assets lagged one year. ΔProfits, ΔEquity are computed as the yearly change in gross profits and equity relative to the operating revenues and total assets lagged one year, respectively.

Appendix F Quantitative Model

There are three main agents in the economy: households, firms and banks. The production chain is now standard and in particular closely follows Mendoza and Yue (2012). To summarize the production chain, there are two production sectors taking part, all of which are owned by households. Intermediate good producing firms rent labor services from households and produce domestic inputs to be sold to final goods producers whose job is to combine domestic inputs, and differentiated imported inputs into a single final good.

Appendix F.1 Final Goods Producers

The firms in the sector f of final goods producers engage in production using labor input denoted as $L^f(t)$, intermediate goods represented as M_t, and a constant level of capital stock denoted as k.[22] These firms also encounter Markovian TFP shocks, denoted as ϵ_t, which follow a transition probability distribution function characterized by $z(\epsilon_t|\epsilon_{t-1})$. In particular, productivity shocks in final goods production follow an AR(1) process:

$$log\epsilon_t = (1-\rho_\epsilon)\mu_\epsilon + \rho_\epsilon + \varepsilon_t, \tag{F1}$$

with $\varepsilon_t \overset{iid}{\sim} N(\mu_\epsilon, \sigma_\varepsilon^2)$. The production function in this sector is assumed to be Cobb-Douglas in nature with the following form:

$$y_t = \epsilon_t \left(M\left(m_t^d, m^i\right)\right)^{\alpha_M} \left(L_t^f\right)^{\alpha_L} k^{\alpha^k}$$

with $\alpha_L + \alpha_M + \alpha^k = 1$ and $0 < \alpha_L, \alpha_M, \alpha^k < 1$.

The mix of intermediate goods M is determined via a CES aggregate of domestic and imported goods, m_t^d and m_t^i, respectively. This aggregation satisfies:

$$M_t = \left[\lambda(m_t^d)^\mu + (1-\lambda)(m_t^i)^\mu\right]^{\frac{1}{\mu}}, \tag{F2}$$

where $\lambda \in [0,1)$ is the weight of m_t^d, and $\mu < 1$ governs the (inverse) elasticity of substitution. Moreover, m_t^i is composed of imperfectly substitutable varieties, for reasons that we discuss below. In particular, m_t^i is a CES aggregate of imported goods varieties:

$$m_t^i = \left(\int_{j\in[0,1]} (m_{j,t}^i)^\nu dj\right)^{\frac{1}{\nu}}, \tag{F3}$$

where $m_{j,t}^i$ is the imported inputs variety j, and the elasticity of substitution across varieties is given by $|\frac{1}{\nu-1}|$. The elasticity of substitution between m_t^d and m_t^i is given by $|\frac{1}{\mu-1}|$.

[22] Following Mendoza and Yue (2012), we are abstracted from introducing capital accumulation. Besides, our framework already solves a portfolio problem and introducing capital as an endogenous variable to the recursive problem will make it computationally challenging.

The following parameters restrictions are imposed: $0 < \nu$, $\mu < 1$ and $0 <\leq \lambda < 1$. Notice that if λ is allowed to be unity, then firms would not need imported inputs for their production and thus the cost of defaulting would be zero.

The imported inputs in the economy are sold in global markets at exogenously determined and time-invariant prices p_j^* for each variety j within the range $[0, 1]$. These prices are defined relative to the price of final goods, which serves as the numeraire. The relative price of domestic inputs, p_t^m, is an endogenous equilibrium price that adjusts within the economy.

A specific subset, denoted as Ω, of the imported input varieties falls within the interval $[0, \theta]$, where θ is a value between 0 and 1. Importantly, the payment for these input varieties in subset Ω needs to be made in advance using working capital financing. This division of imported inputs is designed such that during episodes of default, where access to credit markets is restricted, the availability of imported inputs in subset Ω is not completely eliminated. Instead, although these inputs may undergo significant adjustments, they do not vanish entirely, as observed in empirical data.

The working capital loans, denoted as κ_t, are short-term loans provided by banks within the same period. Different from Mendoza and Yue (2012), working capital loans are not contracted at the risk-free real interest rate. Instead, they carry out the risk of defaulting and the risk is equal to per-period default risk observed in the firm's borrowing rate with standard loans. If the borrower defaults, firms are excluded from accessing credit. We believe it is more plausible to expose working capital loans to default risk, and so we link the firm's balance sheet to its borrowing terms, which is essentially the mechanism we show in our empirical section.

The standard pay-in-advance condition that determines the demand for working capital is:

$$\frac{\kappa_t}{1+r} \geq \int_0^{\theta} p_j^i m_j^i dj.$$

In this equation, κ_t represents the working capital loans, r denotes the real interest rate, and the integral term on the right-hand side represents the cost of purchasing imported intermediate goods. The profit-maximizing producers of final goods select κ_t in a way that satisfies this condition with equality.

It is important to note that domestic inputs and the imported input varieties falling within the $[\theta, 1]$ interval do not require working capital, meaning that they can be obtained without the need for upfront financing.

Final goods producers take prices w_t, r_t, p_t^m and p_t^i given in order to maximize their per period profits:

$$\pi_t^f = \epsilon_t \left(M \left(m_t^d, m^i \right) \right)^{\alpha_M} \left(L_t^f \right)^{\alpha_L} k^{\alpha^k} - w_t L_t^f - P_t^i(r_t) m_t^i - p_t^m m_t^d. \tag{F4}$$

P_t^i is the standard CES price index of imported inputs m_t^i, and given that a random θ fraction of varieties needs to be financed by working capital loans, then $P^i(r_t)$ satisfies the following:

$$P_t^i(r_t) = \left[\int_0^\theta (p_j^i(1+r_t))^{\frac{\nu}{\nu-1}} dj + \int_\theta^1 (p_j^i)^{\frac{\nu}{\nu-1}} dj \right]^{\frac{\nu-1}{\nu}}. \tag{F5}$$

We characterize the solution of final goods producers' optimization problem in two stages. In the first stage, given set of prices w_t, p_t^m and $P_t^i(r_t)$, firms solve equation (F4). The optimality conditions of the first stage are:

$$P^i(r_t) = \alpha_M \epsilon_t k^{\alpha_k} \left(\left(M \left(m_t^d, m_t^i \right) \right) \right)^{\alpha_M - mu} (L_t^f)^{\alpha_L} (1-\lambda)(m_t^i)^{\mu-1} \tag{F6}$$

$$p_t^m = \alpha_M \epsilon_t k^{\alpha_k} \left(\left(M \left(m_t^d, m_t^i \right) \right) \right)^{\alpha_M - mu} (L_t^f)^{\alpha_L} \lambda (m_t^d)^{\mu-1} \tag{F7}$$

$$w_t = \alpha^L \epsilon_t k^{\alpha_k} M_t^{\alpha_M} (L_t^f)^{\alpha_L - 1}. \tag{F8}$$

At the second stage, given firms optimal demand for the aggregate imported goods, final good producers choose their demand for each variety i, subject to a working capital constraint. In particular, they need to finance a θ fraction of their purchase of import varieties. One can show that the demand for each variety i satisfies:

$$m_{jt}^i = \begin{cases} \left(\frac{p_j^i(1+r_t)}{P^i(r_t)} \right)^{-\frac{1}{1-\nu}} M_t^i, & \text{for } j \in [0, \theta]; \\ \left(\frac{p_j^i}{P^i(r_t)} \right)^{-\frac{1}{1-\nu}} M_t^i, & \text{for } j \in [\theta, 1]. \end{cases} \tag{F9}$$

As in Mendoza and Yue (2012), we also assume that firms cannot access working capital loans during exclusion periods.

Appendix F.2 Intermediate Goods Producers

The producers in the m^d sector utilize labor input denoted as $L_t^m$and operate under a production function given by $A(L_t^m)^\gamma$, where γ is a parameter between 0 and 1, and $A > 0$ represents both the role of a fixed factor and an invariant state of TFP in the intermediate goods production sector.

Given the price of domestic inputs, p_t^m, and the wage rate, w_t, the profit maximization problem for firms in the m^d sector can be formulated as follows:

$$\max_{L_t^m} \pi_t^m = p_t^m A(L_t^m)^\gamma - w_t L_t^m \tag{F10}$$

The first order condition for the labor demand satisfies

$$w_t = \gamma p_t^m A(L_t^m)^{\gamma-1}. \tag{F11}$$

Appendix F.3 Household's problem

It is assumed that the household owns firms and makes the borrowing and delinquency (default) decisions on behalf of them. The representative household lacks a commitment technology, and thus cannot commit to its future default and borrowing decisions, and it decides how much non-state-contingent (standard) long-term loan as well as state-contingent (moratorium) long-term loan to borrow at each period after repayment. Introduction of new state-contingent loan which stipulates payment suspensions during risk-off episodes closely follows Hatchondo et al. (2022).[23] The timing of our paper, as in Eaton and Gersovitz (1981), intends to rule out the multiplicity dynamics.

Households choose how much to consume and supply labor to maximize expected discounted utility streams, $E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, L_t)$, where $0 < \beta < 1$ is the subjective discount factor, and c_t and L_t denote consumption and labor, respectively. The period utility function $u(\cdot)$ is continuous, strictly increasing in consumption, strictly decreasing in labor, and strictly concave in both arguments. The expectation operator E_t is conditional on the information set available at period t.

Households receive a real wage per labor hour w_t, profits paid by the final goods producers π_t^f, and net proceeds obtained from intermediate goods producers π_t^i and transfers from the household (T_t). Formally, the household solves the following problem:

$$\max_{c_t, L_t} E_t \left[\sum_{t=0}^{\infty} \beta^t u(c_t, L_t) \right] \tag{F12}$$

subject to the period budget constraint

$$c_t = w_t L_t + \pi_t^f + \pi_t^i + T_t. \tag{F13}$$

Household preferences are governed by a utility function of the Greenwood, Hercowitz and Huffman (1988) type, which ensures no wealth effect on labor supply.[24] In particular, we use the utility function of the form:

$$u(c_t, L_t) = \frac{\left(c_t - \frac{L_t^{1+\omega}}{1+\omega}\right)^{1-\sigma} - 1}{1-\sigma}, \tag{F14}$$

where $\sigma > 0$ is the constant relative risk aversion, and $\omega > 0$ governs the (inverse) Frisch elasticity of labor supply. The optimal labor supply is given by

$$L_t^{\omega} = w_t. \tag{F15}$$

[23]Allowing for long-term maturity helps us to obtain more realistic loan rates and default frequencies (Hatchondo and Martinez (2009), Chatterjee and Eyigungor (2012)).

