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Consumer Debt Moratoria

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Consumer Debt Moratoria[1]

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Abstract

We evaluate the effectiveness of consumer debt moratoria, one of the earliest policy interventions aimed at alleviating debt burdens. Using administrative data from Colombia, our study compares households that narrowly qualified for the moratorium (eligible up to 60 days overdue on their mortgages) against those who narrowly missed eligibility. Our analysis indicates that the moratorium policy boosts consumption among financially strained households while reducing delinquency rates on mortgages and other loans. We then develop a life-cycle incomplete market model, incorporating households subject to idiosyncratic income shocks, to examine both the general equilibrium and long-run effects of the policy. Our model shows that the policy increases aggregate output, consumption, and welfare for both households and bank owners. The policy also facilitates financial stability by attenuating the decline in house prices and increasing aggregate housing demand. Finally, we use our model to explore potential outcomes of debt forgiveness.

Keywords: debt moratoria, regression discontinuity design, heterogeneous agent models
JEL Codes: E44, F34

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Políticas de periodos de gracia para los hogares

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Resumen

Evaluamos la efectividad de las políticas de los periodos de gracia (moratoria de deuda) de los hogares. Utilizando datos de registro de crédito (Formato 341) de Colombia, nuestro estudio compara los créditos que por poco eran elegibles para participar en el programa de moratoria (hasta 60 días de mora en sus créditos hipotecarios) contra aquellos que no alcanzaron a ser elegibles. Nuestro análisis indica que la política impulsa el consumo, al tiempo que reduce las tasas de morosidad, tanto en créditos hipotecarios como en otras modalidades. Para complementar el análisis, desarrollamos un modelo de ciclo de vida con mercados incompletos, incorporando hogares sujetos a choques idiosincráticos de ingresos, para examinar tanto el equilibrio general como los efectos a largo plazo de la política. Nuestro modelo muestra que la política aumenta la producción agregada, el consumo y el bienestar tanto de los hogares como de los bancos. La política también facilita la estabilidad financiera al atenuar la caída en los precios de las viviendas y aumentar su demanda.

Códigos JEL: E44; F34

Palabras clave: Moratoria de deuda, Diseño de regresión discontinua, modelos de agentes heterogéneos

"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

Debt moratoria, which refer to the suspensions of debt payments, are among the oldest policies aimed at alleviating debt burdens. Despite their ancient origins, these policies only gained prominence in the wake of the 2020 pandemic crisis. Since the initial Bankruptcy Act of 1898, the U.S. Bankruptcy Code has undergone several significant overhauls, including major changes in 1938, 1978, 1984, and 2005. None of these changes, as well as the proposed reforms in 2020, included moratoria clauses.[1] Paradoxically, alternative debt resolution practices such as debt forgiveness, debt rescheduling, forbearance measures, and maturity extensions have dominated academic and policy discussions, leaving debt moratoria largely unexplored both empirically and theoretically. To address this gap, our study adopts a multidimensional approach by integrating empirical and quantitative analyses. Given the unprecedented levels of debt in both the public and private sectors, which were already high prior to the COVID-19 crisis, our research provides valuable insights into the longstanding debate about the optimal policy response to alleviate debt burdens.

Our contribution is two-fold. First, we provide a clear-cut empirical assessment of this long-standing, yet unexplored policy. To achieve this, we use administrative household credit registry data from Colombia, merged with social security data. Using a regression discontinuity design (RDD), we compare household consumption (proxied by unsecured debt) of those who narrowly qualified for moratoria (treatment group) with those who narrowly missed it (control group). The regulatory cutoff date, announced on March 17, 2020, stipulated that households should not be more than 60 days past due on existing mortgage loans as of February 29, 2020. We argue that households just below and above this threshold are similar ex ante and differ primarily in their receipt of treatment.[2]

[1] While the federal Bankruptcy Code itself has not typically included moratoria clauses, some American states have passed laws known as "stay laws" to provide debt moratoria. These laws were particularly aimed at protecting farmers during the 1820s against the Panic of 1819 – America's first major economic crisis and depression – and continued into the first half of the nineteenth century (Rothbard, 1962; Domowitz and Tamer, 1997).

[2] Notably, Colombia was among the earliest adopters of moratoria measures in response to the COVID-19 shock, as depicted in Figure A1 of Appendix A. This underscores the fact that these policies were previously nonexistent. Given that households in default prior to February 29th would not have anticipated the implementation of such a policy, nor the onset of COVID-19 cases in Colombia (the first recorded COVID-19 case was reported by the Ministry of Health on March 6, 2020), our case study provides an ideal quasi-experimental framework without the concern of treatment anticipation.

While increasingly influential in conducting causal inference, RDDs are limited to local average treatment effects. This approach has high internal validity but only offers external validity under the strong assumption of homogeneous treatment effects (Lee, 2008). Additionally, our empirical strategy removes confounding factors, which is essential for identification. However, as with any reduced-form estimation, it does not account for nor contribute to general equilibrium (GE) dynamics. Our second contribution addresses these limitations by complementing our RDD analysis with a life-cycle incomplete market model with mortgage default. To discipline our quantitative model, we initially exclude GE effects (turning off all price variations) to align one-to-one with our RDD estimate of the elasticity of households' consumption relative to the decline in mortgage payables. We then incorporate GE effects to explore welfare and long-run impacts. Our approach of combining empirical and quantitative analyses is imperative as it complements the internal validity of RDDs with GE effects of the policy.

In our model, building upon the framework established by Arslan et al. (2023), households are subject to idiosyncratic income shocks and derive utility from consumption and housing services obtained through renting or owning a house. House purchases are financed via long-term amortizing mortgages, which are susceptible to default. Financial intermediaries price individual mortgages based on individual characteristics and implied expected default probabilities. The model explicitly considers the balance sheets of financial intermediaries, enabling us not only to evaluate the policy's effects on households but also to assess its costs through the balance sheet impacts on these intermediaries. We calibrate the model using available Colombian macro and micro administrative data, effectively capturing the rich heterogeneity in wealth, income, debt, and housing tenure. Therefore, the model serves as an ideal laboratory for analyzing the distributional effects of the policy.

Returning to our empirical results, households that barely qualified for the debt moratorium policy experienced an increase in consumption. Specifically, they show a 2.1% increase in credit card purchases in the quarter in which they receive moratoria. This is partly due to the reduction in mortgage payments resulting from the policy. Notably, we observe a significant decline in *existent* mortgage delinquency rates following the expiration of the debt moratorium, ranging from 0.26 to 0.70 percentage points. The consistent decline in delinquency behavior within a year of the policy's implementation suggests that the moratorium helped households facing temporary financial constraints due to the COVID-19 pandemic. By granting payment suspensions, households were able to address liquidity issues and facilitate their recovery. In addition, treated households show a reduced likelihood of defaulting on other debt obligations. Specifically, during the quarter of treatment, the policy reduced the probability of delinquency on short-term loans and car loans by 0.09 and 0.36 percentage points, respectively.

To shed light on the supply side (banking sector), we examine the impact of the policy on banks' profitability, total assets, and liabilities. Namely, while the policy initially imposed costs on banks due to delayed collections, the subsequent reduction in defaults and preservation of loan values resulted in a net benefit to the banking sector. Banks with higher exposure to eligible loans experienced higher profits, total assets, and equity growth, with no significant increase in liabilities.

In our quantitative analysis, in response to an aggregate shock observed in Colombia in the first quarter of 2020, our model projects a 2.4% decline in consumption immediately following the shock, with a further decline to nearly 3% below its steady-state value after one year. This is followed by a gradual recovery, in line with our empirical findings. The debt suspension has a modest impact on consumption and output, marginally mitigating the impact of the shock. It mitigates the decline in consumption (around 7%) and welfare (around 7%), offsetting the negative effects of the shock. Its impact on output is initially small, but increases over time. Nevertheless, the policy has a significant financial stability benefit by facilitating aggregate housing demand through mortgage markets. With increased housing demand, the decline in house prices is reduced by 18%.

While the policy benefits individuals, it imposes a small initial cost on financial intermediaries. Although the policy has a negligible impact on banks' net worth in the first quarter of the downturn, it has a significant impact on their profits. This difference is due to the lower returns on banks' assets in the first two quarters when mortgage payments are suspended. Despite lower profits in the short run, they exceed those of the counterfactual economy without moratoria after the second quarter. This difference is mainly due to the reduced liquidation of bank assets as households reduce mortgage prepayments to stabilize consumption in the midst of the policy implementation. In sum, while the policy has an initial negative impact on bank profits, its long-term effects on the financial system are ultimately positive, aligning with our empirical findings, and bankers' welfare is higher with the policy. We find that general equilibrium effects, particularly the effects of the policy on labor income and house prices, are quantitatively important, which confirms the importance of using a structural general equilibrium model to fully quantify the effects of the policies.

Furthermore, we delve into the exploration of customized policy approaches. We investigate the question of whether interest payments should undergo a reduction (commonly known as a haircut) or be completely waived during the suspension period. The implications of our findings hold significant policy relevance, as we quantitatively demonstrate gains to households if interests **do not accrue** during payment suspensions. With these policy adjustments, the drop in house prices become milder while slightly affecting the short-term bank profits, which highlights the potential tradeoffs. Nevertheless, bankers still experience positive welfare gains if interest on suspended payments does not accrue.

Overall, the implementation of debt moratoria yields benefits for both banks and households. In fact, in light of the recent success in Colombia, the Financial Superintendency is deliberating the potential relaunch of the program.[3] Concurrently, banks in Europe have initiated voluntary payment holidays for individuals experiencing financial hardship (see HM Government, 2022).

Literature Review: Despite debt moratoria being one of the oldest policy recommendations for individuals facing payment difficulties, there is a scarcity of research examining its effects. Most studies have predominantly concentrated on alternative debt alleviation and management measures. For instance, on the empirical side, Dobbie and Song (2015) investigate the impact of consumer bankruptcy protection. Abel and Fuster (2021) explore how mortgage refinancing affects debt, default, and spending using quasi-random access to the Home Affordable Refinance Program (HARP). Similarly, Agarwal et al. (2017) examine the 2009 HARP, focusing on the effect of a policy intervention where intermediaries are provided with significant financial incentives to renegotiate mortgages. Campbell et al. (2021) compare mortgage designs between adjustable-rate mortgages (ARMs) and fixed-rate mortgages (FRMs), as well as maturity extensions.

On the theoretical and quantitative fronts, beginning with Zame (1993), a large body of literature analyzes the trade-offs of discharging unsecured debts by declaring personal bankruptcy. For example, Bolton and Rosenthal (2002) develop a three-period model for debt moratoria and compare equilibria with and without political intervention. Chatterjee et al. (2007) and Livshits et al. (2007) quantitatively explore these trade-offs. Auclert et al. (2019) find that debt forgiveness as part of the debt relief provided during the Great Recession helped stabilize employment levels using both data and models. In our paper, we also show that if moratoria are coupled with debt forgiveness, the gains are larger. Unlike Auclert et al. (2019), we demonstrate that bankers also benefit from mortgage payment forgiveness. More recently, Auclert and Mitman (2023) extend this line of research by studying consumer bankruptcy as an aggregate demand management tool, both theoretically and quantitatively, within a Heterogeneous Agent New Keynesian (HANK) model. They examine the role of bankruptcy in aggregate stabilization through the aggregate demand channel. While this is not the primary focus of our paper, we also have similar

[3] Further details on this announcement can be found in media reports accessible at the following link.

dynamics. Specifically, the moratoria policy in our study has an aggregate stabilization role through aggregate housing demand. This policy mitigates the drop in housing prices, thereby facilitating financial stability and generating a rise in aggregate output.

Other notable exceptions include Hatchondo et al. (2022) and Önder et al. (2023). The first study addresses a normative question by examining the effects of introducing contingent convertible bonds (CoCos) to an otherwise standard quantitative sovereign default model, whereas the latter investigates the impact of debt moratoria on corporate loans. Hence, the main difference with these studies is that we explore the impact of the policy on households by leveraging administrative data and extending our empirical analysis with a life-cycle incomplete market model to examine the long-term and general equilibrium effects.

2 The Colombian Case

2.1 Financial Alleviation Measures in Colombia

At the onset of the COVID-19 pandemic, the Financial Superintendency implemented emergency measures to address its negative impact on the Colombian financial system. One such measure (which is the focus of our investigation) provided grace periods to borrowers who were 60 days or less overdue on their loans as of February 29th. Originally intended to conclude on June 30th, 2020, the program was extended until August 31st, 2021.[4]

Notably, the policy went beyond providing payment relief, which had a maximum duration of 120 days. It also prohibited banks from increasing interest rates or charging interests-on-interests. Furthermore, credit rating assessments were temporarily suspended, overdue days were reset, and the remaining maturity of loans could be adjusted to ensure consistent debt repayment.[5]

The features of the policy and the timing of its implementation relative to Colombia's pandemic timeline allow us to conclude that the policy was not influenced by foreknowledge of the pandemic. At the same time, we can also rule out potential anticipation by households. On the one hand, while the regulation eligibility rules applied to all *existing* mortgages, almost the entirety of mortgages originated before 2020. On the other hand,

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

[5]This feature of the policy was determined on a case-by-case basis with the final decision being the result of a negotiation between the bank and the debtor.

Colombia's first reported COVID-19 case occurred on March 6^{th} 2020, after the policy's enactment. Finally, Colombia was among the first countries out of over 70 other nations to implement such moratorium measures, as depicted in Figure A1 of Appendix A. Overall, this affirms the exogeneity of the policy introduction which is crucial for a clean identification of its impact on household consumption.

2.2 Household-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 Q4-2019 to Q2-2021. The data contain over 10 million observations with information on the outstanding balance, loan repayment, and past due days of mortgages, car loans, credit card debt, and short-term loans extended to households.[6]

Using this dataset, we pinpoint all mortgage loans that originated at or before Q4-2019 (i.e. *existent* mortgages). Our treatment group is restricted to *existent* mortgages receiving moratoria in Q2-2020; this is because only 4% of loans that met the program criteria in Q1-2020 received payment suspensions in that quarter (96% of loans received moratoria in Q2-2020). The comprehensive coverage of the Colombian credit registry data allows us to match the unique ID number associated to an *existent* mortgage with data on consumption loans, specifically: credit card debt, car loans, and short-term loans.[7]

In aggregate, our sample consists of approximately 152,000 mortgages, associated with 149,000 individuals. It covers 26 financial entities, predominantly private banks. From this total pool, our treatment group consists of 17,000 *existent* mortgages that benefited from a payment suspension in Q2-2020. We match this data to, approximately: 66,000 credit cards, 24,000 short-term loans, and 4,100 car loans of *existent* mortgage holders.

With our detailed loan-level data for mortgage holders we first explore the effects of mortgage loan moratoria on consumption. To do so we create a (mostly non-durable) consumption measure based on household credit card purchases (*CC purchases*). The data for credit card debt does not include transactions made by households but rather end-of-quarter balances which we use to build a proxy for credit card purchases. This metric integrates changes in the credit card debt balance (Δ*CC debt*) and end-of-quarter repayments (*CC repayment*). Specifically, for household "i," credit card purchases at the end of

[6]Although mortgage and consumption loan data is reported quarterly, it captures the daily origination of new loans and non-performing days.