[24]This formulation for preferences removes the wealth effect on labor supply and helps to explain key business cycle facts for small open economies. See, for example, Mendoza and Yue (2012).

Following Hatchondo et al. (2022), the bondholders' risk-premium shock $p_t \in \{p_L, p_H\}$ follows a Markov process such that a high-risk-premium episode starts with probability $\pi_{LH}(\epsilon) \in [0, 1]$ and ends with probability $\pi_{HL} \in [0, 1]$. To capture the fact that economies suffer from negative conditions in international capital markets when domestic aggregate income is low (Calvo, Izquierdo and Talvi, 2006), we assume that π_{LH} is a decreasing function of the TFP shock ϵ: $\pi_{LH}(y) = Min\left\{\pi_{LH0}e^{-\pi_{LH1}\log(\epsilon)-0.5\pi_{LH1}^2\sigma_\varepsilon^2}, 1\right\}$.

The price of loans satisfies a no-arbitrage condition with stochastic discount factor $M(\epsilon', \epsilon, p) = exp(-r - p\varepsilon' - 0.5p^2\sigma_\varepsilon^2)$, where r denotes the risk-free rate at which lenders can borrow or lend. This model of the discount factor is a special case of the discrete-time version of the Vasicek (1977) one-factor model of the term structure and has often been used in models of sovereign default (e.g., Arellano and Ramanarayanan, 2012; Bianchi, Hatchondo and Martinez, 2018).

We introduce an endogenous link between default probability and private economic activity. This endogenous link relates to the following three ingredients. First, there is a one-to-one mapping between the household's implied one-period borrowing rate and the firm's short-term working capital loan rate. The channel of that link is as follows: a rise in borrowing increases the likelihood of loan default, and thus amplifies the interest rates that are priced by risk-averse lenders. Banks, thus, pass on the increased cost of household debt holdings to firms by increasing loan rates. The second ingredient is that domestic and foreign goods are imperfectly substitutable. The intuition is that the higher rates would translate into an efficiency loss for the firms for their production because firms will now try to use more local goods with heightened costs of production. Efficiency loss happens since foreign investment goods and their domestic counterparts are assumed to be imperfectly substitutable.

The household borrows using long-term-non-state contingent loans in real goods at a price q_t. Similar to the sovereign debt and default literature, Hatchondo and Martinez (2009) and Chatterjee and Eyigungor (2012), a debt issued at time t promises a stream of geometrically decreasing coupons κ, which depreciate at a rate $\delta \in (0, 1]$. Thus, a household promises to pay $\kappa(1-\delta)^{n-1}$ units of consumption good in period $t+n$ for $n \geq 1$. Coupon payment κ is computed such that in the absence of default risk, the price of non-state-contingent long-term debt is equal to the price of the average one-period debt, denoted as $\frac{r+\delta}{1+r}$. This is a common formulation for long-term debt contracts to avoid keeping track of the entire maturity distribution. Hence, the dynamics of the long-term can be represented as follows:

$$b_{t+1} = (1-\delta)b_t + m_t, \tag{F16}$$

where b_t and b_{t+1} are the total outstanding loan obligations at the beginning of period t and $t+1$ and m_t is the amount of loan that is received by the household in period t. Note that one-period debt is a special case of long-term debt where $\delta = 1$.

Moratorium debt b_m is also modeled to be a long-term debt as well which promise an infinite stream of coupons that decrease at the constant rate δ_m, but also allow for bond payments to be suspended in periods with $p_t = p_H$ during which banks earn the rate

r_m on suspended payments. Per period coupon payments κ_m in the case of moratorium loans would then be $\frac{r+\delta_m}{1+r}$

In Figures F5 and F6 (Supplementary Material F), we visualize the payment structure of standard loans and moratorium loans, respectively, assuming that $\delta = \delta_m$ for ease of exposition. Blue large circles represent coupon payments of moratorium loans while black dots represent coupon payments of standard loans depicted in Figure F5. Notice in Figure F6 that when the payments are suspended at time $t+1$ during a liquidity shock, the firm does not make any coupon payments. When the liquidity shock is over, the coupon accrue interest rate of r_m and the firm pays the coupon plus interest which in this case becomes $e^{r_m}\kappa$. Later, we will explore a policy analysis with this accrued interest rate r_m.

If delinquency is declared, then the household and lenders restructure the debt in a Nash bargaining game. The post delinquent debt recovery rate α is determined following the default decision during a renegotiation episode and depends on the defaulted debt of standard loans b, moratorium asset b_m, TFP shock ϵ and the liquidity state p.

As Hatchondo et al. (2022), a defaulted firm cannot borrow and suffers a one-time utility loss $U^D(y)$.[25]

Thus, if the household is not in default and moratorium debt payments are suspended, consumption is given by

$$\begin{aligned} c &= \epsilon f\left(M\left(m_t^d, m^i\right), L^f, k\right) - P_t^i(r_t) m_t^i \\ &\quad -\kappa b + q(b', b_m', y, p)\left[b' - b(1-\delta)\right] + q_m(b', b_m', y, p)\left(b_m' - b_m e^{r_m}\right), \end{aligned}$$

where q and q_m denote the price of non-contingent loans and moratorium loans, respectively. If moratorium loan payments are not suspended, consumption is given by

$$\begin{aligned} c &= f\left(M\left(m_t^d, m^i\right), L^f, k\right) - P_t^i(r_t) m_t^i \\ &\quad -\kappa b - \kappa b_m + q(b', b_m', y, p)\left[b' - b(1-\delta)\right] + q_m(b', b_m', y, p)\left[b_m' - b_m(1-\delta_m)\right]. \end{aligned}$$

Appendix F.3.1 Cost of defaulting

In our main analysis above, we abstract from assuming additional cost of defaulting and resort to the model's endogenous dynamics. During default episodes, because of the increased cost of firms' working capital financing and the imperfect substitutability of domestic and imported goods, there is a fall in production and thus a decline in income. To improve the model's moment-matching success, as Bianchi, Hatchondo and Martinez

[25]In the calibration, a period in the model is a year and thus the exclusion from debt markets after defaulting lasts for a year, which is a common assumption in quantitative studies of sovereign default (Arellano, 2008; Bianchi, Hatchondo and Martinez, 2018), and is also within the range of empirical estimates (Gelos, Sahay and Sandleris, 2011). Assuming a utility cost of defaulting instead of the also often used income cost allows us to calibrate the income process without using the simulations (because default does not affect aggregate income).

(2018), we assume a defaulting household cannot borrow, suffers a one-time utility loss $U^D(y)$. Consumption during a default episode then reads:

$$c = f\left(M\left(m_t^d, m^i\right), L^f, k\right) - P_t^i(r^{aut})m_t^i,$$

where r^{aut} denotes the interest rate during which firms face for their working capital loans.

Appendix F.4 Recursive representation

We now formulate the household's optimization problem recursively. Let $s \equiv (\epsilon, p)$ denote the vector of exogenous states, V be the value function of the household that has the option of defaulting. The household chooses to repay if the value of repayment V^R is greater than the value of default V^D. The function V satisfies the following functional equation:

$$V(b_m, b, s) = \max\left\{V^R(b_m, b, s), V^D(b_m, b, s)\right\}, \tag{F17}$$

where the household's continuation value for repayment is denoted as

$$\begin{aligned}
V^R(b, b_m, s) \quad &= \quad \qquad \qquad \qquad \qquad \qquad \qquad \qquad \qquad \qquad \qquad \qquad \qquad \text{(F18)} \\
& \max_{m^d \geq 0,\, m^i \geq 0,\, c \geq 0,\, L^m \geq 0,\, L^f \geq 0,\, b_m \geq 0\, b \geq 0} \left\{u\left(c, L\right) + \beta \mathbb{E}_{s'|s} V(b'_m, b', s')\right\}, \\
& \text{subject to} \\
c \quad &= \quad \epsilon f\left(M\left(m^d, m^i\right), L^f, k\right) - P^i(r)m^i \\
& \quad -\kappa b - \left[1 - \mathcal{I}(p)\right] \kappa_m b_m + q(b'_m, b', s)i + q_m(b'_m, b', s)i_m, \\
i \quad &= \quad b' - b(1-\delta), \\
i_m \quad &= \quad b'_m - \left[1 - \mathcal{I}(p)\right] b_m(1-\delta_m) - \mathcal{I}(p) b_m e^{r_m}, \\
q(b'_m, b', s) \quad &\geq \quad \underline{q} \;\forall\; b' > b(1-\delta), \\
q_m(b'_m, b', s) \quad &\geq \quad \underline{q} \;\forall\; b'_m > \left[1 - \mathcal{I}(p)\right] b_m(1-\delta_m) + \mathcal{I}(p) b_m e^{r_m}, \\
L^f + L^m \quad &= \quad L, \\
A(L^m)^\gamma \quad &= \quad m^d,
\end{aligned}$$

where $\mathcal{I}(p)$ is an indicator function that is equal to 1 if the risk premium shock p takes the high value, and is equal to 0 otherwise, and $f(\cdot) = \left(M\left(m_t^d, m^i\right)\right)^{\alpha_M}\left(L_t^f\right)^{\alpha_L} k^{\alpha^k}$. Imported goods and the price of these goods are denoted by m^i and $P^i(r)$, respectively. The term r inside the price of imported goods is the household's implied interest rate on one-period working capital loans. That is, households borrow long-term loans while working capital loans are one-period loans. Thus, the interest rate on the working capital loans is the one-period loan version of the long-term loans. The firms' problem depends on the level of total factor productivity and the household's implied one-period borrowing rate r_t and our interest rate function maps aggregate states to the household's implied one-period borrowing rate

$$\mathcal{S}(\epsilon_t, r_t) = \mathcal{H}_s(b'_m, b', s). \tag{F19}$$

Given the interest rate function, optimal factor allocations characterize a competitive equilibrium in factor markets. Note that the benevolent household faces the same allocations of output and factors of production as the agents in the private economy. To be specific, for a given TFP shock, implied short-term borrowing rate r and long-term bond prices on standard loans and moratorium loans q, q_m, —which will be obtained below under the price function—, as well as current and next-period household loan borrowings, the optimal factor allocations (m^i, m^d, L^f, L^d, L) chosen by the representative household characterize the private sector competitive equilibrium.