[7]Short-term loans are defined as personal loans with maturities of less than two years and which can be guaranteed by real collateral or payroll income.

quarter t are defined as follows:[8]

$$\text{CC purchases}_{it} = \max\left\{\Delta\text{CC debt}_{it} + \text{CC repayment}_{it}, 0\right\} \quad (1)$$

We complement our analysis with additional measures of durable consumption based on new car loans and new mortgages at the quarter of origination. For households receiving debt moratoria, we only include *new loans* that originated after the date in which the household received the policy.

Finally, we assess the impact of the policy on households' delinquency behavior and debt accumulation. Specifically, we aim to comprehend whether the suspension of payments alters the delinquency probability of *existing* mortgages and consumption loans extended to households (i.e., car loans, credit cards, and short-term loans) and how this correlates with changes in total household debt. This analysis concentrates on *existing* mortgages, car loans, and short-term loans. For each loan type, we define two primary variables: (i) the probability of being delinquent for more than 30 days and (ii) the total outstanding debt (financial burden) of households.

2.3 Identification

We restrict our analysis to financially constrained households as they should be more responsive to the benefits of a debt payment suspension. To identify such households, we designate them as stressed if they remain delinquent on their *existing* mortgage (by at least one day) in Q1-2020. For these households, we leverage the discontinuity in the eligibility criterion as per the enactment of Colombian regulations: eligible borrowers could not surpass 60 past due days on their existing credit as of February 29, 2020.[9] Consequently, borrowers in close proximity to this threshold are ex-ante similar (and comparable) across credit-related factors, differing mainly in receiving treatment.

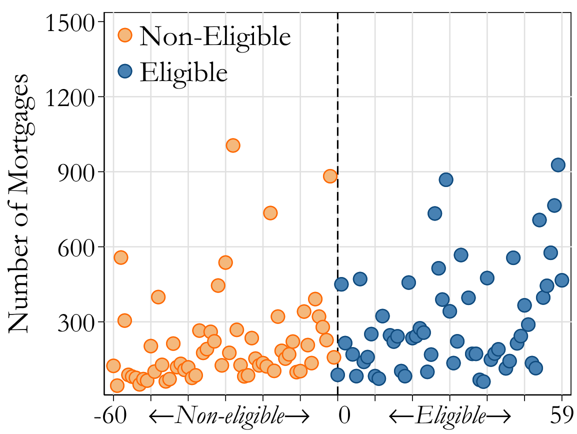
The distribution of eligible and non-eligible mortgages is plotted in Figure 1. Panel (a) shows the frequency (histogram) of *existing* mortgages for a given number of delinquency days (our running variable, centered at zero henceforth). That is, eligible mortgages lie on the positive support of the x-axis, and non-eligible mortgages lie on the negative support. To clarify, -1 and 0 on the x-axis refer to households with 61 and 60 days of delinquency on their mortgages as of February 29th, respectively. Likewise, $+59$ refers to mortgages

[8] For households with multiple credit cards, we define the measure of credit card purchases as the aggregate of applying equation (1) to each credit card owned by the household.

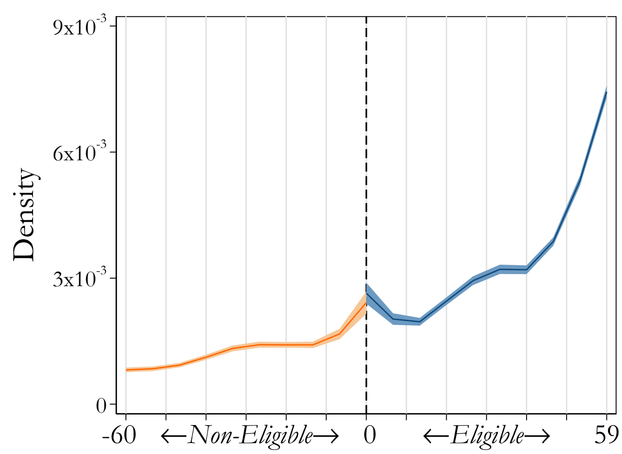
[9] Given the quarterly nature of the credit registry data, we measure delinquency days at the cutoff date using data for Q1-2020 (March 31st) and correct the difference with the actual cutoff date (February 29th) by subtracting thirty days.

with only one day of delinquency as of February 29th. Thus, the increased number of loans towards the right end of the figure is not surprising: it simply depicts a greater number of mortgages with fewer delinquency days, as is the common case. To exemplify, consider that as households make payments, their delinquency records often improve, leading to a decrease in delinquency over time (not all loans remain delinquent). Further, loans that surpass 120 days past due (-60 in the Figure) are more likely to be written off (with the use of provisions) given the low probability of repayment at that point. As a result, it's common to see a higher number of mortgages with only a few days of delinquency on their records. This trend is clearly depicted in Figure B1 (Appendix B), which illustrates the behavior but focuses on the period prior to any intervention, specifically 2019Q4. Similar patterns are observable when examining data from 2019Q2 or 2019Q3 (not reported).

Figure 1: Eligible and Non-Eligible Mortgages



(a) Treatment Distribution



(b) McCrary's Test

Panel (a) shows the histogram of eligible versus non-eligible mortgages along the running variable which we center at zero around the cutoff date, 29th of February 2020. Namely, all non-eligible mortgages (orange) are to the left of the cutoff, while all eligible mortgages (blue) are to the right of the cutoff. Panel (b) statistically evaluates if there are bunching of observations around the cutoff value (McCrary, 2008). The p-value (0.25) does not reject the null, indicating a lack of manipulation of the running variable.

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) of Figure 1 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 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 0.25, indicates a lack of manipulation of the running variable.

We proceed to evaluate the impact of treatment on consumption, delinquency behavior, and debt accumulation. It is important to 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 households did not take part of 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-day cutoff rule and the number of past-due days (as of February 29th, 2020) of household's "i" *existing* mortgage with bank "j". Moreover, let $\tilde{D}_{ij}$ be an indicator variable denoting the eligibility of mortgages under the debt moratoria. Given the regulatory conditions of the policy, we know that $\tilde{D}_{ij}$ is determined by the assignment variable X_{ij}, as follows:

$$\tilde{D}_{ij} = \mathbf{1}\left\{X_{ij} \geq 0\right\} \tag{2}$$

To clarify, treatment assignment takes the value of one if the *existing* mortgage received the policy during Q2-2020 and zero otherwise.[10]

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 does not jump from zero to unity, as in the case of a *sharp* design.[11] 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:

[10] We exclude households with eligible mortgages treated in the first, third and fourth quarter of 2020 so that we have a well-defined treatment and control group during our period of analysis.

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

$$1^{st} \text{ stage:} \qquad \arg\min_{\boldsymbol{\eta}} \sum_{ij=1}^{I\times J} \left[D_{ij} - \eta_0 + \eta_1 \tilde{D}_{ij} + \eta_2 X_{ij} + \eta_3 X_{ij}\tilde{D}_{ij}\right]^2 K\left(\frac{X_{ij}}{h}\right) \tag{3}$$

$$2^{nd} \text{ stage:} \qquad \arg\min_{\boldsymbol{\gamma}} \sum_{ij=1}^{I\times J} \left(Y_{ij} - \gamma_0 + \gamma_1 \hat{D}_{ij} + \gamma_2 X_{ij} + \gamma_3 X_{ij}\hat{D}_{ij}\right)^2 K\left(\frac{X_{ij}}{h}\right) \tag{4}$$

where the variable Y_{ij} denotes our outcome variables. In particular, our analysis for credit card expenditures and household's outstanding debt is conducted at the household level (where "i" denotes the mortgage holder and "j" the bank providing the *existent* mortgage) and for the delinquency probability we follow a loan-level analysis (where "i" denotes the *existent* loan and "j" the bank). We control for bank and quarter fixed effects and a dummy variable switched on if the mortgage was used for Social Interest Housing (SIH). Our period of analysis is from Q2-2020 to Q2-2021 but we additionally use data for Q4-2019, to check for pre-existent differences across *existent* mortgage holders prior to the policy.

The RDD estimate represents the average effect within the first year of the policy implementation. However, to better understand the dynamic effect of the debt moratorium, we also obtain a separate estimate for each quarter. The term $K(\cdot)$ denotes a triangular kernel with optimal bandwidth "h" as described in Calonico et al. (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 3) we estimate the predicted probability of treatment, –intent-to-treat–, and use it to instrument compliant observations in the second stage (equation 4). Consequently, the fuzzy RDD estimand can be formulated as:

$$\gamma_1 = \frac{\lim_{x\downarrow 0} E[Y_{ij}|X_{ij} = x] - \lim_{x\uparrow 0} E[Y_{ij}|X_{ij} = x]}{\lim_{x\downarrow 0} E[D_{ij}|X_{ij} = x] - \lim_{x\uparrow 0} E[D_{ij}|X_{ij} = x]} \tag{5}$$

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).

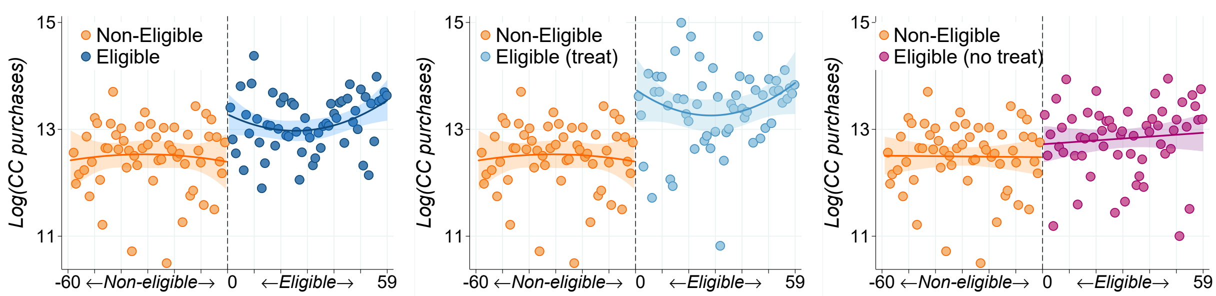
3 Results

The primary goal of our empirical strategy is to examine the impact of the policy on household consumption. Recall that our causal estimate on consumption serves as input to check the validity of the quantitative model's predictions. However, we also investigate changes in household delinquency behavior and repayment decisions for mortgage debt (*direct effect*) and other household debt (*cross effect*), with evident implications for systemic risk and financial stability. As demonstrated later, the behavior of consumption and household indebtedness play a crucial role in understanding the significant macroeconomic effects of moratoria on the aggregate economy. As such, the analysis of delinquency and household debt should qualitatively verify the consistency of the aggregated results implied by our model.

3.0.1 Impact on Consumption

We begin by discussing the results of consumption using credit card expenditures. Our key result reveals that households with moratoria exhibit an increase in (mostly non-durable) consumption proxied by credit card expenditures. Graphically, these effects are illustrated in Figure 2. Panel (a), depicts a positive discontinuous jump when moving along the eligibility cutoff. This upward jump is explained by households receiving moratoria (Panel b) rather than by simply being eligible (Panel c).

Figure 2: Credit Card Expenditures: Eligible and Non-Eligible



(a) Non-Eligible (NE) vs. Eligible (b) NE vs. Eligible Treated (c) NE vs. Eligible Non-Treated

The figure shows the impact of the policy on household consumption along the running variable. We proxy consumption with credit card expenditures measured in logs of Colombian pesos (COP). Each dot represents the mean credit card expenditure during 2020Q2-2020Q4 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 et al., 2019). The colored lines and shaded areas represent a second-order polynomial and confidence interval estimated separately on the right and left of the cutoff. Panel (a) compares credit card expenditures between non-eligible (orange) and all eligible (blue) households. Panel (b) uses only eligible treated households (light-blue), and Panel (c) uses only eligible non-treated households (purple) on the right-hand side of the cutoff.

Next, we provide a formal estimation of the fuzzy RD estimates as specified by equation (5). Table 1 presents our benchmark estimates using credit card purchases data for Q2-2020. We chose to focus on that specific quarter because our treatment group consists of households receiving grace periods on mortgage payments during Q2-2020 and we want to estimate the contemporaneous effect of being treated by moratoria at the end of the quarter of treatment.

In summary, households benefiting from the debt moratorium policy exhibit a 2.1% (first column) increase in credit card purchases in the quarter of treatment which in monetary values represents an increase of 2.4 million COP (second column), equivalent to 625 USD at an average exchange rate of 3,840 COP/USD. Given that households reduce mortgage payments by approximately 3 million COP (third column) in the quarter of treatment this implies that credit card expenditures increase by 77 cents for each peso of mortgage payment reduction during moratoria (i.e. semi-elasticity).

Table 1: Contemporaneous Effect of Moratoria

	CC Expenditure		Mortgage Payment
	(log)	(COP)	(COP)
Fuzzy-RD	2.10**	2.39*	-3.09***
	(1.06)	(1.30)	(0.27)
	First Stage		
D_{ij}	0.27***	0.27***	0.18***
	(0.041)	(0.035)	(0.010)
Observations	16,504	16,504	149,867
Bandwidth (in days)	19.2	28.5	22.3

Authors' calculations. The table shows the main estimates for the contemporaneous effect of debt moratoria on stressed households' consumption. The first and second column present the estimates for logs and levels of credit card expenditures in millions of Colombian pesos (COP). The third column shows the results for mortgage payments in millions of COP. Estimates in the first row correspond to Fuzzy RD estimate in equation (5). The second row shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (3). Robust Bias-corrected standard errors in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. In all columns we control for *existent* mortgage bank fixed effects and an indicator if the *existent* mortgage is for Social Interest Housing (SIH). To estimate the contemporaneous effect, we define Q2-2020 as the quarter of treatment. We employ loan-level data of credit cards and mortgages for Q2-2020, we compute purchases with a credit card following equation (1) and obtain total credit card purchases by aggregating across all credit cards associated to an individual "*i*". We measure repayment on mortgages as the negative value of quarterly changes in outstanding balance principal and interests. We exclude any individual receiving moratoria on other type of loans except for *existent* mortgages in 2020.

Next, to better understand the dynamic response of credit card expenditures, in Table 2 we provide fuzzy RDD estimates for quarters before and after treatment. Specifically, column "T" denotes the contemporaneous response which we presented previously. For robustness, column T-1 reports the estimate prior to the policy (Q4-2019) which serves as a placebo treatment.

Our results indicate that the positive response of credit card purchases is statistically significant within the first two quarters of the policy. In particular, households benefiting from debt moratoria increase credit card purchases by 2.1% in the quarter of treatment and by 4.2% one quarter after the policy. As expected, the effect prior to the policy is not statistically significant, implying a lack of systematic differences in consumption pre-trends across eligible and non-eligible households.[12]

Table 2: Credit Card Purchases: Dynamic Response

	T-1	T	T+1	T+2	T+3	T+3
Fuzzy-RD	-1.07	2.10**	4.24*	0.66	-0.49	-2.66
	(1.90)	(1.06)	(2.47)	(1.66)	(2.63)	(2.25)
	First Stage					
D_{ij}	0.26***	0.27***	0.29***	0.25***	0.28***	0.26***
	(0.029)	(0.041)	(0.042)	(0.037)	(0.033)	(0.026)
All Observations	17,344	16,504	17,954	19,696	20,630	23,456
Bandwidth (in days)	36.2	19.2	15.9	24.7	27.9	35.7

Authors' calculations. The table shows the quarter-by-quarter estimate of the effect of mortgage moratoria on credit card purchases. The dependent variable is the log of mortgage holders' credit card purchases at the end of the quarter. Each column reports the estimates for a period before the implementation of the policy ($T-1$), during quarter of treatment (T), and up to four quarters after moratoria ended ($T+1$, $T+2$, and $T+3$). All estimates in the first row correspond to Fuzzy RD estimate in equation (5). The second row shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (3). Robust Bias-corrected standard errors clustered at the two-digit industry code reported by the mortgage holder in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. In all columns we control for fixed effects of the bank issuing the *existent* mortgage, and an indicator if the *existent* mortgage was used for a Social Interest Housing (SIH). In our estimation procedure we define: (i) Q2-2020 as the quarter of treatment, (iii) 2019-Q4 as the pre-policy period, and (iii) 2020Q3-2021Q2 as the post-policy period. We employ loan-level data for credit card debt during 2019Q4-2021Q2, we compute purchases with a credit card (in COP) following equation (1) and obtain total credit card purchases by aggregating across all credit cards associated to an individual "i". We restrict our sample to individuals with an *existent* mortgage holding credit card debt, but we exclude any individual receiving moratoria on other type of loans except for mortgages in 2020.

3.0.2 Impact on Mortgage Delinquency and Debt Accumulation

We next evaluate the impact of the debt moratorium policy on household debt and delinquency behavior. First, we present our analysis on the direct effect of debt moratoria, that is, on delinquency and debt accumulation applicable to *existent* mortgages. In essence, we find that the policy improves repayment behaviour even one year after the alleviation measure ends. Moreover, the accrued interest on missed payments during moratoria does not materialize into higher debt burden in the short run. Finally, we find that the lower delinquency of households with moratoria translates into lower mortgage debt obligations.

Table 3 presents the dynamic response of delinquency for *existent* mortgages. Notice that delinquency rates (i.e., loans with more than 30 days past due) are not different across

[12]For comparability purposes, in Appendix D we provide summary statistics for our main variables (Table D1).

treated and non-treated households prior to the policy (first column).[13] Moreover, we observe that during the quarter of treatment (second column), mortgages with moratoria are 0.98 percentage points (pp) less likely to be delinquent. This is a direct consequence of the policy enforcing a reset of delinquency days on mortgages receiving a payment suspension. More notably, we find that treated households are consistently reducing their delinquency probability on mortgage payments after the payment suspension ends: they are between 0.26 pp. to 0.70 pp. less likely to be delinquent over the next four quarters after the policy ended.

Table 3: Existent Mortgage Delinquency and Moratoria

	T-1	T	T+1	T+2	T+3	T+4
Fuzzy-RD	-0.05	-0.98***	-0.67***	-0.70***	-0.31***	-0.26***
	(0.08)	(0.07)	(0.1)	(0.04)	(0.05)	(0.06)
	First Stage					
$D_{i,j}$	0.24***	0.21***	0.23***	0.22***	0.24***	0.25***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
All Observations	119,981	152,879	147,628	143,105	138,268	102,596
Bandwidth (in days)	14.8	8.2	8.5	20.13	14.6	13.8

Authors' calculations. The table shows the quarter-by-quarter estimate of the effect of mortgage moratoria on delinquency probability for *existent* mortgages. The dependent variable is an indicator taking the value of one if the mortgage is more than 30 days late on repayments at the end of the quarter. Each column reports the estimates for a period before the implementation of the policy ($T-1$), during quarter of treatment (T), and up to four quarters after moratoria ended ($T+1$, $T+2$, $T+3$, and $T+4$). All estimates in the first row correspond to Fuzzy RD estimate in equation (5). The second row shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (3). Robust Bias-corrected standard errors clustered at the two-digit industry code reported by the mortgage holder in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. In all columns we control for fixed effects of the bank issuing the mortgage, and an indicator if the *existent* mortgage was used for a Social Interest Housing (SIH). In our estimation procedure we define: (i) Q2-2020 as the quarter of treatment, (iii) 2019-Q4 as the pre-policy period, and (iii) 2020Q3-2021Q2 as the post-policy period. We employ loan-level data for mortgages between individual "i" and bank "j" during 2019Q4-2021Q2. We restrict our sample to individuals with an *existent* mortgage, but we exclude any individual receiving moratoria on other type of loans except for mortgages in 2020.

Table 4 shows the dynamic outstanding balance of *existent* mortgages before and after receiving moratoria. Our results show that the financial burden on mortgage holders does not increase with a temporary payment suspension, in fact, it ends up decreasing a year after the policy ends. In particular, we find that the outstanding balance for eligible treated mortgage holders is reduced by 0.22% relative to households without moratoria, four quarters after the policy implementation (last column). As expected, we note that the impact prior to the policy is not statistically significant (first column), implying no systematic differences across eligible and non-eligible households.

[13] For this result we exclude *existent* mortgages in T-1 with more than 90 days past due to avoid capturing differences with serially delinquent mortgage holders.

The results on outstanding debt are consistent with our findings on mortgage delinquency. The reasoning is as follows: during the quarter of treatment, the suspension of payments materialize into higher outstanding debt as interests on missed payments accrue. However, non-eligible mortgage holders are more likely to miss payments in that period, so differences in mortgage debt accumulation between treated and non-treated households cancel out. However, we know that treated households are consistently less delinquent on their mortgage payments over the next four quarters, which eventually, results in lower financial obligations on their *existent* mortgages.

Table 4: Existent Mortgage Debt and Moratoria

	T-1	T	T+1	T+2	T+3	T+4
Fuzzy-RD	-0.17	-0.16	-0.19	-0.17	-0.15	-0.22**
	(0.16)	(0.16)	(0.16)	(0.13)	(0.14)	(0.11)
	First Stage					
$D_{i,j}$	0.21***	0.21***	0.21***	0.21***	0.21***	0.24***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
All Observations	152,734	149,383	144,872	140,284	135,606	100,420
Bandwidth (in days)	24.6	23.7	22.6	20.8	20.4	18.6

Authors' calculations. The table shows the quarter-by-quarter estimate of the effect of mortgage moratoria on outstanding debt for *existent* mortgages. The dependent variable is the log of the outstanding balance of mortgage debt at the end of the quarter. Each column reports the estimates for a period before the implementation of the policy ($T-1$), during quarter of treatment (T), and up to four quarters after moratoria ended ($T+1$, $T+2$, $T+3$, and $T+4$). All estimates in the first row correspond to Fuzzy RD estimate in equation (5). The second row shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (3). Robust Bias-corrected standard errors clustered at the two-digit industry code reported by the mortgage holder in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. In all columns we control for fixed effects of the bank issuing the *existent* mortgage, and an indicator if the *existent* mortgage was used for a Social Interest Housing (SIH). In our estimation procedure we define: (i) Q2-2020 as the quarter of treatment, (iii) 2019-Q4 as the pre-policy period, and (iii) 2020Q3-2021Q2 as the post-policy period. We employ loan-level data for mortgages during 2019Q4-2021Q2 and aggregate the outstanding balance on principal and interests (in COP) that each individual "*i*" has with any bank. We restrict our sample to individuals with an *existent* mortgage and we exclude any individual receiving moratoria on other type of loans except for mortgages in 2020.

3.0.3 Delinquency and Debt Accumulation for other Household Debt

We next explore the cross loan effects of receiving moratoria. Namely, for a given household with multiple loans we explore whether the alleviating conditions on its mortgage impacts the delinquency probability and outstanding debt for car loans and short-term loans.

Tables 5 and 6 present our findings. We observe a similar albeit short-lived decline in the delinquency probability and debt accumulation. In particular, Table 5 shows that the delinquency probability for households receiving moratoria is reduced by 0.09 p.p. and 0.36 p.p for short-term and car loans, respectively, in period "T". For short term loans, the decline in the delinquency probability (0.16 p.p.) extends to "T+1". In turn, Table 6 shows that mortgage holders receiving moratoria reduce their outstanding debt: (i) 2.7% and 2.4% on car loans, and (ii) 0.52% and 0.58% on short-term loans, for period "T" and "T+1", respectively.

Table 5: Delinquency and Mortgage Moratoria: Other Household Loans

	T-1	T	T+1	T+2	T+3	T+4
(A) Short Term Loans						
Fuzzy-RD	-0.02	-0.09**	-0.16***	-0.09	0.03	-0.09
	(0.03)	(0.04)	(0.06)	(0.06)	(0.05)	(0.06)
	First Stage					
$D_{i,j}$	0.42***	0.42***	0.42***	0.32***	0.34***	0.44***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
All Observations	27,158	28,158	29,348	31,134	32,823	34,783
Bandwidth (in days)	30.3	28.7	28.3	50.8	60.1	28.6
(B) Car Loans						
Fuzzy-RD	-0.11	-0.36**	0.13	0.24	0.21	0.27
	(0.23)	(0.18)	(0.26)	(0.18)	(0.19)	(0.51)
	First Stage					
$D_{i,j}$	0.31***	0.29***	0.28***	0.30***	0.31***	0.18***
	(0.03)	(0.06)	(0.04)	(0.03)	(0.04)	(0.04)
All Observations	5,489	4,187	4,110	4237	4,335	4,702
Bandwidth (in days)	38.2	22.8	28.8	36.1	28.0	23.9

Authors' calculations. The table shows the quarter-by-quarter estimate of the effect of debt moratoria on delinquency probability for short-term loans and car loans. The dependent variable is an indicator taking the value of one if the loan is more than 30 days late on repayments at the end of the quarter. Each column reports the estimates for a period before the implementation of the policy ($T-1$), during quarter of treatment (T), and up to four quarters after moratoria ended ($T+1$, $T+2$, $T+3$, and $T+4$). All estimates in the first row of Panel (A) and (B) correspond to Fuzzy RD estimate in equation (5). The second row of Panel (A) and (B) shows the first stage estimates for the probability of treatment (D_{ij}), as described in equation (3). Robust Bias-corrected standard errors clustered at the two-digit industry code reported by the mortgage holder in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. In all columns we control for fixed effects of the bank issuing the loan (i.e. short-term loan or car loan), and an indicator if the *existent* mortgage was used for a Social Interest Housing (SIH).In our estimation procedure we define: (i) Q2-2020 as the quarter of treatment, (iii) 2019-Q4 as the pre-policy period, and (iii) 2020Q3-2021Q2 as the post-policy period. We employ loan-level data for short-term loans and car loans between individual "i" and bank "j" during 2019Q4-2021Q2. We restrict our sample to short-term loans and car loans of individuals with an *existent* mortgage, but we exclude any individual receiving moratoria on other type of loans except for mortgages in 2020.

Table 6: Outstanding Debt and Mortgage Moratoria: Other Household Loans

	T-1	T	T+1	T+2	T+3	T+4
(A) Short Term Loans						
Fuzzy-RD	0.06	-0.52*	-0.58**	-0.09	-0.06	-0.35
	(0.25)	(0.29)	(0.27)	(0.34)	(0.39)	(0.31)
	First Stage					
$D_{i,j}$	0.24***	0.24***	0.24***	0.23***	0.24***	0.25***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
All Observations	24,971	25,897	26,306	26,964	27,557	28,278
Bandwidth (in days)	27.8	18.4	25.4	22.6	25.6	17.8
(B) Car Loans						
Fuzzy-RD	-1.60	-2.7**	-2.4***	-0.77	0.94	0.92
	(0.77)	(1.22)	(0.91)	(0.86)	(1.10)	(1.12)
	First Stage					
$D_{i,j}$	0.20***	0.19***	0.18***	0.21***	0.15***	0.21***
	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)
All Observations	5,362	4,105	4,006	4,141	4,235	1,837
Bandwidth (in days)	26.9	18.6	29.3	16.9	19.1	

Authors' calculations. The table shows the quarter-by-quarter estimate of the effect of mortgage moratoria on outstanding debt for short-term loans and car loans. The dependent variable is the log of mortgage holders' total debt on short-term loans and car loans at the end of the quarter. Each column reports the estimates for a period before the implementation of the policy ($T-1$), during quarter of treatment (T), and up to four quarters after moratoria ended ($T+1$, $T+2$, $T+3$, and $T+4$). All estimates in the first row of Panel (A) and (B) correspond to Fuzzy RD estimate in equation (5). The second row of Panel (A) and (B) show the first stage estimates for the probability of treatment (D_{ij}), as described in equation (3). Robust Bias-corrected standard errors clustered at the two-digit industry code reported by the mortgage holder in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. In all columns we control for fixed effects of the bank issuing the *existent* mortgage, and an indicator if the *existent* mortgage was used for a Social Interest Housing (SIH). In our estimation procedure we define: (i) Q2-2020 as the quarter of treatment, (iii) 2019-Q4 as the pre-policy period, and (iii) 2020Q3-2021Q2 as the post-policy period. We employ loan-level data for short-term loans and car loans during 2019Q4-2021Q2 and aggregate the outstanding balance on principal and interests (in COP) that each individual "i" has with any bank. We restrict our sample to individuals with an *existent* mortgage holding debt short-term loans and car loans, but we exclude any individual receiving moratoria on other type of loans except for mortgages in 2020.

3.1 Effect on Banks

In our analysis, we shed light on several key points regarding the potential impact of the policy on banks. At a glance, the costs of the policy seem to be borne ex-ante by banks. By mandating banks to defer the collection of their claims during the suspension periods without providing subsidies for these costs, it can be argued that banks have shouldered the burden of the policy. This is particularly significant considering the timing of the moratoria, which coincided with periods when lenders had a high value for cash.

However, our examination, as detailed in Sections 3.0.2 and 3.0.3, leads us to infer that banks stand to benefit from the policy as well. Our results indicate that stressed households receiving the policy defaulted less on their mortgages and other types of consumer loans compared to those who narrowly missed eligibility for the program. Furthermore, in the Colombian context, loan interest continued to accrue during suspension periods. This meant that banks did not experience a reduction in the value of their claims. Instead, they received more than they would have without the program, as households that narrowly missed eligibility exhibited higher delinquency rates.

In sum, while the policy did impose upfront costs on banks through delayed collections, the subsequent reduction in defaults and the preservation of loan values appear to have resulted in a net benefit for the banking sector.

To strengthen this argument, we present additional evidence that sheds light on the impact of exposure to debt moratoria on banks' profits, equity, assets, and liabilities. We use a measure of bank's exposure to debt moratoria, which we construct as the percentage growth in the portfolio size for eligible loans (i.e., loans with less than 60 days delinquency as of February 2020). To deal with endogeneity issues between exposure and the main outcomes of interest we use a Bartik instrument that exploits the interaction between bank-level pre-policy variation in shares of eligible loans with ex-post aggregate time variation in the growth of eligible loans portfolio. We refer to Appendix E for details on the bank-level analysis and the construction of the Bartik instrument.