A defaulting firm stay in default for one period and goes into a restructuring with the bank. In the context of debt renegotiation, a generalized Nash bargaining game is employed. The bargaining agreement determines that the market value of defaulted debt is reduced to a fraction $\alpha(b_m, b, s)$ of its original value. This means that the firms and the bank engage in negotiations, and the final outcome of the debt restructuring process results in the borrowers repaying only a portion of the original debt. Thus, the continuation value of default takes into account the restructuring process when the firm regains access to the credit markets. We assume that debt in arrears grows at the international risk-free rate r during the firm's exclusion from the credit markets. Along these lines, the value of default is

$$\begin{aligned} V^D(b, b_m, s) = & \underset{c\geq 0,\, L^m\geq 0,\, L^f\geq 0,\, m^d\geq 0,\, m^i\geq 0}{Max} \Big\{ u(c, L) - U^D(\epsilon) \\ & + \beta \mathbb{E}_{s'|s} \left[V(\hat{\alpha}(b_m, b, s) b_m, \hat{\alpha}(b_m, b, s) b, s') \right] \Big\}, \\ & subject\ to: \\ & c = \epsilon f\left(M\left(m^d, m^i\right), L^f, k\right) - P^i(r^{aut}) m^i, \\ & L^f + L^m = L, \\ & A(L^m)^\gamma = m^d. \end{aligned} \tag{F20}$$

In our Nash-bargaining game, the renegotiation stage takes only once for a single default event and a settlement is reached.[26] The threat to the borrower is that it may remain in default for another episode and then can find a different bank/source to finance its

[26]This is typically how it is designed in the literature (see Yue (2010)). Even if we allow for multiple rounds of renegotiation to have delays, we find that both the lender and the borrower typically reaches a settlement in a single renegotiation episode unless one introduces significant costs of a settlement.

borrowing and working capital. Banks, on the other hand, can only receive the defaulted value of assets.[27]

We can then define the household's surplus in the Nash bargaining game for a given recovery rate $\alpha(b_m, b, s)$ by Δ^H, which is the difference between settling on a debt recovery rate α or remaining excluded from the banking sector forever. That is,

$$\Delta^H(\alpha; b_m, b, s) = u(c, L) + \mathbb{E}_{s'|s}\left(V^R(\alpha b_m, \alpha b, s')\right) - V^D(0, 0, s). \tag{F23}$$

The surplus to the holders of defaulted loan depend on the portfolio value of defaulted loans. If banks do not agree on a settlement, they still recoup some of their losses as the market value of debt may still carry a positive value. Below we define them. Banks agree on a settlement proposal α if the market value of their debt portfolio after accepting this offer, $M(\alpha b_m, \alpha b, s)$ is greater or equal than the market value of rejecting the proposal, $M^D(b_m, b, s)$.

Debt portfolio market value. The market value of a debt portfolio with b and b_m at the beginning of a repayment period is given by:

$$\begin{aligned}
MV(b_m, b, s) &= b\left[\kappa + (1-\delta)q\left(\hat{b}\left(b_m, b, s\right), \hat{b}_m\left(b_m, b, s\right), s\right)\right] \\
&+ b_m\left[\left[1 - \mathcal{I}(p')\right]\left[\kappa_m + (1-\delta_m)q_m\left(\hat{b}\left(b_m, b, s\right), \hat{b}_m\left(b_m, b, s\right), s\right)\right]\right. \\
&+ \left.\mathcal{I}(p')e^{r_m}q_m\left(\hat{b}_m\left(b_m, b, s\right), \hat{b}\left(b_m, b, s\right), s\right)\right]
\end{aligned}$$

Then the surplus to the bank from the renegotiation stage would be:

$$\Delta^B(\alpha; b_m, b, s) = MV(\alpha b_m, \alpha b, s). \tag{F24}$$

Intuitively, if lenders have all the bargaining power, they can extract the entire amount and make the borrower pay fully. If the borrower has all the bargaining power, then the borrower can make a take-it-or-leave-it offer and can get away with paying nothing. Thus,

[27] In another version of the paper, we also consider a case in which the threat to the household is it stays excluded from the banking sector permanently. In this case the expected value of remaining excluded from the credit markets becomes

$$V^{aut}(s) = \underset{c\geq 0,\, L\geq 0,\, I^f\geq 0,\, I^d\geq 0}{Max}\left\{u(c, L) - U^D(\epsilon) + \beta\mathbb{E}_{s'|s}\left[V^{aut}(s')\right]\right\}, \tag{F21}$$

$$\begin{aligned}
&subject\ to: \\
&\quad c = \epsilon f\left(M\left(m^d, m^i\right), L^f, k\right) - P^i(r^{aut})m^i, \\
&L^f + L^m = L, \\
&A(L^m)^\gamma = m^d.
\end{aligned}$$

Then, equation F23 becomes

$$\Delta^H(\alpha; b_m, b, s) = V^R(\alpha b_m, \alpha b, s) - V^{aut}(s). \tag{F22}$$

Our results remain equivalent to what we currently have.

in general, we assume that the borrower has a bargaining power of $\theta \in [0,1]$ and the lender has a bargaining power of $1-\theta$. With this set up, the debt recovery rate $\alpha(b_m, b, s)$ solves the following bargaining problem:

$$\hat{\alpha}(b_m, b, s) = arg \max_{\alpha \in [0,1]} \left[\left(\Delta^H(\alpha; b_m, b, s) \right)^{\theta} \left(\Delta^B(\alpha; b_m, b, s) \right)^{(1-\theta)} \right], \tag{F25}$$

$$\begin{aligned} & subject\ to: \\ \Delta^H(\alpha; b_m, b, s) &\geq 0, \\ \Delta^B(\alpha; b_m, b, s) &\geq 0. \end{aligned}$$

The price of non-contingent bonds is given by

$$\begin{aligned} q(b'_m, b', s) \quad = \quad & \\ & \mathbb{E}_{s'|s} \left[M(\varepsilon', p) \left[d' \hat{\alpha} q \left(\hat{\alpha} b'_m, \hat{\alpha} b', s' \right) + (1-d') \left[\kappa + (1-\delta) q \left(b''_m, b'', s' \right) \right] \right] \right], \end{aligned} \tag{F26}$$

and the price of a moratorium debt is given by

$$\begin{aligned} q_m(b'_m, b', s) \quad = \quad & \mathbb{E}_{s'|s} \left[M(\varepsilon', p) \left[d' \hat{\alpha} q_m \left(\hat{\alpha} b'_m, \hat{\alpha} b', s' \right) \right. \right. \\ + \quad & (1-d') \left[\left[1 - \mathcal{I}(p', g') \right] \left[\kappa_m + (1-\delta_m) q_m \left(b''_m, b'', s' \right) \right] \right. \\ + \quad & \left. \left. \left. \mathcal{I}(p', g') e^{r_m} q_m \left(b''_m, b'', s' \right) \right] \right] \right], \end{aligned} \tag{F27}$$

where $d' = \hat{d}\left(b'_m, b', s'\right)$ denotes the next-period equilibrium default decision, $b'' = \hat{b}\left(b'_m, b', s'\right)$ denotes the next-period equilibrium non-contingent debt decision and $b''_m = \hat{b}_m\left(b'_m, b', s'\right)$ denotes the next-period equilibrium moratorium loan decision.

The short-term interest rate r that is used by the imported good producers in the economy for their working capital financing is computed by setting $\delta = 1$. Notice that when $\delta = 1$, equation (F26) boils down to the price of one-period debt, which is determined by tomorrow's default probability and the recovery rate.

Appendix F.5 Definition of equilibrium

This paper focuses on a Markov perfect equilibrium. The household cannot commit to any future (repayment and borrowing) decisions. Hence, the household's strategies depend only on the payoff-relevant state variables.

Definition 1 (Markov perfect equilibrium) *A Markov perfect equilibrium is characterized by value functions $V(b_m, b, s)$, $V^D(b_m, b, s)$, $V^R(b, b_m, s)$, bond pricing functions $q(b'_m, b', s)$, $q_m(b'_m, b', s)$, recovery rate $\hat{\alpha}(b_m, b, s)$, default rule $\hat{d}$, transfers rule $T(b_m, b, s)$ and borrowing rules $\hat{b}, \hat{b}_m$ such that*

1. *Given the bond pricing functions q. q_m, loan recovery rate $\hat{\alpha}(b_m, b, s)$, household policy rules $\left\{\hat{d}, \hat{b}, \hat{b}_m\right\}$ solve the utility maximization problem defined in equations (F17), (F19), and (F20).*

2. Given V, q, q_m, $\hat{d}$, $\hat{b}$, $\hat{b}_m$, the recovery rate solves the bargaining problem in equation (F25).

3. *Given household policy rules* $\left\{\hat{d}, \hat{b}, \hat{b}_m\right\}$*, and the recovery rate* $\hat{\alpha}(b_m, b, s)$*, the pricing function* q *and* q_m *satisfy conditions (F26) and (F27), respectively.*

4. The transfers policy $T(b_m, b, s)$ satisfy the household's budget constraint $q(b'_m, b', s)i + q_m(b'_m, b', s)i_m - \kappa b - [1 - \mathcal{I}(p)]\,\kappa_m b_m$.

In a Markov perfect equilibrium solution, various components are resolved, including the allocations of factors within different sectors, the production processes with and without access to credit markets. From these solutions, further equilibrium variables such as wages, profits, and the price of domestic inputs are derived. This derivation is based on the optimization conditions of firms and the earlier-defined profit definitions.

To break it down:

1. Sectoral Factor Allocations and Production: The equilibrium solution involves determining how factors of production (like labor, imported and domestic inputs) are distributed across different sectors of the economy. This allocation influences the production processes in those sectors under different scenarios, including credit market access and non-access.

2. Equilibrium Wages, Profits, and Input Prices: Equilibrium values for wages (payments to labor), profits (earnings of firms), and the price of domestic inputs (cost of inputs for production) can be computed jointly while establishing the factor allocations and production processes. These values are derived from the firms' optimization strategies and the previously outlined definitions of profits.

Appendix F.6 Numerical Solution

This section briefly sketches the main numerical algorithm, relegating the details of the implementation to Supplementary Material E. To solve the model, we take a two-pronged approach. First, the competitive equilibrium is solved using the Euler equations characterized in the text. We obtain the optimal private sector allocations for any productivity shock and the short-term bond price. With these optimal private allocations in hand, we then solve the household's problem with global solution methods. In particular, solving the model relies on iterating the value functions V^R and V^D, price functions q, q_m, and the recovery rate α as well as an approximation scheme to the private sector's allocation problem. To avoid the potential multiplicity problem outlined in Krusell and Smith (2003), we first solve the equilibrium of the finite-horizon economy. We start with an initial guess for the terminal value and iterate backward until the differences in value and price functions for two subsequent periods are less than 10^{-5}. We then use the obtained values as the equilibrium of the infinite horizon economy.