Table 7 showcases the results of the 2SLS estimation procedure using the Bartik instruments. The estimates for the first stage in the second row show, on average, that a one pp increase in the Bartik instrument B_{jt} is associated with a 0.98 pp increase in the banks' growth of eligible loan portfolio. The Bartik instrument seems to capture a significant portion of the variation in banks' exposure to the debt moratorium policy, evidenced by the F-statistic of 26 for the first stage, above the usual threshold of 10 used to reject the null of weak instruments. Graphically, Figure 3 depicts the strong positive correlation between the Bartik instrument and our measure of bank exposure to the debt moratorium policy. Most notably, our IV-estimates in Table 7 reveal that exposure to the debt moratorium policy improves banks' financial performance in terms of higher profits and equity growth. Specifically, a 1 pp increase in banks' growth rate of the eligible loan portfolio predicted by the Bartik instrument leads to a 0.46 pp increase in profits and a 0.21 pp increase in equity growth. We also observe that a 1 pp increase in the predicted exposure to debt moratoria increases banks' asset growth by 0.37 pp with no statistically significant response in the growth rate of liabilities. This implies that banks' asset accumulation largely explains the increase in equity of highly exposed banks. These empirical findings align with the predictions of our quantitative model, offering a positive outlook on the impact of debt moratoria on banks' financial health.

Table 7: Bartik-IV benchmark results: Bank-level outcomes

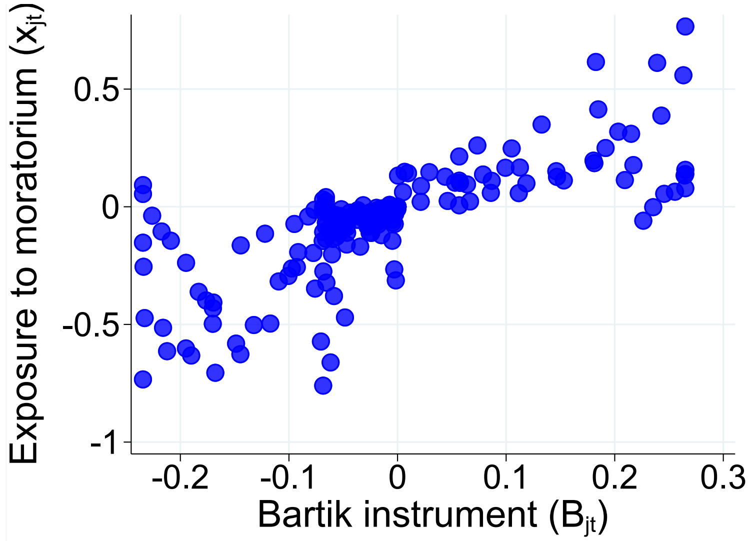
	ΔProfit	ΔEquity	Δ Assets	ΔLiab.
Bartik-IV	0.46**	0.21***	0.37***	0.06
	(0.038)	(0.18)	(0.021)	(0.16)
	First Stage			
B_{jt}	0.98***	0.98***	0.98***	0.98***
	(0.192)	(0.192)	(0.192)	(0.192)
F-first stage	26.06	26.06	26.06	26.06
Observations	200	200	200	200
Bank fixed effects	✓	✓	✓	✓
Time-quarter fixed effects	✓	✓	✓	✓

Authors' calculations. The table shows the effect of exposure to debt moratoria on banks. We employ bank balance-sheet data from Q2-2020 to Q4-2020 for the main outcome variables. Profits are net profits relative to average total assets over the past four quarters. We express all outcome variables as yearly symmetric growth rates. For the debt moratorium exposure, we employ data from the Colombian credit registry. We define bank exposure (x_{jt}) as the yearly change in the outstanding balance of all loans with less than 60 days of delinquency by 02/2020 (i.e., eligible loans) aggregated across the mortgage, consumption loan, and commercial (corporate) loan portfolios. The Bartik instrument (B_{jt}) is computed as the inner-product of banks' share of mortgages, consumption loans, and corporate loans with less than 60 days of delinquency by Q4-2019, and the aggregate growth of the eligible loans portfolio of mortgages, consumption loans, and corporate loans during 2020Q2-2020Q4, respectively. The estimates in the first row correspond to the 2SLS estimator in equation (E7). The second row shows the first stage estimates as described in equation (E5). Standard errors in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively.

3.2 Robustness checks

For expositional purposes, we present robustness checks focusing on our consumption measures. Specifically, we conduct exercises with placebo cutoffs (Section 3.2.1), and a test for balanced covariates (Section 3.2.2).

Figure 3: Bank-level Outcomes: First Stage



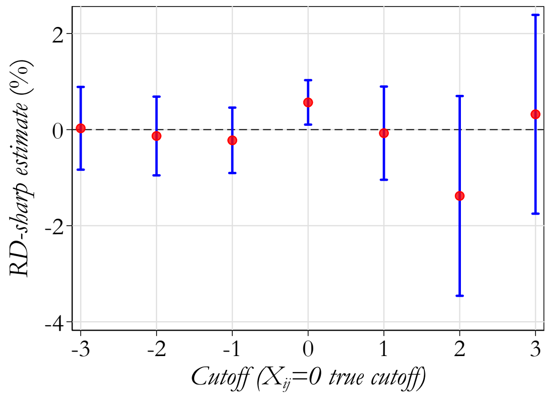
The figure shows the scatter plot of the first stage estimates described in (E5). We employ bank-level data for 2020Q2-2020Q4. The Y-axis represents the measure of bank exposure to debt moratoria, defined as the yearly change in the loan portfolio with less than 60 days of delinquency by 02/2020 aggregated across the mortgage, consumption loan, and corporate loan portfolios. The X-axis captures the Bartik instrument defined as the sum of the inner-product of banks' share of loans with less than 60 days of delinquency by Q4-2019 and the aggregate growth of the eligible loans across the mortgages, consumption loans, and corporate loans portfolio.

3.2.1 Placebo Cutoffs

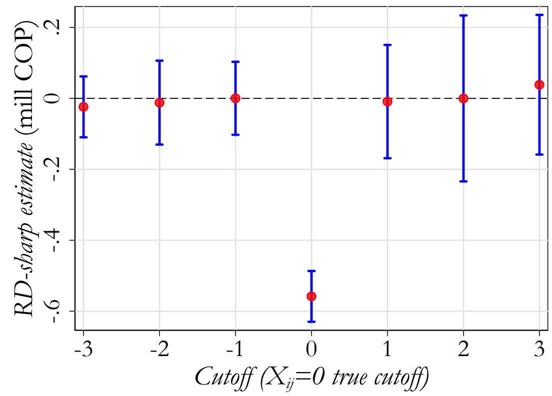
We begin our robustness checks by evaluating arbitrary cutoff points different from the one triggering treatment. In principle, a significant placebo cutoff could indicate either: (i) a concurrent policy, potentially contaminating our results, or (ii) systematic differences among eligible and non-eligible borrowers. In Figure 4 and 5, we evaluate placebo cutoffs for up to ± 3 days before and after the actual cutoff $X_{ij} = 0$. To test the robustness of baseline estimates we focus on the contemporaneous effect of receiving mortgage moratorium. The only exceptions are debt balance on *existent* mortgages and short term loan, where we evaluate placebos on estimates four quarters after treatment and one quarter after treatment, respectively.[14] As expected, none of these different cutoffs are statistically significant across all the outcome variables for consumption, delinquency and outstanding debt of stressed households.

[14]The reason is to use the most significant estimated effects for both variables.

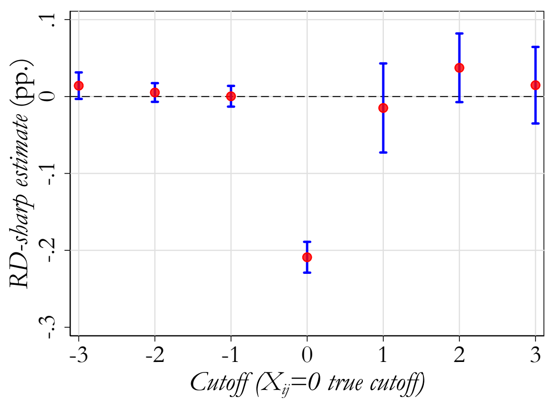
Figure 4: Placebo Cutoffs: Credit Cards and *Existent* Mortgages



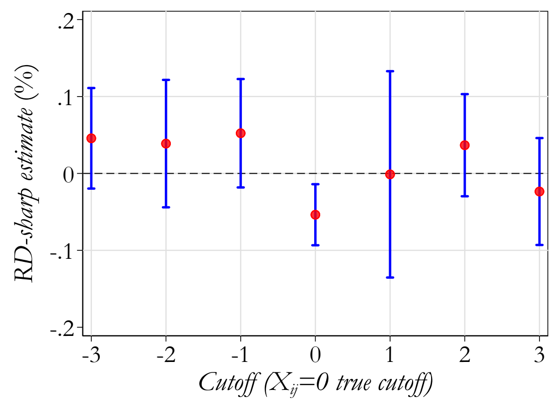
(a) Log(CC Expenditures)



(b) Mortage Payment



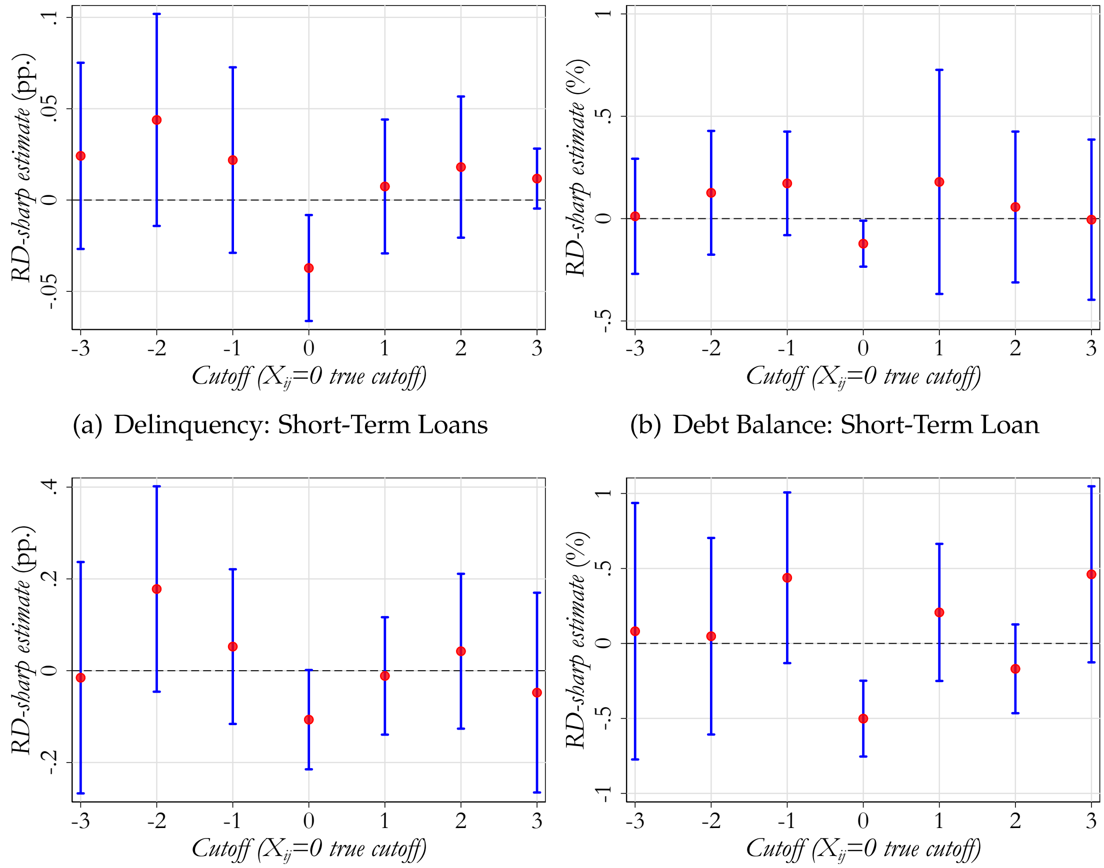
(c) Delinquency: Mortgages



(d) Debt Balance: Mortgages

The figure shows RD estimates for alternative placebo cutoffs. Each placebo cutoff denotes the closest possible value (from the cutoff) for the running variable. We employ data on credit cards and mortgages for households. Red dots and vertical blue lines capture the point estimates and 95% robust confidence intervals, respectively. Estimates at the center of each plot (policy cutoff) correspond to the sharp-RD (i.e. intention to treat) estimates for: (i) four quarters after treatment for debt balance on *existent* mortgages (log) and (ii) during the quarter of treatment for credit card purchases (log), *existent* mortgages re-payment (mill of COP) and delinquency probability. Panel (a) and (b) present the results for credit card expenditures and mortgage repayments, and panel (c) and (d) correspond to delinquency and debt balance on *existent* mortgages. To compute RD estimates for positive (negative) placebo cutoffs, we restrict the sample to only eligible (non-eligible) households to avoid potential "*contamination*" coming from eligibility to the debt moratorium policy (see Cattaneo et al. (2019)).

Figure 5: Placebo Cutoffs: Other Household Debt



(a) Delinquency: Short-Term Loans

(b) Debt Balance: Short-Term Loan

(c) Delinquency: Car Loans

(d) Debt Balance: Car Loan

The figure shows RD estimates for alternative placebo cutoffs for short-term loans and car loans. Each placebo cutoff denotes the closest possible value (from the cutoff) for the running variable. We employ data on short term loans and car loans for households. Red dots and vertical blue lines capture the point estimates and 95% robust confidence intervals, respectively. Estimates at the center of each plot (policy cutoff) correspond to the sharp-RD (i.e. intention to treat) estimates for: (i) one quarter after treatment for debt balance on short term loans (log), and (ii) during the quarter of treatment delinquency probability on short term loans, car loans, and debt balance on car loans (log). Panel (a) and (b) correspond to for delinquency and debt balance on short term loans, and panel (c) and (d) is for delinquency and debt balance on car loans. To compute RD estimates for positive (negative) placebo cutoffs, we restrict the sample to only eligible (non-eligible) households to avoid potential "*contamination*" coming from eligibility to the debt moratorium policy (see Cattaneo et al. (2019)).

3.2.2 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). Additionally, in Appendix F.1, we present a "donut-hole" test, which re-estimates our benchmark results but excluding 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. With the exception of new mortgages, we find similar results when excluding up to 3 days before and after the actual cutoff.

Moreover, we analyze which observable characteristics explain the decision of households to get payment suspension. The idea is to check if variation in the running variable is relevant to explain treatment close to the cutoff. In particular in F1 of Appendix F.3 we regress the treatment status (D_{ij}) on our running variable and other observable characteristics for *existent* mortgages measured on Q1-2020, specifically: (i) outstanding balance, (ii) expected repayment, (iii) remaining maturity, and (iv) LTV ratio. Column 1 provide the estimates with the entire sample, while columns 2 to 5 restrict the sample for a bandwidth of the running variable of 40, 30, 25, and 15, respectively. For the entire sample (column 1), treatment is partially explained by other observable characteristics of the *existent* mortgage. However, when we restrict the sample to smaller bandwidths (within the vicinity of the triggering threshold), treatment status becomes uncorrelated from these covariates. Nonetheless, our running remain the only variable with explanatory power across all samples: the coefficient for the running increases as we restrict the sample to observations close to the cutoff. This exogenous variation around the cutoff is precisely what our empirical strategy exploits for the case of stressed households.