Appendix F.7 Calibration

We calibrate the model economy at an annual frequency as our firm level variables are observed at annual frequency. For most parameters, we resort to the administrative Colombian data and estimate it ourselves. For the remaining parameters, we use conventional estimates reported in the literature. Table F4 presents the calibrated parameter values.

Table F4: Parameter values

	Parameter	Value	Target
Risk aversion	σ	2	Standard RBC value
Risk-free rate	r^f	4%	Standard RBC value
Standard loan decay rate	δ	0.121	Average duration of 5 years
Labor supply curvature parameter	ω	1.4	Frisch wage elasticity (2.5)
Armington weight of domestic investment	λ	0.62	Mendoza and Yue (2012)
Armington curvature parameter	ϵ	0.62	Mendoza and Yue (2012)
Dixit-Stiglitz curvature parameter	ν	0.59	Mendoza and Yue (2012)
Upper bound to use working capital	θ	0.7	Mendoza and Yue (2012)
Share of capital	α_k	0.17	Standard capital share
Share of labor	α_L	0.40	Standard labor share
Share of intermediate goods	α_M	0.43	Mendoza and Yue (2012)
Labor share of in GDP of int. goods	γ	0.70	Standard labor share
Labor share of in GDP of int. goods	A	1	Invariant TFP in m^d
Calibrated			
Discount factor	β	0.89	Default frequency (2%)
Income autocorrelation coefficient	ρ_ϵ	0.613	Operating income (0.752)
Standard deviation of innovations	σ_ϵ	3.55%	Opr. income std. deviation (0.015)
Borrower's bargaining power	θ	0.61	recovery rate
Income cost of defaulting	d_0	6.40	Spread and loan-to-assets ratio
Income cost of defaulting	d_1	55.64	Spread and loan-to-assets ratio
Probability of entering high risk premium	π_{LH0}	0.25	3 high-risk-premium episodes every twenty years
Probability of entering high risk premium	π_{LH1}	12	4% lower average income
Risk-premium shock	p_H	25	3% spread increase during high-risk-premium

The risk aversion parameter is set to 2 and the annual risk free interest rate r^f is set to 4%, the conventional values used in the literature. Amodio and de Roux (2021) estimate the elasticity of labor supply using Colombian plants data and reports it to be 2.5. Thus, we set the labor supply curvature parameter, ω, to 1.4. This value yields a Frisch elasticity of labor supply, $\frac{1}{\omega-1}$, equal to 2.5, and is well within the range reported in the literature.[28]

The weight of domestic investment goods in the Armington aggregate of investment is based on the OECD Trade-in Value Added (TiVA) database. We set these values as in Mendoza and Yue (2012). Moreover, we set factors shares $\alpha^k = 0.17$ and $\alpha^L = 0.40$ to standard RBC values and set $1 - \alpha^k - \alpha^L$ equal to 0.43. For the remaining parameters for production, ϵ, ν, θ, we follow Mendoza and Yue (2012) and set them equal to 0.62, 0.59, and 0.70, respectively.

The median loan-to-assets ratio equals to 15.7% in our administrative data. The productivity shocks in the model follow an AR(1) process as in equation (F1). Using the operating income process of firms in our administrative data, for the period 2004 to 2019, this is the longest time frame during which the data are available prior to the inception of

[28] See, for example, Rogerson and Wallenius (2009), Christiano, Trabadt and Walentin (2009), and references therein.

moratorium laws, the standard deviation coefficient and the autocorrelation coefficient of the cyclical component of operating income is 3.55% and 0.613, respectively.

Further, a penalty scheme is necessary in this class of models because otherwise the household would always default, and lenders would price it accordingly. So in equilibrium, only a limited amount of debt issuance at very high spreads can be generated. We initially resort to our model's dynamics. The endogenous penalty scheme in our model is the decline in efficiency that is followed by a fall in output. With this alone, we fail to match the spreads. Yet, our model implications remain equivalent to what we currently have in the manuscript and we are not reporting them for brevity. To improve the model's moment-matching success, we introduce an exogenous utility cost of defaulting as in Bianchi, Hatchondo and Martinez, 2018 which is typical in quantitative default studies. In our calibration, we target the standard loan-to-operating income ratio of 15.7 percent which corresponds to the median loan-to-operating income ratio in Colombia. We calibrate the value of the parameters of the utility cost of defaulting (d_0 and d_1) targeting the mean levels of debt and interest rate. Mendoza and Yue (2012) use the invariant state of TFP in the m^d sector, (A), to determine the cost of defaulting. As we are relying on quadratic utility cost of defaulting, we take A to be unity.

We do not observe bankruptcy in our data. Thus, we instead use non-performing loans (NPL) to target the default rate with $\beta = 0.89$.

We set δ at 0.121. With that value, the maturity of loans 5 years, which is the average loan maturity in our administrative data. The definition of duration in Macaulay (1938) is standard in calculating the long-term loan duration. Duration D is the weighted average maturity of future cash flows. A loan issued at time t makes periodic payments κ for the subsequent periods with a geometrically decay rate δ.[29] Observe that equation (F29) is 1 for $\delta = 1$. The spread r_s is defined as the difference between yield i and the risk-free rate

[29]Duration D satisfies,

$$D(\kappa) = \frac{1}{q}\left(\sum_{j=1}^{J} j \frac{\kappa(1-\delta)^{j-1}}{(1+i)^j}\right)$$

where i is the periodic yield an investor would earn if the bond is held to maturity without any defaults and it satisfies

$$q = \sum_{j=1}^{\infty} \frac{\kappa(1-\delta)^{j-1}}{(1+i)^j},$$

and the periodic yield i reads as

$$i = \frac{\kappa}{q} - \delta$$

with which D becomes

$$\begin{aligned} D &= \frac{1}{q(1-\delta)} \lim_{J\to\infty} \sum_{j=1}^{J} j \left(\frac{1-\delta}{1+i}\right)^j && \text{(F28)} \\ &= \frac{1+i}{i+\delta}. && \text{(F29)} \end{aligned}$$

r. The annualized spread reported in the tables is computed as

$$1 + r_s = \left(\frac{1 + i}{1 + r} \right)^4 .$$

The debt levels obtained from the simulations are equivalent to the present value of future debt obligations, which are discounted at the risk-free rate and computed as $\frac{b(1+r)}{\delta+r}$.

Supplementary Material
NOT FOR PUBLICATION

Supplementary Material A A tree-period model

In this section we present a simple analytical model to highlight the main effects of the moratorium policy and show that the moratorium policy can have different effects depending on whether the default risk is accounted. The economy runs for three periods. We focus on a closed economy where a single good is produced and traded. The economy consists of competitive lenders and firms. Firms and lenders have different initial endowments and preferences, allowing for intertemporal trade.

Specifically, firms have zero endowment in the first period ($y_1 = 0$), indicating that they do not possess any resources initially. Firms discount the future at a constant rate denoted as β, which is less than one. On the other hand, for simplicity, banks are assumed to have a discount rate of unity. The key requirement for intertemporal trade is that banks' discount rate is higher than that of firms.

In periods 2 and 3, the firm is endowed with one unit of the produced good. To incorporate a loan moratorium policy into this simple three-period framework, we introduce a liquidity shock in the second period. This shock occurs with a probability denoted as π and implies that firms cannot access a portion (ℓ) of their resources in the second period. However, this amount can be accessed and utilized in the third period. Consequently, with the implementation of the moratorium policy, firms will postpone the payment of their liabilities if they are affected by the shock and will repay all their obligations in the final period. In our initial formulation of the simple three-period model, we intentionally exclude the possibility of default on loans. This allows us to examine the dynamics of the model without default and establish a baseline understanding of the economic interactions.

However, we recognize the importance of incorporating default into our analysis to capture more realistic scenarios. By relaxing the initial assumption of no default, we can investigate how default affects the dynamics of the model. Indeed, the incorporation of default into the model will highlight the necessity of solving an infinite horizon model.

The utility function for both the bank and the firm is assumed to take the quasi-linear form, that $u(c) = Ac$ for the initial period and $v(c) = Ac - \frac{\phi}{2}c^2$ with $A > \phi > 0$.

In the initial period, the firm's sole choice to fund its consumption is by borrowing. This borrowing takes the form of a long-term loan denoted as b, which is acquired at a price q. This loan is initiated in the first period and involves an agreement to deliver δ units of a good in the subsequent (second) period, while the remaining portion of the loan, equivalent to $(1 - \delta)$ units of the good, is settled in the third period. In the following analysis we let $\delta = \frac{1}{2}$ for simplicity.

The maximization problem of the firm without the loan moratorium policy can then be written as

$$\max_{b>0} \; u\,(qb) + \beta\left[(1-\pi)v\left(1-\frac{b}{2}\right) + \pi v\left(1-\frac{b}{2}-\ell\right)\right]$$
$$+\beta\left[(1-\pi)v\left(1-\frac{b}{2}\right) + \pi v\left(1-\frac{b}{2}+\ell\right)\right]$$
$$\text{subject to } 1-\frac{b}{2}-\ell \geq 0. \tag{A1}$$

The FOC with respect to b yields the demand curve for loans:

$$b(q): \;\; 2\frac{A(q-\beta)+\beta\phi}{\beta\phi}. \tag{A2}$$

And in an economy with the loan moratorium policy, the firm's repayments are deferred to the next period, Thus, instead of paying $\frac{b}{2}$ this period, the firm is going to pay all of its loan b in the next period.[30] The maximization problem of the firm becomes

$$\max_{b^p} \; u(qb^p) + \beta\Big[(1-\pi)v\left(1-\frac{b^p}{2}\right) + \pi v\,(1-\ell)\Big] +$$
$$\beta\Big[(1-\pi)v\left(1-\frac{b^p}{2}\right) + \pi v\,(1+\ell-b^p)\Big]$$
$$\text{subject to } c \geq 0. \tag{A3}$$

The solution to this problem is

$$b^p(q): \;\; 2\frac{A(q-\beta)+\beta\phi}{\beta\phi} + \beta\frac{\pi(A-\phi)+\pi\phi\ell}{\beta\phi}. \tag{A4}$$

The last term (in blue) in equation (A4) is the additional term compared to equation (A2). This term turns out to be always positive so that the firm always prefers higher loan with the policy.