In Table F2 of Appendix F.3, we present a formal analysis to test for systematic differences of relevant variables related to *existing* mortgages, car loans, short term loans, and credit cards such as delinquency probability, outstanding balance, interest rate, loan-to-value ratio, remaining maturity, and credit ratings. As shown, these results provide evidence of equally balanced distributions across the running variable before the treatment was enacted.

4 Quantitative Model

Using our empirical methodology, we have estimated the local average treatment effects of mortgage moratoria. Our results show a clear causal relationship: both households and banks experience improved financial and economic conditions when relief is provided during times of stress. While RDD offers strong causal insights, a notable limitation is its inability to capture general equilibrium and long-term effects. Therefore, a comprehensive evaluation of these policies on the overall economic landscape remains limited.

To address this methodological gap in RDD estimation and to explore the longer-term effects and broader economic implications, we employ an incomplete life-cycle market model. This model not only illuminates extended dynamics but also serves as a policy tool for refining strategies to enhance aggregate welfare.

Our quantitative model incorporates ingredients to capture the effects of the introduction of debt moratorium policy that are highlighted in section 2.1. Our model builds on the framework of Arslan et al. (2023). The model economy consists of five sectors: households, financial intermediaries (banks), rental companies, firms, and the government. There is no aggregate uncertainty, but individuals are subject to idiosyncratic income shocks. These shocks lead to heterogeneity in income, wealth, housing tenure and mortgage debt across households. We study the effects of debt policies in response to unexpected and persistent shocks to the economy. Perfect foresight is assumed along the transition.

We tighten the link between our empirical estimates and the model by using Colombian administrative data to estimate our parameters. To achieve this, we analyze how household consumption changes when mortgage payables decrease by 100 Colombian pesos, using administrative data to calculate an elasticity measure. This measure is then applied for model validation by initially disabling the general equilibrium effects within our model. By holding price responses constant, we focus solely on the policy's impact, ensuring alignment with our RDD estimates. Both the empirical and model-based estimates of consumption elasticity due to moratoria are around 3.7%. Subsequently, we enable the model's general equilibrium effects for further analysis. We then use the model to test whether the short-run predictions are consistent with our empirical estimates. Having established that our model is consistent with its empirical counterpart, we then turn on the general equilibrium structure of the model to estimate the general equilibrium effect of the mortgage moratoria.

4.1 Households

There is a continuum of households. They are all born as young individuals endowed with inherited wealth drawn from an endogenous distribution. They draw their initial labor productivity, z, from an invariant distribution $F_y(z)$. Households are subject to two types of idiosyncratic shocks: age and labor efficiency. Households go through three phases of life-cycle: (i) young (ii) middle (iii) old. Transition between age groups is governed by the transition matrix $\pi_z(j'|j)$. When old individuals receive age shock, they die, and all their net wealth is transferred to the newborns. They do not receive any utility from their bequests.

Households derive utility from consumption and housing services and can choose between renting or owning a house of their desired size.

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_{t,j}, s_{t,j}),$$

where β is the discount factor, c_j is consumption, and s_j is the housing services of an age j household with $j \in \{y, m, o\}$ representing young, middle and old ages.

Young and middle-aged households supply labor inelastically and earn the market wage w per their labor efficiency. When they retire, they receive fixed retirement benefits as a function of their labor efficiency at the time of retirement. Retirement benefits are financed through proportional labor income taxes, τ, on the working age households. Labor efficiency before retirement is subject to idiosyncratic shocks. The log of labor efficiency includes a deterministic component $f(j)$, which only depends on age, and a stochastic component z_j, which is an AR(1) process. Thus, a household's labor income $y(j, z_j)$ can be summarized by

$$y(j, z_j) = \begin{cases} w\,(1-\tau)\exp(f(j) + z_j), & \text{if } j \in \{y, m\} \\ w y_R(z_R), & \text{if } j = o \end{cases} \tag{6}$$

$$z_j = \rho z_{j-1} + \varepsilon_j, \quad \varepsilon_j \sim i.i.d. \quad N(0, \sigma_\varepsilon^2),$$

where w is the wage per efficiency units of labor, τ is the tax rate, and $y_R(z_R)$ is a progressive pension benefit system as in Guvenen and Smith (2014) conditional on the realization of labor efficiency z_R upon retirement shock.

Housing Choices: Households, after observing their income shock, make their housing tenure choices in addition to the consumption and saving choices. The only financial investment option for the households is the mutual funds, which offer a rate of return r_k. Households can choose to be either a renter or a homeowner to receive their desired housing services. Renters pay the endogenous rental rate p_r per unit of housing services, s, they choose. They can also obtain housing services by owning a house. House purchases can be financed through long-term, defaultable mortgages. Terms of mortgage contracts are endogenous and priced by the financial intermediaries taking into account default risk which depends on household characteristics. Homeowners can choose to stay as homeowners or become renters again, by either selling their houses or defaulting on their mortgages if they have any. Homeowners can refinance their houses at any point in time. Refinancing is the same as obtaining a mortgage at the time of purchase. Households also have the option of upgrading or downgrading the house size by selling the current house and buying a new one.

Several transaction costs are associated with owning a house. The purchase price of a house is p_h per unit of housing. To finance the purchase, the household can obtain a mortgage from the financial intermediaries. However, mortgages involve two types of costs. First, there is a fixed cost by the bank, φ_f, for originating a mortgage.[15] Second, financial intermediaries charge a variable cost of origination for mortgages. This cost is φ_m fraction of the mortgage debt at the origination. Selling a house is also costly. A seller has to pay φ_s fraction of the selling price.[16] Houses are subject to depreciation. Homeowners need to spend δ_h fraction of their house value for maintenance in every period. Lastly, since mortgages are risky, lenders charge a premium for the risk of defaulting. This premium shows up in the origination price of the mortgage.

Defaulting on a mortgage is possible, but it is costly. After default, households become *inactive* renters; that is they temporarily lose access to owning a house and are forced to rent a house. Inactive renters become active renters with probability π.

Mortgage Payments: Mortgages are long term. Following Hatchondo et al. (2015), we assume that mortgage payments decay at the rate δ_m in every period. Then, given a mortgage interest rate r_ℓ, the mortgage formula is given by the expression below.

$$m = d\left(r_\ell + \delta_m\right) \tag{7}$$

The default risk on mortgages differs across households since ex post households are heterogeneous. In principle, this should imply that the amortization schedule should be computed at the individual mortgage interest rate instead of r_ℓ. However, to save from an additional state variable, we assume that mortgage amortization is computed at the risk-free mortgage rate, as in Arslan et al. (2023), Hatchondo et al. (2015) and Kaplan et al. (2020). As will be clear later, individual default risk will show up in the pricing of the mortgages at the origination rather than in the mortgage interest rate. Thus, essentially

[15] Some examples of these costs are attorney fees, appraisal fees, and title company fees. These costs are fixed and do not depend on the size of the mortgage.

[16] Fees paid to real estate agents are the main part of these costs.

all households pay points at the origination to reduce the mortgage interest rate to the risk-free rate r_ℓ.

Value Functions: At any point in time households can be in one of the three statuses regarding their housing decision: homeowner, active renter, or inactive renter. The difference between an active renter and an inactive renter is the ability to own a house. An active renter has access to purchase a house whereas an inactive renter does not. A homeowner becomes an inactive renter upon defaulting on a mortgage. Inactive renters become active renters with probability ϕ.

We denote the state variables as $\theta \equiv \{a, z, j, d, h\}$, where a is the current financial wealth, z is the labor efficiency, j is the age, d is the mortgage debt, if any, and h is the house size if the household owns one.[17] The most important value function is the purchaser's problem, an active renter who decides to purchase a house. Here, we discuss the purchaser's value function and leave the presentation of all other household value functions to the Appendix Appendix H.

If an active renter chooses to purchase a house, she can access the mortgage market to finance her purchase. She chooses a mortgage debt level d that determines $q^m(\theta)$, the price of the mortgage at the origination, which will be a function of the current state of the household. Denoting the purchaser's value function as V^{rh}, we can write her problem as:

$$V^{rh}(\theta) = \max_{c,d',h',a'\geq 0} \left\{ u(c,h') + \beta E V^h(\theta') \right\} \tag{8}$$

subject to

$$\begin{aligned} c + p_h h' + \delta_h p_h h' + \varphi_f + a' &= w\,(1-\tau)\,y(j,z) + a\,(1+r_k) + d'\left(q^m(\tilde{\theta}) - \varphi_m\right) \\ d' &\leq p_h h'\,(1-\phi)\,. \end{aligned}$$

where $\tilde{\theta} \equiv \{a', z, j, d', h'\}$, p_h is the housing price, δ_h is the proportional maintenance cost of housing, φ_m is the variable cost of mortgage origination, φ_f is the fixed cost paid at the origination if the individual gets a mortgage. Home buyers face minimum down-payment constraint: their total borrowing for the housing cannot exceed a fraction $(1-\phi)$ of house value.

[17]Notice that for renters the mortgage debt, d, and house size,h, will be set to zero as they do not own any house.

4.2 Mutual Funds

Mutual funds own the good-producing firms and rental companies. They borrow from the households and use the funds to operate the firms and the rental companies. The borrowing rate of the mutual funds is r_k.

4.2.1 Firms

A perfectly competitive firm produces final output by combining capital K rented and labor N hired from households. The rental rate of capital is r_k and wage per efficiency of labor is w. Capital depreciates at the rate δ_k. We deviate from the standard formulation of the firm's problem in two ways following Arslan et al. (2023). First, we assume that firms need to finance a certain fraction, ζ, of their wage bill from the financial intermediaries. Second, firms, in addition to the quantity of labor, can also choose the utilization rate, u, of each worker. Then, the firm's problem is given by

$$\max_{K,N,u} \mathbb{Z}K^{\alpha} \left(Nu\right)^{1-\alpha} - (r_k + \delta_k)K - (1 + \zeta r_l)\, wN,$$

where wage per efficiency of labor is defined as

$$w = \bar{w} + \vartheta \frac{u^{1+\psi}}{1+\psi}$$

$\bar{w}$ can be interpreted as the base wage per efficiency of labor and the other term, $\vartheta \frac{u^{1+\psi}}{1+\psi}$, is the adjustment in wages due to the changing utilization of the worker. We assume $\psi > 0$ implying a convex cost for utilization and guarantees a globally concave problem for the firm. $\mathbb{Z}$ denotes the aggregate productivity of the firms.

4.2.2 Rental Companies

Rental companies own the rental housing units. They buy and sell these units from households and from each other. They rent their remaining stock of housing to the households and receive rental payments p^r per unit of house in every period. They incur maintenance cost of κ per unit of housing and their holding of houses are also subject to depreciation at the rate δ_h. Rental companies are also subject to quadratic cost for adjusting their rental supply. The problem of the rental companies can be represented as:

$$(1 + r_k)\, V^{rc}\,(H_r) = \max_{H_r'} \left\{ \left(p^r - \kappa - p^h\right) H_r' + (1 - \delta_h) H_r + \eta \frac{(H_r - H_r')^2}{2} + V^{rc}\,(H_r') \right\} \tag{9}$$

In equilibrium, the rate of return for the rental companies should be equal to the rate of return on capital, r_k. As a result, the equation pinning down the rental price becomes:

$$p_r = \kappa + p_h + \eta p_h \left(H_r' - H_r\right) - \frac{(1 - \delta_h + \eta\,(H_r'' - H_r'))\, p_h'}{1 + r_k}. \tag{10}$$

where η governs the size of the adjustment cost for rental supply and H_r denotes the amount of the rental supply.

4.3 Financial Intermediaries

As in Arslan et al. (2023), we assume that there are infinitely many stand-alone risk averse financial intermediaries operating in a perfectly competitive to maximize the present discounted value of their dividends. They borrow from the international market at the rate r_t and lend to the households in the form of long-term mortgage, to the goods production companies and to international borrowers in the form of short-term credit. The problem of the financial intermediaries can be summarized as follows:

$$\max_{L_{t+1}, B_{t+1}} \sum_{t=0}^{\infty} \beta_L^{t-1} \log\left(d_t^B\right),$$

subject to

$$\begin{aligned} d_t^B + L_{t+1} &= \omega_t + B_{t+1} \\ \omega_{t+1} &= L_{t+1}\,(1 + r_{\ell,t+1}) - B_{t+1}\,(1 + r_{t+1})\,, \end{aligned}$$

where d_t is the dividends, ω_t is the bank's net worth, B_{t+1} is the borrowing of the financial intermediary from the international market, L_{t+1} is the total lending of the financial intermediaries to the household, firms and international borrowers.[18]

Following Gertler and Kiyotaki (2010), we assume that financial intermediaries can default at the beginning of a period after stealing a fraction, ξ, of their total assets. When they default, they can only save in the risk-free rate r_t. Unlike Gertler and Kiyotaki (2010), we assume a small open economy, consistent with Colombia's financial openness, allowing banks to borrow internationally. While banks never default in equilibrium, the possibility of default generates an endogenous leverage constraint on the borrowing of the financial intermediaries:

$$(1-\phi_{t+1})\left(1+r_{\ell,t+1}\right)L_{t+1} \geq \left(1+r_{t+1}\right)B_{t+1},$$

where ϕ_t is defined recursively as:

$$\phi_t = \xi^{1-\beta_L}\left(\left(1+r_{t+1}\right)/\left(1+r_{\ell,t+1}\right)-\left(1-\phi_{t+1}\right)\right)^{\beta_L}.$$

If the bank is not allowed to steal, $\xi = 0$, then the spread between bank's borrowing rate $r_{\ell,t}$ from the international market and its lending rate r_t would have been zero and the bank would not be able to accumulate net worth.

4.4 Government:

The government runs a pay-as-you-go pension system. It collects social security taxes from working-age households and distributes them to retirees. We assume the pension system runs a balanced budget:

$$\sum_{j\in\{y,m\}}\sum_{z}\tau y\left(j,z\right)\pi_j\left(z\right) = \sum_{z} y_R\left(j=o,z\right)\pi_o\left(z\right)$$

where $\pi_j\left(z\right)$ is the measure of individuals with income shock z at age j.

[18] In principle, the lending choices of the financial intermediaries are more involved. The financial intermediaries extend loans to firms and households. Although all firms and international borrowers are assumed to be identical, households are heterogenous in many dimensions. This heterogeneity results in different default risk for each individual and makes each mortgage loan unique. However, as in Arslan et al. (2023), in the absence of aggregate risk and assuming law of large numbers apply for households, we can show that financial intermediaries make the same return from each loan, which allows us to aggregate the loan portfolio problem of the financial intermediaries. See Arslan et al. (2023) for details.

4.5 Equilibrium

Labor market: The total labor demand, N_t should be equal to the total measure of working age population, which is normalized to 1.

$$N_t = 1$$

Asset market: Total financial assets of the households, A_t should be equal to the total demand of assets: firms capital, K_t and rental companies demand $V_t^{rc}\left(H_{t-1}^r\right)$, which denotes the present discounted value of profits of the rental companies.

$$A_t = K_t + V_t^{rc}\left(H_{t-1}^r\right).$$

Loan market: Let $\Gamma_t(\theta)$ be the distribution of all existing mortgages at the beginning of period t and ℓ_t be the mortgage loans in the balance sheets of the financial intermediaries at the beginning of period t. The loan market clearing condition becomes

$$\begin{aligned} \ell_t(\theta) &= \Gamma_t(\theta) \\ L_{t+1} &= \zeta w\left(\bar{w}_t, u_t\right) + \int_\theta p_t(\theta)\,\Gamma_t(\theta) + \bar{L} \end{aligned}$$

where $\bar{L}$ denotes the loans to the international borrowers.[19] The first equation implies that the representative financial intermediary holds the equilibrium mortgage portfolio and the second equation implies that the financial intermediary is indifferent between originating a loan to firms or any type of households. The second equation pins down $r_{\ell,t+1}$.

Housing market: The total housing supply is fixed and equal to the total housing demand:

$$\begin{aligned} H &= \int_\theta h_t(\theta) d\Gamma^h(\theta) + H_t^r \\ H_t^r &= \int_\theta h_t(\theta) d\Gamma^r(\theta) \end{aligned}$$

[19]We need these loans to match the composition of loans in the bank balances in Colombia. We do not model the demand for these loans, and assume the demand for these loans is constant over time.

where Γ^h is the conditional distribution of households who are homeowners and Γ^r is the conditional distribution of households who are renters. The first equation pins down the house price p_t^h and the second equation pins down the rental price, p_t^r.

5 Model Calibration

A model period is a quarter. The model is calibrated to Colombia targeting the averages of 2010 to 2019.[20] Table 8 and 9 present externally set and internally calibrated parameters under the columns labeled "External" and "Internal" respectively.

Demographics and Preferences: We set the aging probabilities such that individuals spend 15 years as young, 25 years as middle-age and 15 years as old. We assume that households receive utility from consumption and housing services captured by the following Cobb-Douglas utility specification:

$$u\left(c,s\right)=\frac{\left(c^{1-\gamma}s^{\gamma}\right)^{1-\sigma}}{1-\sigma}.$$

Following the literature, we set $\sigma=2$, which implies an elasticity of intertemporal substitution of 0.5. We calibrate γ to match the share of housing services in GDP as 15 percent and the discount factor β to match the capital-output ratio of 2 when converted to annual units.

Income Process: We set the deterministic component of labor efficiency such that labor income grows by 45% from young to old, and also average efficiency for the working population is 1. That results in $f(y)=-0.1$ and $f(m)=0.1$. We also set the annual persistency of the income process as 0.93 and standard deviation of the innovations to the log of the labor efficiency as 0.37, which are all estimated from the Colombian data. We, then, converted these annual numbers to their quarterly counterparts.[21] The retirement system is modeled as in Guvenen and Smith (2014), where we set the average level of the benefits so that the social security tax is set to 12.5%.

Housing Markets: Housing transactions and mortgage issuances are costly. We set the selling cost of the house, φ_h, as 7% to replicate the typical real-estate agent cost and mov-

[20]We provide the sources of the data for the moments in the Appendix.

[21]We set $\rho=\rho_y^{1/4}$ and $\sigma_\varepsilon=\sigma_\varepsilon^y\sqrt{\frac{1-\rho^2}{1-\rho_y^2}}$, where ρ_y is the annual persistency and σ_ε^y is the annual standard deviation of the innovations to the income process.

ing costs for a seller. The price discount for foreclosed properties, φ_e is set to 25%. The fixed cost of mortgage origination, φ_f, is set to 8% of the quarterly output, which corresponds to 2% annual output. These costs represent the typical title costs, attorney fees, appraisal fees charged at the time of mortgage origination. The variable cost of mortgage origination, φ_m, is set to 0.75%, which represents typical lender's fees. The minimum downpayment to get a mortgage, ϕ, is set to 0.3, which allows for loan-to-value ratio up to 70% at the mortgage origination as is standard in Colombian mortgage market. Since refinancing is practically not allowed in Colombia, we set the cost of originating a loan when refinancing to infinity so that in equilibrium no refinancing is observed.

The probability of an inactive renter to become an active renter, π, is set to 3.6% to replicate the fact the default credit flags stay on the credit history, on average, around 7 years. The housing depreciation rate, δ_h, is set to 0.63% quarterly, which corresponds to 2.5% annual depreciate rate for housing stock.

We normalize the total housing stock, $\bar{H}$, to be 1. We use the minimum house size, $\underline{h}$, to match the homeownership rate of 43%.

Financial Sector: We calibrate the discount factor of the financial intermediaries, β_L, to match an annual lending premium $r_\ell - r$ of 1.5%, financial intermediaries' asset seizure rate, ξ, to match leverage ratio of 10, borrowing rate of the financial intermediaries, r_t, to match the mortgage debt to quarterly GDP ratio of 1.12, and mortgage payment depreciation rate, δ_m, to match the average mortgage maturity of 10 years.

Production Sector: The capital share in production, α, is set to 0.4 and quarterly capital depreciation rate, δ_k, is set to 2.5%. Following Arslan et al. (2023) we set $\psi = 0.5$ and calibrate ϑ to match a utilization rate of 1 in the steady-state. We assume $\zeta = 1$ implying the firms need to finance the whole wage bill from the financial intermediaries.[22] We normalize the aggregate productivity of the firms, $\mathbb{Z}$, to 1.

Rental Companies: We set $\eta = 3$ implying fairly segmented owner-occupied and rental market as suggested by Greenwald and Guren (2021). We calibrate the rental maintenance cost, κ, to match the house price to rental price ratio of 30 at a quarterly frequency.

[22]Given that the model period is quarterly, the implied firm credit in the balance sheet of the financial intermediaries is understated even when we set $\zeta = 1$. A better approach would be to allow for longer duration firm credit to match the relative share of firm credit and mortgages in the balance sheet of financial intermediaries. We avoid this to keep the firm's problem simpler.

6 Model Results

We use the calibrated model to study the effectiveness of the debt suspension policy around the crisis periods. The economy is assumed to be at steady-state in 2020, and we shock the economy with an unexpected but permanent aggregate productivity shock to replicate the crisis around the COVID time. According to the World Bank data, the aggregate output around the COVID time decreased by 17% in Colombia. To generate the same size of drop in output, we decrease the aggregate productivity of the firms ($\mathbb{Z}$) by 12.67% and assume that the shock reverts back to its initial steady-state level with annual persistency of 0.1.[23]

6.1 Comparing the Model with the Empirical Section

We first start with evaluating how well the quantitative model aligns with the empirical estimates, bearing in mind that this comparison is inherently challenging. The primary reason for this complexity is the fundamental differences in the methodological approaches of our empirical strategies and the general equilibrium (GE) model. Our empirical strategy employs a local approach, abstracting from broader GE effects. This means that any price changes are not accounted for in the empirical analysis. In contrast, the GE model endogenously determines all prices (wages, lending rate, house prices, rental prices, etc.).

In our empirical approach, the empirical estimates focus on the effect of suspending moratoria payments on mortgages, examining the partial equilibrium response which abstracts from broader price changes. Essentially, our empirical analysis measures the incremental effect of policy interventions (like suspending mortgage payments) on consumption, without considering broader price adjustments. To mimic the empirical strategy, we solve a partial equilibrium model, shutting down all price responses within the model during the policy intervention and compute the consumption elasticity with respect to debt suspension under these constraints.

Our quantitative model shows a good alignment with the empirical estimates. Both the empirical and quantitative methodologies yield a consumption elasticity of approximately 3.7% in response to the suspension of moratoria payments. This indicates that,

[23] Although capital is predetermined at the time of the crisis and labor supply is fixed, the presence of endogenous labor utilization allows us to calibrate a smaller drop in aggregate productivity to generate the 17% decline in output.

within the partial equilibrium framework, our model accurately captures the empirical effect observed.[24]

After validating our model with our empirical estimates, in the sections to follow, we activate all GE effects within the model to evaluate how these broader economic interactions influence the policy outcomes, and assessing the long-term impacts of the policy under a full general equilibrium framework. By following this approach, we ensure a comprehensive understanding of the policy's implications, both in the short-run and the long-run.

6.2 Benchmark Economy

Figure 6 presents the response of the economy to the aggregate productivity shock. The drop in productivity lowers the utilization rate on impact and lowers the output by 17% as calibrated. The drop in productivity together with the drop in utilization rate lowers the labor income by 20%, and transmits to the rest of the economy. As labor income decreases, consumption drops by 2.4% on the impact of the shock and continues to drop to almost 3% lower than its steady-state value after a year. After that, it slowly recovers. Lower labor income also depresses the new housing demand and lowers the house prices around 2% in the first quarter and reaches to a drop of 3% after a year. Although lower purchasing power initially lowers mortgage debt around 2%, lower house prices together with higher price and labor income growth increase mortgage debt in the medium run.

Bank lending rate drops slightly in the first quarter due to the decrease in credit demand, but quickly recovers to its steady-state level. The decline in the lending rate slightly increases the market value of the existing mortgages in bank balances in the first quarter. Higher mortgage valuations increase the bank net worth, which further transmits to lower lending rate. However, the decrease in the lending rate lowers bank net worth in

[24]The model cannot generate stressed households as in the data since we impose 30% minimum down-payment requirement in mortgage origination as in Colombia. This results the foreclosure rate to be essentially negligible since households find it optimal to sell the house rather than default as they have sufficient equity in their houses. As a result, we computed the consumption elasticity for the suspended mortgage payments for all households with mortgages both in the data and the model. In the data, as shown in Table 1, households reduce mortgage payments by approximately 3 million COP (third column) in the quarter of treatment this implies that credit card expenditures increase by 77 cents for each peso of mortgage payment reduction during moratoria. Hence, using the 0.16 average credit mortgage payment-to-card expenditures for 2019Q4-2020Q1 we can compute the elasticity for credit-card expenditures to mortgage moratoria of approximately 12%. This elasticity measured applies to stressed households. We also compute the elasticity for non-stressed households (i.e., non-delinquent) using a Difference-in-Difference estimation. Our RDD methodology cannot be employed for the computation of non-stressed households, given that both treated and non treated groups are in this case eligible. In essence, a weighted average of stressed and non-stressed households yields a consumption elasticity of approximately 3.7%. We refer the reader to Appendix G for additional details on the DID methodology and the way we compute the weighted average elasticity.

the following periods, which then slowly recovers. Since bank profits closely follow bank net worth, profits increase in the first quarter followed by a decline and gradual recovery. Welfare of both households and the bank owners (both computed in consumption equivalent terms) sharply decrease and gradually recover to its initial steady-state level.

6.3 Debt Suspension Policy

To replicate the policy implemented in Colombia, we assume that on the impact of the shock, the government implements a debt suspension policy. The policy is implemented for two quarters and during this time all mortgage payments for the existing mortgage owners are suspended. However, as in the case of Colombia, we assume mortgage interest accrues during the debt suspension policy. That is, we assume that households pay no mortgage payments for two quarters upon the impact of the shock and mortgage debt evolves following $d' = d(1 + r_\ell)$, where d is the current mortgage balance, d' is the next period balance, and r^ℓ is the risk-free mortgage rate.

Figure 8 presents the comparison of the debt suspension policy to the benchmark economy. Debt suspension has a mild effect on consumption and output. It slightly lowers the drop in the consumption (around 7%), welfare (around 7%) and mitigates the effects of the shock. Its effects on output is mild in the first quarter, but gets larger over the time. Its effects on housing and mortgage markets are much larger. It lowers the drop in house prices by 18% and substantially increases the mortgage due to the accrual of interest on the existing mortgages.

As expected, the policy benefits the individuals. Although the policy has no significant effect on banks' net worth in the first quarter of the bust, its effect on banks' profits is sizable. The reason for this discrepancy is the lower return on banks' assets in the first two quarters when the mortgage payments are suspended. Although the profits of the banks are lowered in the first two quarters, they become higher than the benchmark economy after the second quarter. The main reason for this difference is the lower liquidation of banks' assets as households prepay mortgages less to smooth the drop in their consumption when the policy is implemented. Overall, although the policy has adverse effects on the banks' profits in the very short-run, the long-run effects of the policy are also positive for the financial system. In terms of the welfare of the banks, computed in consumption equivalent terms, the long-run positive effects of the debt suspension policy dominates and the welfare of the banks turns out to be higher.

6.4 Decomposition of the Debt Suspension Policy

To better understand the causes of the effects of the debt suspension policy, we run several counterfactuals. Figure 7 shows the decomposition of the change in consumption after two quarters into several components. The first bar shows the change in consumption of the benchmark economy without the policy. The second bar shows the change of the consumption with the policy. The difference between these two bars shows the *total* effect of the policy. In the rest of the bars, we fix several prices to their benchmark counterparts and run the economy with the debt suspension policy. The difference between the consumption responses of these counterfactuals and the benchmark economy gives the effect of the fixed prices.[25] These counterfactuals reveal that the majority of the consumption difference between the benchmark economy and the debt suspension policy is due to the indirect effects of the policy.

The direct effect of the policy, measured by the difference between the bar named benchmark and all fixed, which fixes all the prices in the debt suspension economy to their counterparts in the benchmark economy, is around 10%. The largest effect comes through wages. Fixing the wages to the benchmark economy explains the 70% of the effect of the policy on consumption. The second biggest effect (20%) comes from the effect of the policy on house and rental prices. These counterfactuals show the significance of accounting for general equilibrium effects of the policy. Empirical designs, which typically capture the partial equilibrium effects, can miss a large part of the total effect of the policy.

6.5 Alternative Policies

Lastly, we examined the effects of different policies on the economy. As alternative policies, we consider debt forgiveness and mortgage payment forgiveness. In the debt forgiveness policy, we assume 10% reduction in debt balances for all existing mortgage holders. In the mortgage payment forgiveness policy, we assume that the mortgage payments are suspended for two quarters and mortgage interest is not accrued on the existing debt balances.

Figure 9 presents the results for the policy comparison. As expected, debt forgiveness has the largest effect on households. With debt forgiveness, the drop in consumption is significantly reduced. The drop in house prices becomes very mild. However, this policy has strong adverse effects on bank profits. Although in the benchmark economy and the

[25]Although the order which we fix the prices might effect the result of these exercises, we find these differences to be quantitatively very small

economy with debt suspension, banks make positive profits in the first quarter, with debt forgiveness, profits become negative.

Interestingly, mortgage payment policy has large effects on household balances with mild effects on bank balances except the first quarter. When mortgage payments are forgiven for two periods, the drop in consumption, house prices and output is much smaller compared to the benchmark economy or the debt suspension policy. However, this policy has mild adverse effects on the welfare of the bank owners compared to the debt suspension policy.