We can now write the lenders' maximization problem with and without the moratorium policy as follows. First without the policy:

$$\max_{b>0} \; u\,(1-qb) + v\left(1+\frac{b}{2}\right) + v\left(1+\frac{b}{2}\right)$$
$$\text{subject to } 1-qb \geq 0. \tag{A5}$$

[30] For simplicity, we assume that the deferred payments do not accrue interest rate.

With the policy it reads

$$\max_{b^p} \; u(1-qb^p) + \left[(1-\pi)v\left(1+\frac{b^p}{2}\right) + \pi v(1)\right] + \tag{A6}$$
$$\left[(1-\pi)v\left(1+\frac{b^p}{2}\right) + \pi v\left(1+b^p\right)\right]$$
subject to $c \geq 0$.

The solution to these problems yield the supply curves as

$$b(q): \;\; 2\frac{A(1-q)-\phi}{\phi}, \tag{A7}$$

$$b^p(q): \;\; 2\frac{A(1-q)-\phi}{\phi(1+\pi)}. \tag{A8}$$

Theorem 1 *Let $b_s^p(q)$ and $b_s(q)$ represent the loans supplied by lenders with and without the policy, respectively. Similarly, $b_d^p(q)$ and $b_d(q)$ denote the loans demanded by borrowers, with and without the policy. Assume that both borrowers and lenders have quasi-linear utility functions, defined as $u(c) = Ac$ and $v(c) = Ac + \frac{\phi}{2}c^2$ with $A > \phi > 0$. It follows that, for a positive loan amount, $b_s > 0$, lenders are inclined to offer a smaller amount of loan to firms under the loan moratorium policy, denoted as b_s^p, as compared to the situation without the policy (b_s), that is, $b_s^p < b_s$. Additionally, firms exhibit an increased demand for loan from lenders under the policy (b_d^p), compared to the scenario without the policy (b_d), for the same given price "q", that is $b_d^p > b_d$.*[31]

Intuitively, risk-averse lenders are not willing to lend to firms when they need the resources the most. Figure A1 (a) visualizes this intuition. For each level of price (which is inversely related with the interest rate) lenders are willing to save more and require a higher interest rate to meet the exact demand of the firms without the policy. Firms, on the other hand, are willing to borrow more for each level of interest rate.

In our basic three-period model, we initially disregarded the possibility of borrowers defaulting. This means that the loan price, denoted as q was assumed to be independent of the loan amount b. Now, we can introduce the idea that the loan price can also be influenced by the loan amount b.

Furthermore, we are expanding the model to accommodate uncertainty regarding incomes in the second and third periods. These income values are considered as random variables and are drawn from a distribution represented by a probability density function (pdf) denoted as $f(y)$ and a cumulative distribution function (cdf) denoted as $F(y)$. In cases of default, borrowers incur a cost associated with defaulting, denoted as $C(y)$. Without this default cost, borrowers would always choose to default in the terminal period.

[31] Proof: Equation (A4) is always greater than equation (A2). Thus, it follows that $b_d^p > b_d$. Similarly, the equation (A8), which denotes the supply curve, is always lower than the supply curve without the policy given in the equation (A8). Thus, $b_s^p < b_s$. ∎

Within this revised framework, the borrower has the potential to default based on the realized income outcomes in the second and third periods. To capture this, we define an income threshold denoted as $y^\star(b, y)$. When the realized income falls below this threshold, borrowers find it optimal to choose for defaulting on their obligations.

Incorporating the possibility of default, we can reformulate the borrower's problem by partitioning the integral as follows:

$$\begin{aligned}
&\max_{b>0}\ u\left(qb\right)+\beta(1-\pi)\Bigg(\underbrace{\int_{y^\star} v\left(y-\frac{b}{2}\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\Bigg)dF(y) \\
&+\beta\pi\Bigg(\underbrace{\int_{y^\star} v\left(y-\frac{b}{2}-\ell\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\Bigg)dF(y) \\
&+\beta(1-\pi)\Bigg(\underbrace{\int_{y^\star} v\left(y-\frac{b}{2}\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\Bigg)dF(y) \\
&+\beta\pi\Bigg(\underbrace{\int_{y^\star} v\left(y-\frac{b}{2}+\ell\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\Bigg)dF(y) \\
&\text{subject to } y-\frac{b}{2}-\ell\geq 0,\ y-C\left(y\right)>0.
\end{aligned} \tag{A9}$$

and the lender's problem who takes the default threshold y^* given as

$$\begin{aligned}
&\max_{b>0}\ u\left(1-qb\right)+\left(1-\pi\right)\Bigg(\underbrace{\int_{y^\star} v\left(y+\frac{b}{2}\right)}_{repaid}+\underbrace{\int^{y^\star} v\left(y\right)}_{defaulted}\Bigg)dF(y) \\
&+\pi\Bigg(\underbrace{\int_{y^\star} v\left(y+\frac{b}{2}\right)}_{repaid}+\underbrace{\int^{y^\star} v\left(y\right)}_{defaulted}\Bigg)dF(y) \\
&+(1-\pi)\Bigg(\underbrace{\int_{y^\star} v\left(y+\frac{b}{2}\right)}_{repaid}+\underbrace{\int^{y^\star} v\left(y\right)}_{defaulted}\Bigg)dF(y) \\
&+\pi\Bigg(\underbrace{\int_{y^\star} v\left(y+\frac{b}{2}\right)}_{repaid}+\underbrace{\int^{y^\star} v\left(y\right)}_{defaulted}\Bigg)dF(y) \\
&\text{subject to } 1-qb\geq 0.
\end{aligned} \tag{A10}$$

Notice that the integrals in the equations may not be canceled, as the default threshold y^* in each line may vary which we will elaborate below.

Moving forward, the solution to the firm's problem without the policy becomes

$$b(q): \quad 2\frac{A(q-\beta)+\beta\phi}{\beta\phi - 2A\frac{\partial q}{\partial b}}. \tag{A11}$$

Similarly, when we make the same adjustments in equation (A3) to the equation (A9) to solve the impact of the policy, details of which are provided in equations (A15) and (A16), the solution to the firm's problem becomes

$$b^p(q^p): \quad 2\frac{A(q^p-\beta)+\beta\phi}{\beta\phi - 2A\frac{\partial q^p}{\partial b}} + \beta\frac{\pi(A-\phi)+\pi\phi\ell}{\beta\phi} - 2A\frac{\partial q^p}{\partial b}. \tag{A12}$$

The next follows the solution to the lender's problem which yields

$$b(q): \quad 2\frac{A(1-q)-\phi}{\phi + 2A\frac{\partial q}{\partial b}}, \tag{A13}$$

$$b^p(q^p): \quad 2\frac{A(1-q^p)-\phi}{\phi(1+\pi) + 2A\frac{\partial q^p}{\partial b}}. \tag{A14}$$

It's important to emphasize that the optimal default thresholds in the maximization problem could vary for both firms and lenders, with and without the policy. This introduces an additional layer of complexity to the analysis. In order to obtain a clearer understanding of the potential effects of the policy alteration, we resort to a straightforward numerical example, akin to the one depicted in Figure A1 (a).

The direct comparison between equations (A12) and (A14) is not straightforward. The derivative term $\frac{\partial q}{\partial b}$ might not be identical since default thresholds could differ across economies. However, there are quantitative observations: $\frac{\partial q}{\partial b} \leq 0$ and $\frac{\partial q^p}{\partial b} \leq 0$, aligning with the typical finding that the likelihood of default increases with larger loans. Furthermore, it's again quantitatively noted that $\frac{\partial q^p}{\partial b} > \frac{\partial q}{\partial b}$ due to the policy reducing default risk for a given loan size. Consequently, the additional blue term to the solution of the firm's optimization problem turns out to be always positive when we account for the risk of default. In other words, firms request more loans from lenders at the same price, factoring in default risk.

On the lender's side, the situation may change based on the price's sensitivity to loans, $\frac{\partial q}{\partial b}$. During non-crisis periods, where the likelihood of default is low, price responsiveness is generally negligible, thus Theorem 1 remains valid. During a crisis, however, prices become highly responsive, leading lenders to be more willing to offer loans to firms for the same price $q(b)$ under the loan moratorium policy. This distinction is illustrated in Figure A1 (b).

The intuition is that for such high premiums levied on the firm, lenders are willing to supply more credit while firms are more likely to default compared to the same level of loans held in an economy without the policy.

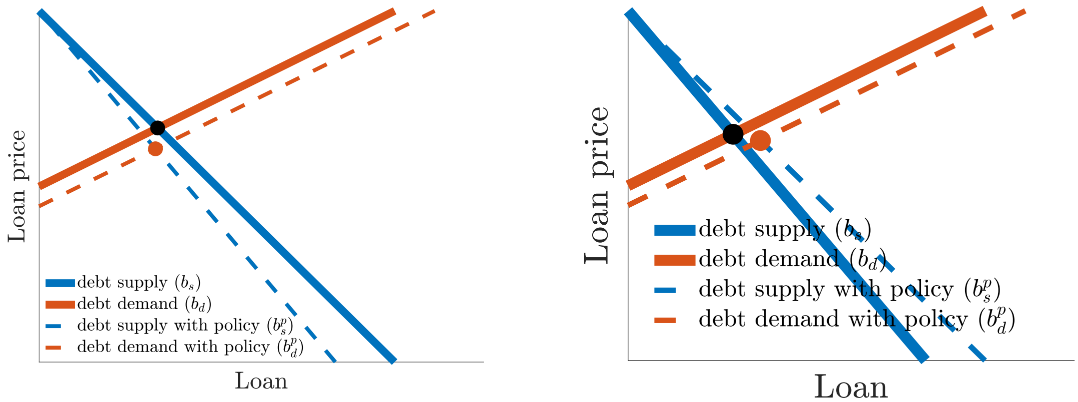
In the manuscript, we validate our theoretical findings through empirical analysis. Additionally, we extended our three-period analysis to an infinite horizon model, allowing us to explore the dynamic implications of the loan moratorium policy in a more comprehensive framework. This allows us to examine the long-term effects of the policy on key variables such as indebtedness and default rates as well as real variables such as employment and income.

$$
\begin{aligned}
&\max_{b>0}\ u\left(qb\right)+\beta(1-\pi)\left(\underbrace{\int_{y^\star} v\left(y-\frac{b}{2}\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\right)dF(y) \qquad \text{(A15)}\\
&+\beta\pi\left(\underbrace{\int_{y^\star} v\left(y-\ell\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\right)dF(y)\\
&+\beta(1-\pi)\left(\underbrace{\int_{y^\star} v\left(y-\frac{b}{2}\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\right)dF(y)\\
&+\beta\pi\left(\underbrace{\int_{y^\star} v\left(y-b+\ell\right)}_{repayment}+\underbrace{\int^{y^\star} v\left(y-C\left(y\right)\right)}_{default}\right)dF(y)\\
&\text{subject to}\\
&y-b-\ell\geq 0,\ y-b>0,\ y-C\left(y\right)>0.
\end{aligned}
$$

and the lender's problem who takes the default threshold y^* given as

$$
\begin{aligned}
&\max_{b>0}\ u\left(1-qb\right)+(1-\pi)\left(\int_{y^\star} v\left(y+\frac{b}{2}\right)+\int^{y^\star} v\left(y\right)\right)dF(y) \qquad \text{(A16)}\\
&+\pi\left(\int_{y^\star} v\left(y\right)+\int^{y^\star} v\left(y\right)\right)dF(y)\\
&+(1-\pi)\left(\int_{y^\star} v\left(y+\frac{b}{2}\right)+\int^{y^\star} v\left(y\right)\right)dF(y)\\
&+\pi\left(\int_{y^\star} v\left(y+b\right)+\int^{y^\star} v\left(y\right)\right)dF(y)\\
&\text{subject to } 1-qb\geq 0.
\end{aligned}
$$

Figure A1: Demand and supply of loans with and without the policy.



(a) Default risk not accounted (b) Default risk accounted

Supplementary Material B Policy enforcement on existing loans

This section corroborates that the policy had the intended effect on *existing loans*, regarding the (i) suspension of debt repayments and (ii) reset of delinquency days. In particular, we focus on the effect of the policy during and after the quarter of treatment. We employ information on delinquency days, changes in expected payments, and the outstanding loan value (principal and interest) relative to Q1-2020 (i.e., one quarter before the policy was implemented).

Our results, presented in Table B1, correspond to sharp RDD estimates that consider eligible treated loans as the treatment group with ineligible loans as the control group. The first two columns confirm the results presented in Figure 2: past due days of loans receiving moratoria are reduced on average by 108 days, while the change in expected loan payments are reduced by almost 90%. This confirms that the policy was effectively enforced and limited to the 1-3 month duration established in the regulation. As expected, the number of delinquency days remains lower than untreated loans, albeit in large magnitude. This is because, unlike loan repayments (flow variable), the number of delinquency days carries persistence (behaving more like a stock variable). Intuitively, a newly reset loan will take time (if any) to re-incur in nonperforming days.

On the other hand, the third column of Table B1 shows that the outstanding amount of the loan (principal and interest) increases by almost 8% for loans receiving a moratoria. This is consistent with a suspension of debt repayments which should raise the total debt.

In addition, we trace the *same existing loans* two quarters after treatment to assess if: (i) the changes in delinquency behavior remain and (ii) the repayment schedule and total value of the debt fully adjust. As shown in the right part of the Table (last three columns), we observe that after treatment, delinquency days are still 174 days less for treated loans, while loan repayments increase by 52% to compensate for the time that the loan received

Table B1: Repayment and delinquency days: Existent Loans

	During quarter of treatment			After quarter of treatment		
	Delinquency days	ΔPayment due	ΔLoan	Delinquency days	ΔPayment due	ΔLoan
Sharp-RD	-107.77***	-0.90***	0.076**	-174.19***	0.52***	-0.056*
	(8.7)	(0.10)	(0.037)	(0.09)	(16.9)	(0.034)
Observations	34,369	30,997	20,809	53,771	54,511	38,691
BW (in days)	47.7	34.7	25.6	40.0	10.9	27.0

Authors' calculations. The table shows the effect of the policy on repayment amount, delinquency days, and outstanding debt for existent loans during the quarter of treatment and after treatment ends. Estimates correspond to Sharp RD estimate in equation (4). Robust bias corrected standard errors in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. The last row report the Bandwidth (BW) in days used to compute the local RD estimate. ΔPayment and ΔLoan represent the changes in payment and total debt balance computed as the growth rate of monetary payments and debt balance (principal+interests) at the end of each quarter relative to Q1-2020. The treatment quarter corresponds to existing loans receiving a moratorium in the second, third, or fourth quarter of 2020.

moratoria. The last two results explain why we observe a 5.6% drop in the loan value for treated firms relative to non-eligible loans without moratoria.

Supplementary Material C Other robustness Checks

Supplementary Material C.1 Excluding firms with Multiple Existing Loans

The results in Table C2 present RDD estimates for new loans restricting the sample to bank-firm pairs with a single *existing* loan relationship at the time that the debt moratorium policy was implemented. Similarly, Table C3 shows the results for firm-level outcomes; in this case, our sample includes only firms with a single *existing* loan when the moratorium policy started. Our aim with this exercise is twofold: (i) to exclude firms that ex-ante had multiple bank relationships, (ii) to exclude firms receiving multiple debt payment suspensions.

Table C2: RD Loan Outcomes: bank-firm pairs with single *existing* loan relationships

	Intensive	Extensive	Interest	Maturity	Collateral	Rating	Default Prob.	
	Log(Loan)	$\mathbb{1}\{\text{loan}\}$					Ex-ante	Ex-post
Fuzzy-RD	27.41**	1.61*	-0.73*	12.27	1.52	8.42*	-2.15	-3.28**
	(11.0)	(1.00)	(0.4)	(13.5)	(1.5)	(4.9)	(1.5)	(1.3)
				First Stage				
D_{ij}	0.09***	0.09***	0.12**	0.04	0.09***	0.08***	0.08***	0.09***
	(0.0)	(0.0)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Observations	32,411	65,909	32,411	32,411	32,411	32,411	32,411	64,120
BW (in days)	16.9	12.8	7.6	12.0	12.9	19.9	20.5	17.9

Authors' calculations. Table show the estimates for the effect of the debt moratoria on new loan conditions for stressed firms. We exclude bank-firm pairs with multiple *existing* loan relationships. Estimates in the first row correspond to Fuzzy RD coefficient δ_1 in equation (4). The second row shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (2). Robust Bias-corrected standard errors in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. The last row report the Bandwidth (BW) in days used to compute the local RD estimate. We employ data on new loan conditions during 2020Q1-2021Q4. To capture the intensive margin for new loans, we use the amount (in logs of COP) at the quarter of origination. The extensive margin of new loans is captured by a dummy taking the value of one in the quarter of origination. Maturity is denoted in number of years, collateral is expressed as percentages of the loan amount, credit rating is a categorical variable from 1-5 where 5 is the highest rating, ex-ante default represents the expected default probability assigned to the loan by the bank, and ex-post default is a dummy variable that takes the value of one if the loan has more than thirty days of delinquency at the end of each quarter. The interest rate, maturity, collateral, rating of new loans, and ex-ante default are measured only at the quarter of origination of the loan. All columns control for bank, quarter, and two-digit industry code fixed effects. For the intensive margin (first column) and the interest rate (third column), we control for the balance of the existing loan and its interest rate at the end of Q1-2020, respectively.

Table C3: RD Firm Outcomes: Firms with single *existing* loan relationships

	ΔEmp.	Inv.rate	ΔOp. Rev.	Δ Assets	ΔLiab.	ΔProfit	ΔEquity
Fuzzy-RD	1.50	0.19***	5.72***	1.83*	2.01***	1.37***	1.11
	(1.090)	(0.047)	(1.157)	(1.079)	(0.712)	(0.319)	(0.708)
	First Stage						
D_{ij}	0.17***	0.20***	0.25***	0.14***	0.18***	0.21***	0.14***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Observations	10,389	5,830	19,133	18,122	17,965	17,769	18,122
BW (in days)	23.2	10.0	7.0	14.8	10.5	9.1	14.6

Authors' calculations. Table show the estimates for the effect of the debt moratoria on firm level variables for stressed firms. We exclude firms with multiple *existing* loan relationships. Estimates in the first row correspond to the Fuzzy RD coefficient δ_1 in equation (4). The second row shows the first stage estimates for the probability of treatment (D_{ij}) described in equation (2). Robust Bias-corrected standard errors clustered at the firm's province in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. The last row report the Bandwidth (BW) in days used to compute the local RD estimate. We use employment and balance sheet data for firms during 2020-2021. ΔEmp., ΔOp. Rev., ΔAssets and ΔLiab. denote yearly symmetric growth rates of the number of employees, operating revenues, total assets, and liabilities, respectively. Inv.rate represents the investment rate computed as the ratio of new purchases of buildings, plants, and equipment to total assets lagged one year. ΔProfit, ΔEquity are computed as the yearly change in gross profits and equity relative to the operating revenues and total assets lagged one year, respectively. All columns control for bank and two-digit industry codes' fixed effects.

Supplementary Material C.2 Controlling for existing credit risk prior to the policy

Tables C4 and C5 show the RD estimates for new loans and firm outcomes controlling for the exisitng credit rating prior to the policy. Intuitively, controlling for firms' credit rating on *existing* loans should absorb any effect of the debt moratoria coming from the "artificial" boost in credit ratings to firms receiving suspension of payments on existent loans.

Table C4: RD New Loans: Controlling for firms' credit risk

	Intensive	Extensive	Interest	Maturity	Collateral	Rating	Default Prob.	
	Log(Loan)	$\mathbb{1}\{\text{loan}\}$					Ex-ante	Ex-post
Fuzzy-RD	32.19*	0.70	-1.07**	12.11***	3.82**	0.58	-0.22	-5.34***
	(19.5)	(0.94)	(0.5)	(4.0)	(1.8)	(2.5)	(0.8)	(1.9)
	First Stage							
D_{ij}	0.07**	0.08***	0.10**	0.13***	0.10***	0.13***	0.12***	0.08***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Observations	35,072	70761	35,072	35,072	35,072	35,072	35,072	71,750
BW (in days)	15.6	14.4	7.5	19.9	14.2	19.2	17.6	16.1

Authors' calculations. Table show the estimates for the effect of the debt moratoria on new loan conditions for stressed firms controlling for the existing credit rating prior to the policy. Estimates in the first row correspond to Fuzzy RD coefficient δ_1 in equation (4). The second row shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (2). Robust Bias-corrected standard errors in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. The last row report the Bandwidth (BW) in days used to compute the local RD estimate. We employ data on new loan conditions during 2020Q1-2021Q4. To capture the intensive margin for new loans, we use the amount (in logs of COP) at the quarter of origination. The extensive margin of new loans is captured by a dummy taking the value of one in the quarter of origination. Maturity is denoted in number of years, collateral is expressed as percentages of the loan amount, credit rating is a categorical variable from 1-5 where 5 is the highest rating, ex-ante default represents the expected default probability assigned to the loan by the bank, and ex-post default is a dummy variable that takes the value of one if the loan has more than thirty days of delinquency at the end of each quarter. The interest rate, maturity, collateral, rating of new loans, and ex-ante default are measured only at the quarter of origination of the loan. All columns control for bank, quarter, and two-digit industry code fixed effects. For the intensive margin (first column) and the interest rate (third column), we control for the balance of the existing loan and its interest rate at the end of Q1-2020, respectively.