Overall these comparisons show that policies that help mitigating the liquidity problems of the highly indebted households during the crisis time has strong positive effects on households. Particularly, policies that directly target the liquidity problems such as mortgage payment forgiveness and debt suspension policies achieve these goals with little or even positive effects on bank balances.

7 Conclusion

In conclusion, our study underscores the effectiveness of consumer debt moratoria as a policy intervention aimed at alleviating debt burdens. By utilizing administrative data from Colombia, we demonstrate that such policies can significantly boost consumption among financially distressed households and reduce delinquency rates on mortgages and other new loans.

Building upon a life-cycle incomplete market model, we reveal that moratoria policies generate positive short- and long-term effects, enhancing aggregate output, consumption, welfare, and bank profitability. Additionally, our exploration of debt forgiveness and extended suspension linked to the moratorium suggests further potential benefits, highlighting the broader implications for debt management strategies and economic stability.

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9 Tables and Figures

9.1 Tables

9.1.1 Empirical Model

9.1.2 Quantitative Model

9.1.2.1 Data Sources:

Whenever we can find, we use the Colombian data to compute the moments used to calibrate the model. In cases we could not available Colombian data, we use the US counterpart of those moments. Below, we list all the moments used in calibrating the model and discuss the source of the data.

Production Sector:

- **Capital-Output ratio:** Ratio of physical capital to annual GDP. We target 2 using US data.
- **Share of housing services in GDP:** Using US data, we target 15%
- **Capital depreciation rate:** Using US data, we target 10% annually
- **Capital share in production:** Using US data, we set it to 0.4

Income Process: We calibrate the deterministic and stochastic parts of the income process using using employer-employee administrative data (PILA database) for Colombia during the period 2010-2019. The PILA dataset provides with monthly labor income received by employees working for employers in the formal sector. We use the monthly wages and aggregate across employees to obtain earnings received by workers each year.

We follow a two stage approach to obtain the necessary parameters that characterize labor earnings income risk: (i) We regress log of annual earnings against a full set of age, education, gender, and year fixed effects and obtain the residual. (ii) We estimate and AR(1) process using the residual earnings.

Our results for the coefficient in the AR(1) process is 0.933496, while the standard deviation of the error term in the AR(1) process is 0.37452. We employ both estimates to calibrate the parameters related to the annual persistence of income (ρ_ϵ) and annual standard deviation of AR(1) innovation term (σ_ϵ).

Housing Sector:

- **Transaction costs:** Transaction cost to sell a house (real estate agent fee and maintenance fees), fixed cost to obtain a mortgage (attorney fees, title fees, appraisal fees, etc), variable cost to originate a mortgage (lender fees) are set using US data.

- **Minimum downpayment:** We set it to 30% in order to match the average Loan-to-Value ratio of 60%. The latter is computed using Credit Registry loan data (Formato 341) for mortgages originated during 2018-2019
- **Housing depreciation rate:** We target 2.5% annually using US data.
- **Homeownership rate:** We target 43% which represents the ratio of total homeowners to total households. We use Colombian data from Quality of Life Survey (ECV) for 2017.
- **Price-to-rent ratio:** Ratio of average house prices to average annual rent payments. We set it to 7.5 annually using Colombian data (source: DANE)

Financial Sector:

- **Mortgage maturity:** We set it to 10 years to match the average maturity for mortgages originated during 2018-2019 using the Colombian Credit Registry database (Formato 341).
- **Lending Premium:** Average premium of mortgage rates over risk-free rate. We target 1.5% annually using US data. (In US, we target the difference between 30 year fixed rate mortgage and 10-year treasury bond. For Colombia, is 3.01%, using the difference between the interest rate for 15 and 20 years mortages and 10 years Colombian treasury bonds from the Financial Superintendency (SEN) during 06/2022-04/2023)
- **Leverage ratio:** The ratio of bank assets to bank net worth. We target 10 using US data.
- **Mortgage debt to GDP ratio:** Ratio of aggregate mortgage debt to annual GDP ratio. We target 28% using IMF global debt database.

Table 8: Externally Set Parameters

Parameter	Explanation	Value
σ	risk aversion	2
α	capital share	0.4
ρ_ε	annual persistence of income	0.93
σ_ε	annual std of innovation to AR(1)	0.37
φ_h	selling cost for a household	7%
φ_e	selling cost for foreclosures	25%
φ_f	fixed cost of mortgage origination	8%
φ_m	variable cost of mortgage origination	0.75
δ_h	annual housing depreciation rate	2.5%
π	annual prob. of being an active renter	14%
$\bar{H}$	housing supply	1
ψ	wage curvature	0.5
ϕ	down payment requirement	0.3
ζ	share of wage bill financed	100%
δ_k	annual capital depreciation rate	10%
δ_m	annual mortgage depreciation rate	10%

Table 9: Internally Calibrated Parameters

Parameter	Explanation	Value
β	discount factor	0.96
$\underline{h}$	minimum house size	0.69
r	bank borrowing rate	1.5%
γ	weight of housing services in utility	0.20
κ	rental maintenance cost	0.06
ϑ	wage parameter	2.35
ξ	bank seizure rate	0.18
β_L	bank discount factor	0.94

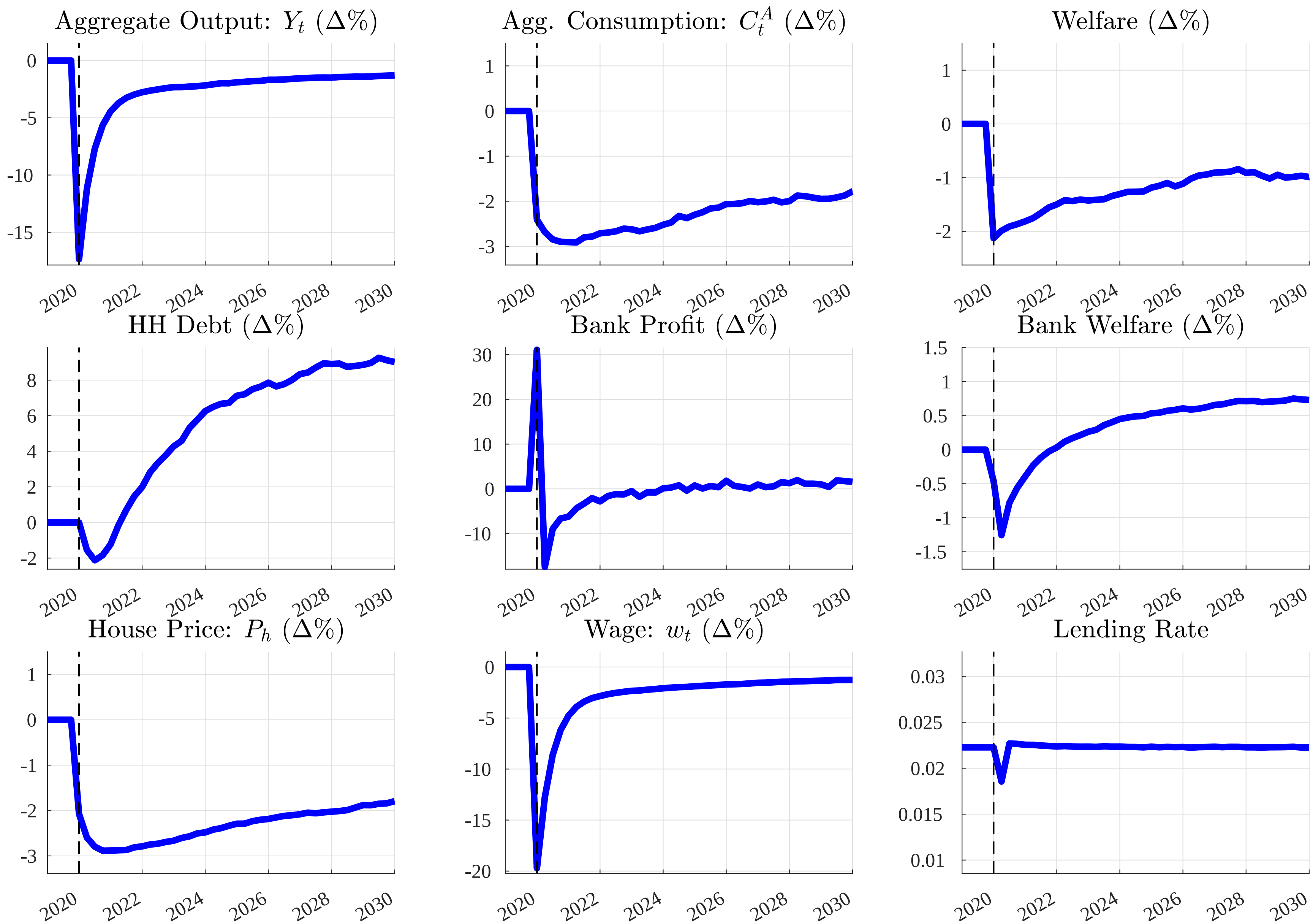
Table 10: Moments

Statistic	Data	Model
Capital- quarterly GDP ratio	8	8
Homeownership rate–aggregate	43%	43%
Mortgage debt to quarterly GDP ratio	112%	112%
Share of housing services in GDP	15%	15%
House price- quarterly rental price ratio	30	30
Utilization rate	1	1
Bank leverage ratio	10	10
Lending premium	0.375%	0.375%

9.2 Figures

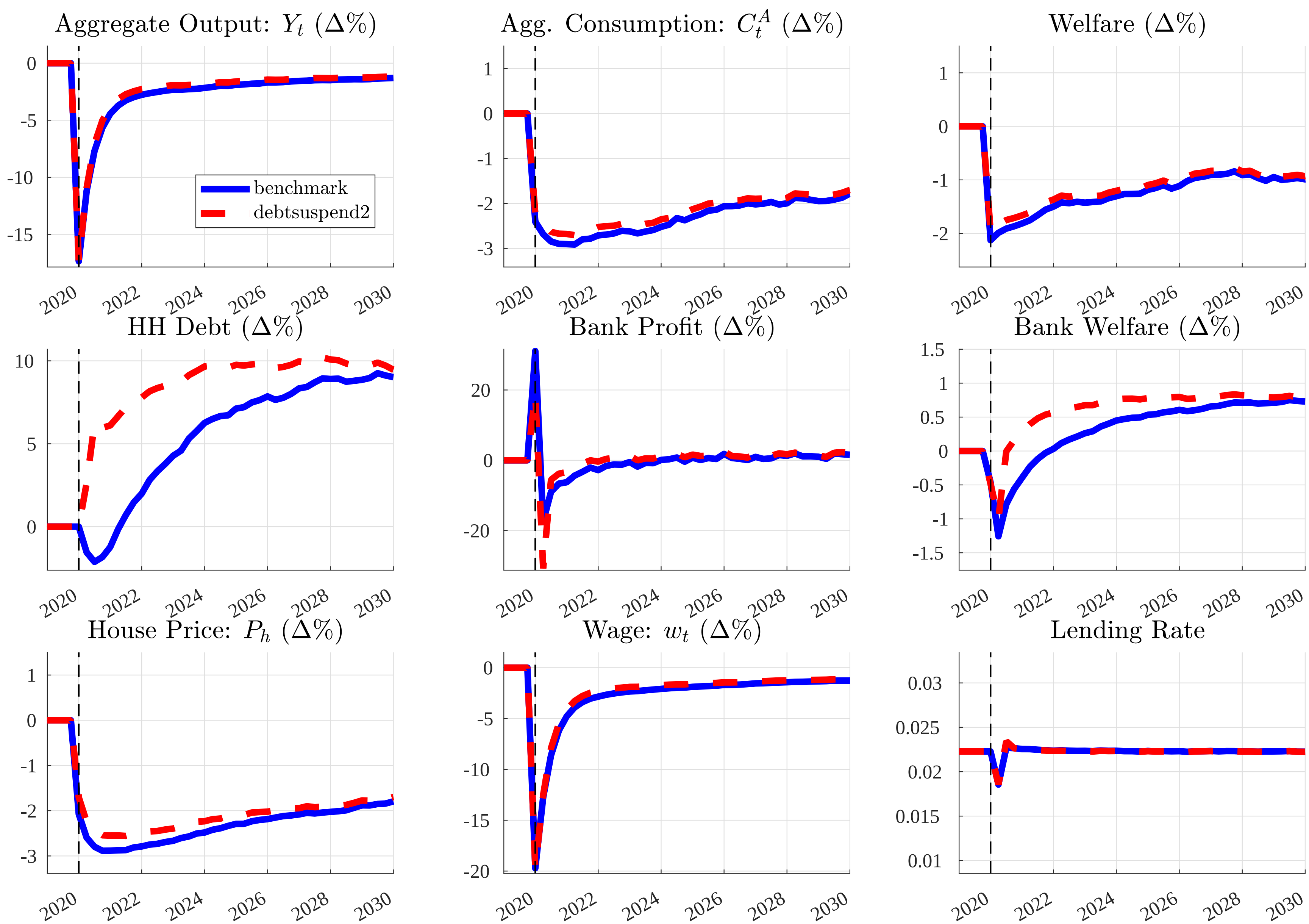
9.2.1 Quantitative Model

Figure 6: Benchmark Results



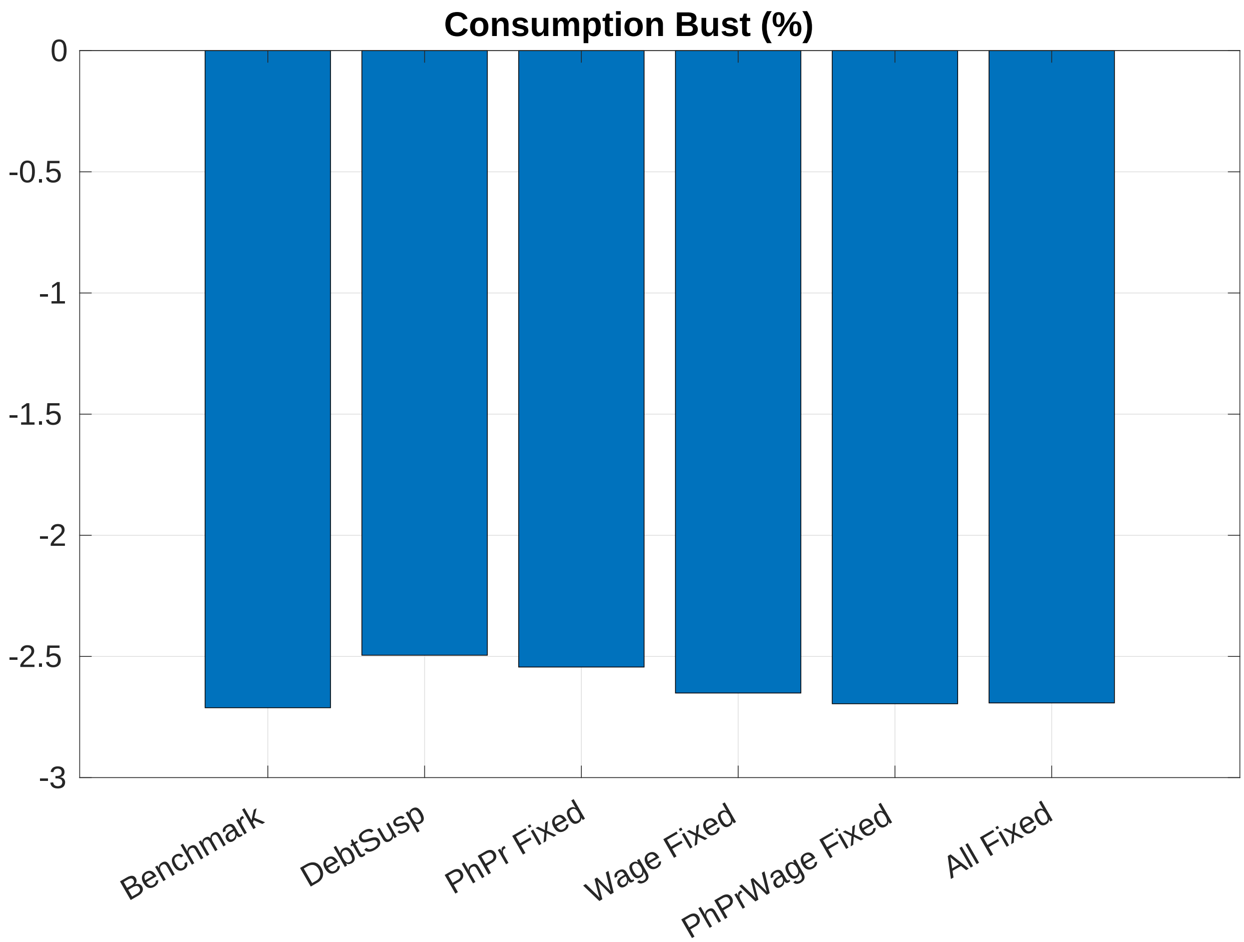
Notes: The figure displays the response of the economy to a productivity shock.