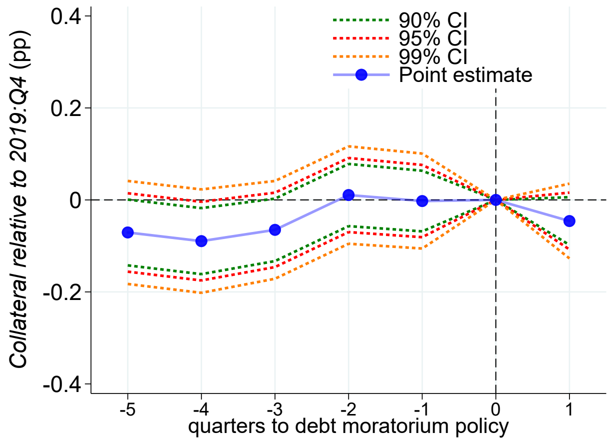
Table C5: RD Firm Outcomes: Controlling for firms' credit risk

	ΔEmp.	Inv.rate	ΔOp. Rev.	Δ Assets	ΔLiab.	ΔProfit	ΔEquity
Fuzzy-RD	3.55*	0.11*	2.87***	1.24*	1.58***	4.63*	0.80*
	(2.0)	(0.1)	(0.6)	(0.6)	(0.5)	(2.5)	(0.4)
	First Stage						
D_{ij}	0.10**	0.25***	0.45***	0.16***	0.21***	0.22***	0.16***
	(0.0)	(0.0)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)
Observations	15,379	11,386	31,786	30,887	30,660	29,762	30,887
BW (in days)	22.9	9.4	6.3	14.2	9.3	9.7	14.3

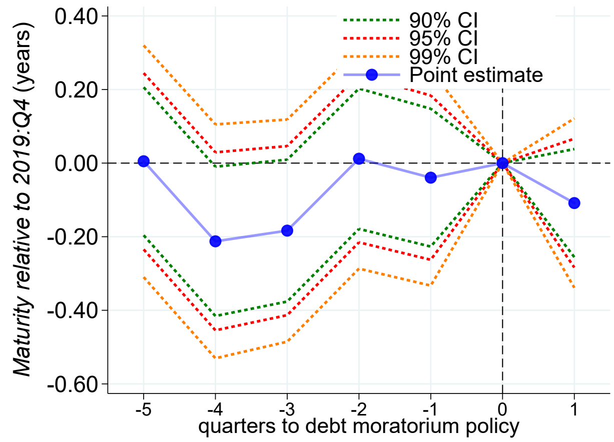
Authors' calculations. Table show the estimates for the effect of the debt moratoria on firm level variables for stressed firms controlling for the existing credit rating prior to the policy. Estimates in the first row correspond to the Fuzzy RD estimate in equation (4). The second row shows the first stage estimates for the probability of treatment (D_{ij}) described in equation (2). Robust Bias-corrected standard errors clustered at the firm's province in parentheses , *, **, ***, indicate significance at the 10%, 5%, and 1% respectively. The last row report the Bandwidth (BW) in days used to compute the local RD estimate. We employ firm's balance sheet data for 2020-2021 to measure firm outcomes. ΔEmp., ΔOp. Rev., ΔAssets and ΔLiab. denote yearly symmetric growth rates of number employees, operating revenues, total assets and liabilities, respectively. Inv.rate represent the investment rate computed as the ratio of new purchases of buildings, plant and equipment to total assets lagged one year. ΔProfit, ΔEquity are computed as the yearly change in gross profits and equity relative to the operating revenues and total assets lagged one year, respectively. In all columns we control for bank and two-digit industry codes fixed effects.

Supplementary Material D Checking for Parallel Trends: Non-Stressed Firms

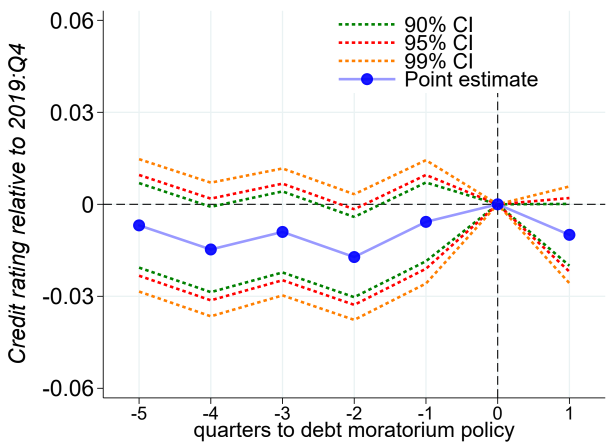
Figure D2: Event Study Analysis: Other Loan level outcomes



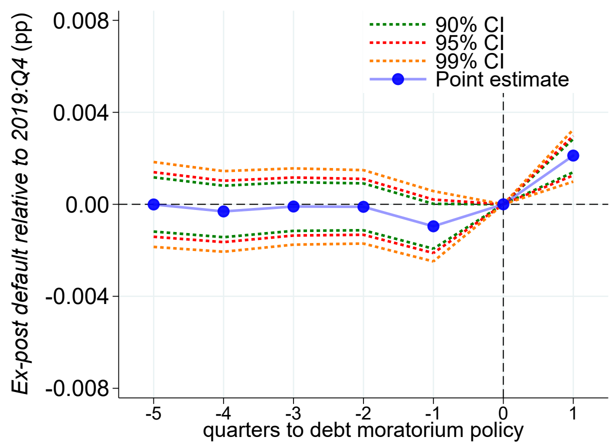
(a) Collateral requirement



(b) Maturity



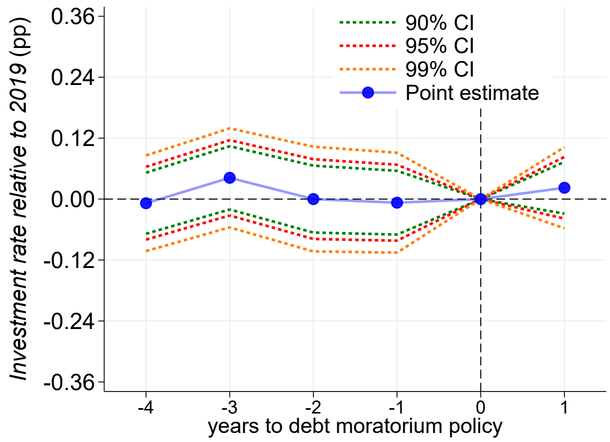
(c) Credit rating



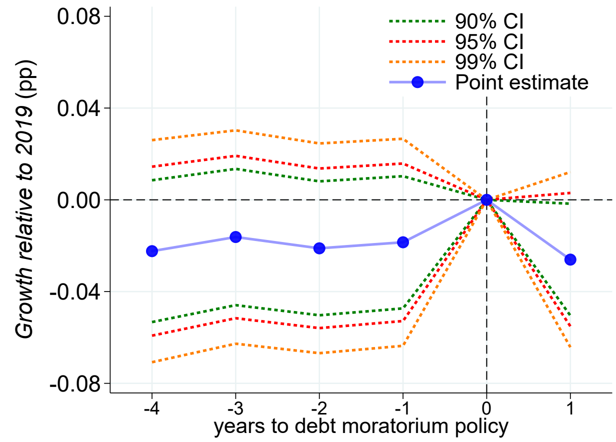
(d) Ex-post default probability

Figure plots the point estimates and confidence intervals for the lead (ϕ_{-1},..,ϕ_{-5}) and contemporaneous (β) coefficients of equation (5). We employ data on new loans at the quarter of origination during 2018Q4-2021Q4. Panel (a) shows the results for collateral requirement. Panel (b) maturity. Panel (c) credit rating. Panel (d) ex-post default probability.

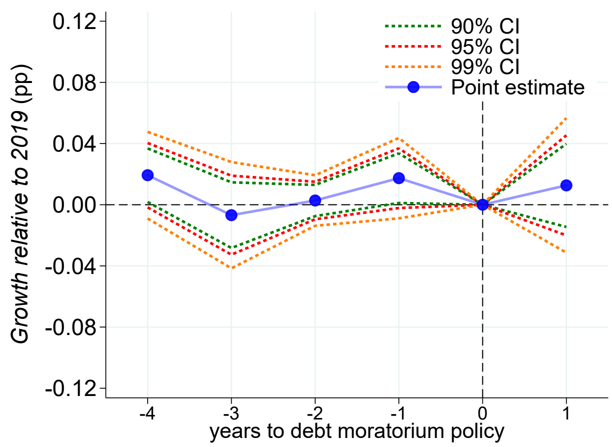
Figure D3: Event Study Analysis: Firm level outcomes I



(a) Investment



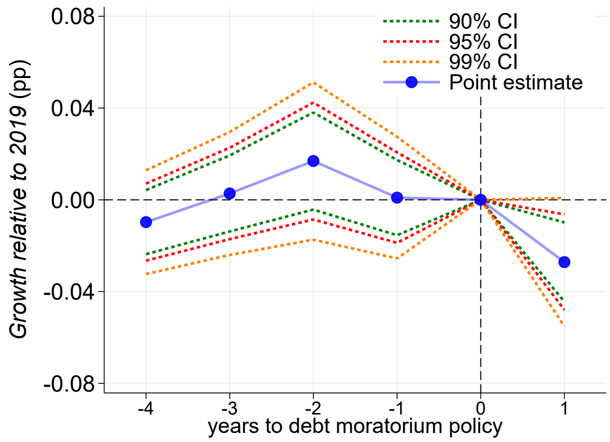
(b) Employment



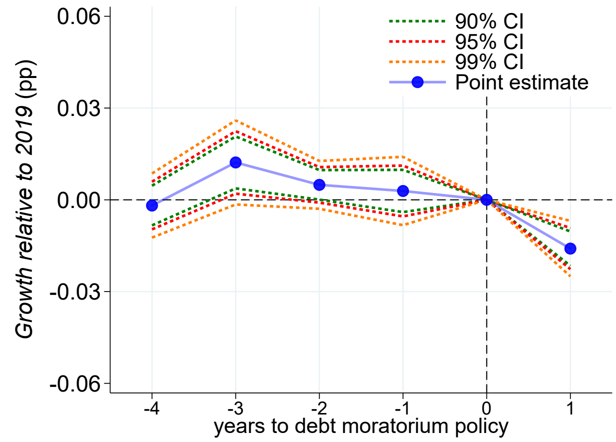
(c) Operating Revenue

Figure plots the point estimates and confidence intervals for the lead (ϕ_{-1},..,ϕ_{-4}) and contemporaneous (β) coefficients of equation (5). We use employment and balance sheet data for firms during 2015-2021. Panel (a) shows the results for investment rate. Panel (b) and (c) for the growth rate of employment and operating revenues, respectively.

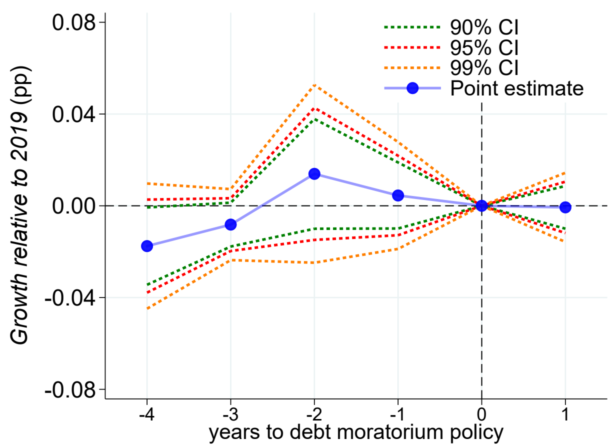
Figure D4: Event Study Analysis: Firm level outcomes II



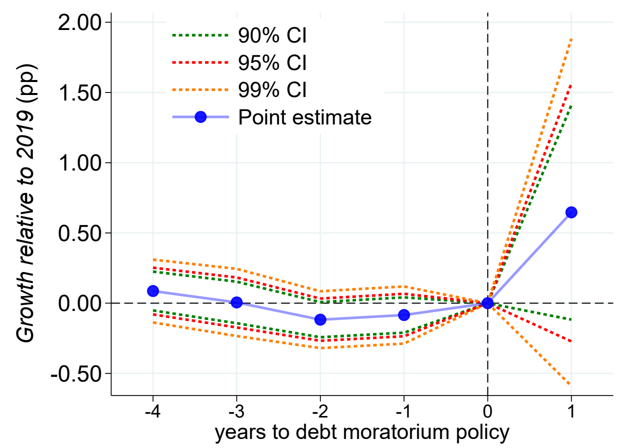
(a) Liabilities



(b) Assets



(c) Profits



(d) Equity

Figure plots the point estimates and confidence intervals for the lead (ϕ_{-1},..,ϕ_{-4}) and contemporaneous (β) coefficients of equation (5). We use balance sheet data for firms during 2015-2021. Panel (a), (b), (c), and (d) shows the results for the growth rate of liabilities, assets, profits, and equity, respectively.

Supplementary Material E Numerical approximation algorithm

Continuing from Appendix F.6, we utilize a two-pronged approach. We detail these approaches below. First, set grid points for TFP shocks (ϵ) and interest rate r. For a given interest rate r, compute the standard CES price index of imported inputs $P^i(r)$ given in equation F5. Then the competitive equilibrium is solved by first defining excess demand function for the domestic input m^d as $\phi(p^m) = A(L^m)^\gamma - m^d$, given the price of domestic inputs p^m and the labor market clearing wage w which is obtained by defining an excess demand function for labor as $\phi(w) = L^f + L^m - L$ given the price of domestic inputs p^m. That is, excess demand functions are used to solve the market clearing intermediate good price p^m and the market clearing wage w. We then feed these two prices into a bi-dimensional BOBYQA (Powell) routine to obtain the optimal allocations of m^d and m^i by computing the final producers profit provided in equation (F4). With these, both excess demand functions of $\phi(p^m)$ and $\phi(w)$ are zeroed using a bisection method.

After solving the competitive equilibrium for factor allocations, we then proceed to solve the household's optimization problem which requires iterating on the value and price functions until a convergence criteria of 10^{-5} is obtained. Functions are evaluated at equally spaced grid points. When evaluations fall outside of the grids, we approximate our functions by interpolating them with B-splines for both loan types and linearly interpolating them for income. For standard and moratorium loans b, b_m, 40 grid points each, and for TFP shock ϵ, 30 grid points are used, whereas we utilize 100 Gauss-Legendre quadrature points to evaluate expectations over income into the subsequent period. Below we outline these steps in detail.[32]

1. First solve the competitive equilibrium using the Euler equations characterized in the text and then obtain the optimal private sector allocations for any TFP shock and the short-term bond price.

2. Initial guesses of V^R, v^D, q, q_m and α are set at the their corresponding levels in a finite-horizon economy as follows:

   - $V^R(b_m, b, s) = u(c, L)$ where $c = \epsilon f\left(M\left(m^d, m^i\right), L^f, k\right) - P^i(r^{aut})m^i - \kappa b - \kappa_m b_m$.
   - $v^d(b_m, b, s) = u(c, L)$ where $c = \epsilon f\left(M\left(m^d, m^i\right), L^f, k\right) - P^i(r^{aut})m^i$.
   - and $q = 0$, $q_m = 0$, $\alpha = 0$.

   All factor allocations that are obtained in the first step are functions of the TFP shock ϵ and the interest rate r which is a one-period debt version of q, can be obtained through a mapping function in equation (F19).

[32] Önder (2023a) shows the superiority of using black-box optimizers over taste-shocks, particularly when solving a portfolio allocation problem.

3. The optimization problem described by equations (F17) and (F20) is solved at multiple grid points for loans (b, b_m), TFP shock ϵ, and global liquidity shock p. The goal is to find the globally optimal solution for the borrowing decisions in the next period. To achieve this, a search is conducted by generating 100 grid points for each of the portfolio components b' and b'_m. The initial values of the standard and moratorium loans b and b_m are set with 40 grid points each. Initially, for a fixed choice of b', the corresponding optimal grid for b'_m is found. This optimal point is then utilized as the initial guess for a one-dimensional Brent routine in FORTRAN, which helps pinpoint the precise optimal value of b'_m for a fixed b' with double precision. Finally, having obtained the fixed value of b' and the corresponding optimal value of b'_m, a two-dimensional optimization Powell routine is employed. This routine is used to solve for the optimal portfolio of (b', b'_m) for each combination of (b_m, b, ϵ, p) resulting from the grids. In summary, this iterative process involves solving the optimization problem at multiple grid points to identify the globally optimal portfolio choices for borrowing decisions under various combinations of shocks and loan components.

4. With obtained policy functions, solve the bargaining game between lenders and borrowers defined in equation (F25)

5. Iterate the procedure defined above for equations (F17) to (F27) until the ergodic differences in two iterations remains the same.

6. Invoke local search methods within the neighborhood of the obtained candidate optima (b', b'_m) for each grid points of (b_m, b, ϵ, p) in the previous step.

7. Iterate the local search methods for equations (F17) to (F27) in the text until convergence criteria of 10^{-5} is obtained.

With the equilibrium value functions, pricing and recovery rate functionals as well as the decision rules for borrowing and default, we simulate the model. In particular, we:

1. Set the number of samples $N = 2000$, number of periods $T = 1501$ and $T_0 = 500$.

2. Use a random number generator to draw sequences of ε_t for $t = 1, 2, ..., T$ to compute the income of the subsequent periods and to evaluate the continuation value of default. We fix these drawn shocks to use them for each sample $n \in N$.

3. Set the initial TFP shock ϵ to be mean $\epsilon = 1$ with no global liquidity shocks and debt holdings b_m, b to be zero.

4. Cut the first T_0 periods of each sample before computing the moments of the simulation so that randomly chosen initial values will not have any influence on moments.

The moments reported in all tables are computed from the 2000 simulated sample paths such that each sample includes 5 years without a default observation. The sample period begins at least 5 years after regaining access to the credit markets following a default episode. Business cycle moments are reported after HP-detrending them with a smoothing parameter of 100. We also make sure that both global search methods and local search methods generate almost the same moments and policy functions.

Supplementary Material F Coupon Structure and Debt Moratoria

Figure F5: Coupon structure of standard loans.

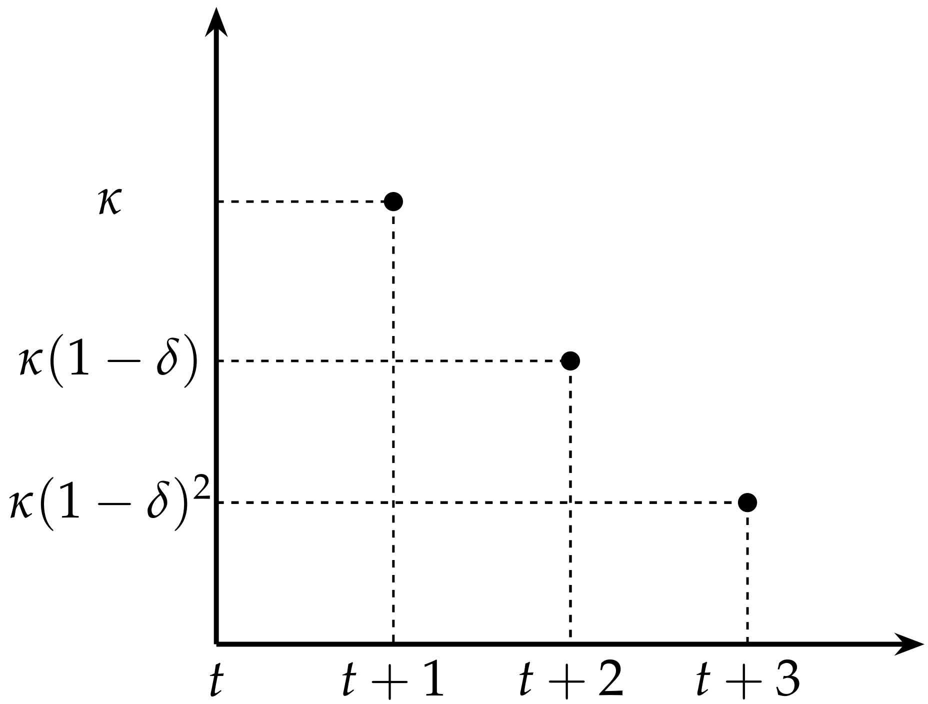


Figure F6: Coupon structure of the moratorium loans are denoted by blue dots while standard loans are denoted by black dots.