Figure 7: Debt Suspension



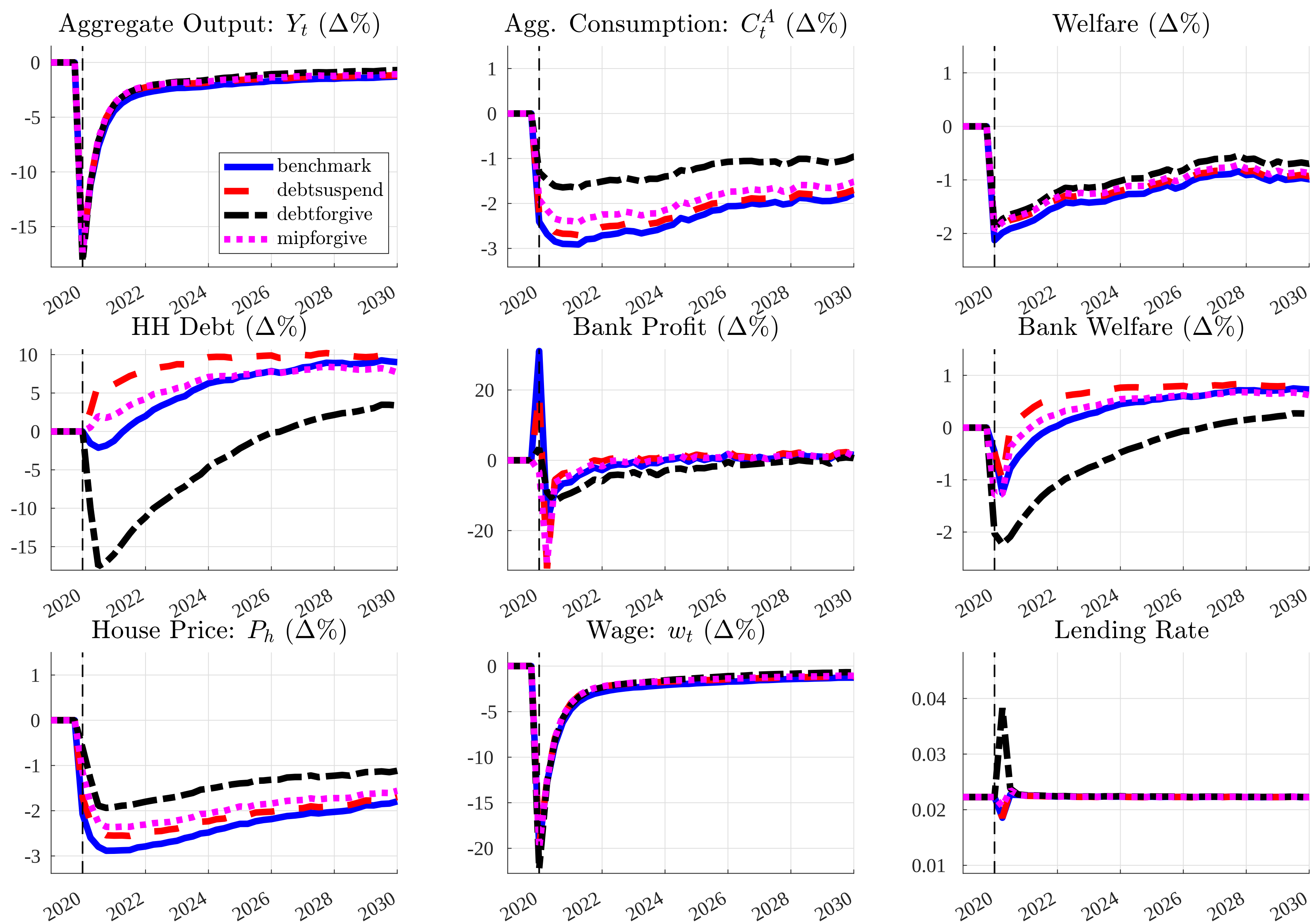
Notes: The figure displays the comparison of the response of the economy to a productivity shock with and without the debt suspension policy. The blue solid line displays the response of the benchmark economy, which is without the debt suspension policy. The red dashed line shows the response of the economy with the debt suspension policy implemented for two quarters.

Figure 8: Consumption Decomposition



Notes: The figure displays the decomposition of the consumption response after two quarters. The first bar is for the benchmark economy. The rest of the bars shows the response of the consumption with the policy. The second bar displays the total response with the policy. In the third bar, we fix only the house price and the rental price to the benchmark economy, the one without the debt suspension policy. The fourth bar fixes only the wages to the benchmark economy. The fifth bar fixes house prices, rental prices and the wages to the benchmark economy. Lastly, the sixth bar fixes all the prices to the benchmark economy, which essentially displays the direct effect of the policy.

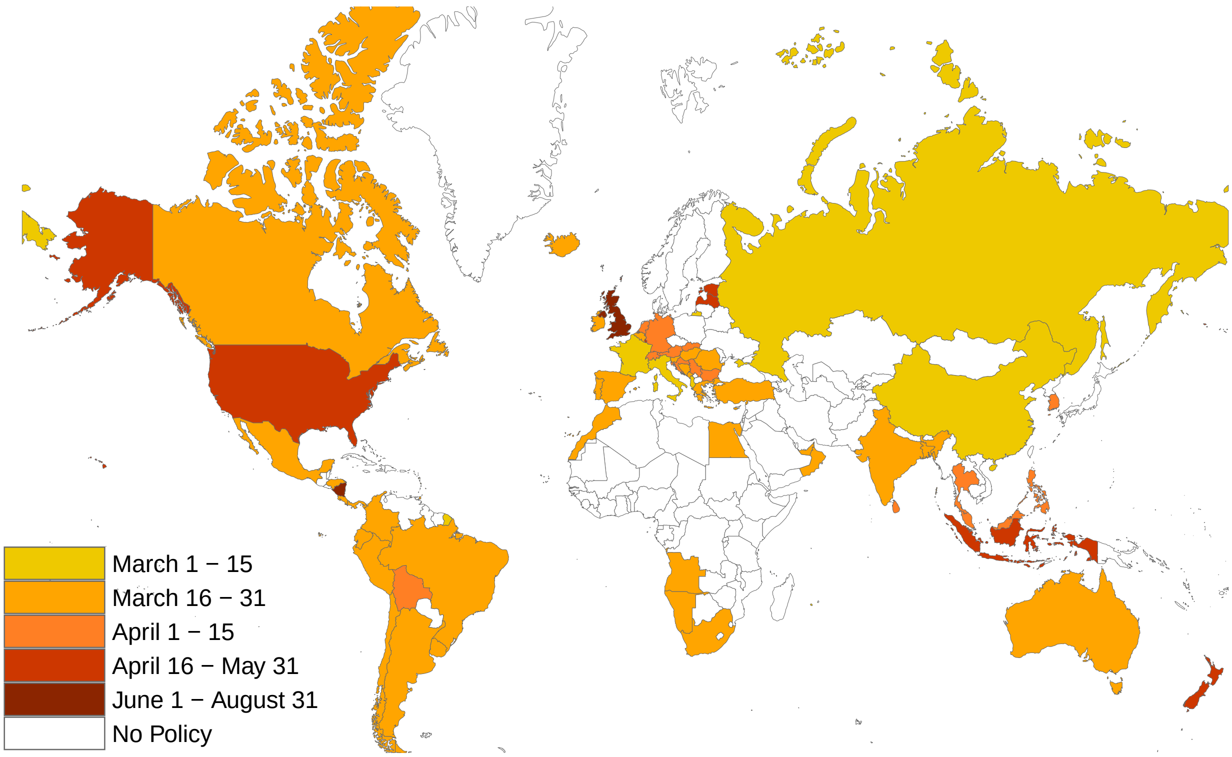
Figure 9: Policy Comparison



Notes: The figure displays the comparison of the response of the economy to a productivity shock with alternative debt policies. The blue solid line displays the response of the benchmark economy. The red dashed line shows the response with the debt suspension policy. The black long-dashed line shows the response with the debt forgiveness policy. Lastly, the pink dotted line shows the response with the mortgage payment forgiveness policy. See the text for the details of each policy.

Appendix A Moratorium measures in other countries

Figure A1: Moratorium Policies (COVID-19)



The figure displays the nations that have implemented a form of moratorium policy.

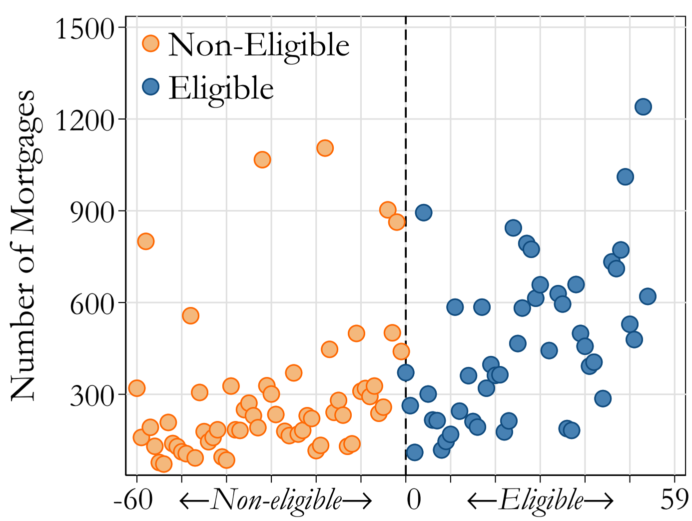
Appendix B Pre-treatment Distribution of Loans along the running variable

Figure 1 illustrates a trend where the number of mortgages increases towards the right side of the figure, indicating a rise in loans with fewer delinquency days. This pattern is typical because as mortgages are paid off, delinquency records diminish, resulting in a higher count of households with fewer delinquency days. The notation "+59" denotes mortgages with just 1 day of delinquency.

Further support for this observation is provided in Figure B1, which showcases data from a period prior to any policy intervention, akin to if the policy had been implemented in 2019Q4. Remarkably, this chart mirrors the trend seen in Figure 1. The consistency persists even when utilizing data from 2019Q2 or 2019Q3.

These findings bolster the understanding that households with fewer delinquency days are a natural consequence of mortgage payment dynamics.

Figure B1: Pre-treatment distribution of loans along the running variable

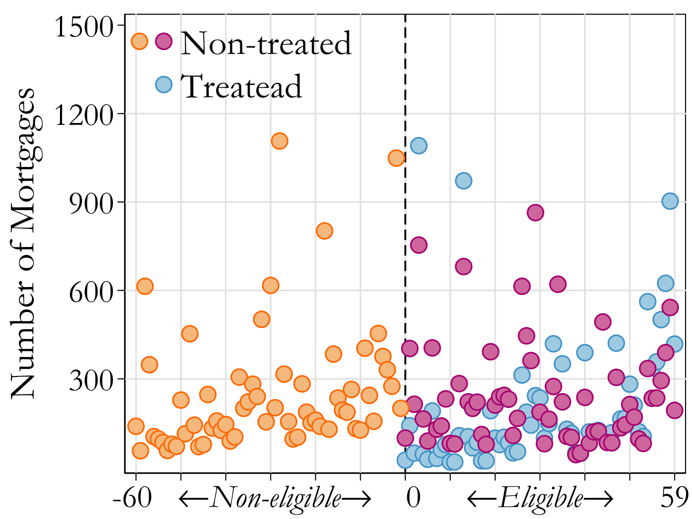


The figure displays the number of mortgages along a placebo running variable computed with pre-treatment information on delinquency days. Red dots are loans with more than 60 days of delinquency by the end of 2019Q4. Black dots represent loans with less than 60 days of delinquency by the end of 2019Q4.

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 households decided not to take part in the government policy. Figure C1 clearly depicts this, by showing eligible borrowers (positive support of the running variable) that either received (light-blue dots) or did not receive the policy (purple dots).

Figure C1: Treated and non-Treated Mortgages



The figure displays the number of *existent* mortgages along the running variable. Non-eligible loans (orange) are to the left of the cutoff. Eligible loans (right of the cutoff) are either treated (light-blue) or non-treated (purple) 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.

Appendix D Summary Statistics

Table D1: Main variables: Stressed Households

	Eligible Treated						Eligible Non-Treated						Non-Eligible					
	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}
Consumption																		
CC Purchases	2.0	4.1	0.2	0.7	2.0	10,379	2.3	4.3	0.2	0.8	2.4	4,035	1.3	3.1	0.1	0.4	1.2	1,992
CC purchases growth	4.8	101.2	-40.2	16.9	67.9	7,534	-1.4	195.0	-36.1	26.1	77.3	3,043	-63.7	245.3	-96.3	-25.3	34.1	1,522
Existent Mortgages																		
Repayment	0.8	1.1	0.0	0.5	1.2	76,343	1.4	1.6	0.5	1.0	1.8	27,597	1.6	2.4	0.3	0.9	1.9	19,982
Delinquency probability	4.9	21.6	0.0	0.0	0.0	79,228	43.9	49.6	0.0	0.0	100.0	32,606	94.8	22.2	100.0	100.0	100.0	41,045
Outstanding debt	51.7	49.0	20.6	38.2	64.2	76,629	50.4	54.8	16.6	33.9	62.6	32,052	53.1	58.0	18.3	35.2	64.1	40,702
Delinquency days	4.6	15.6	0.0	0.0	0.0	79,183	47.0	56.9	0.0	14.0	94.0	32,539	127.9	71.2	78.0	149.0	187.0	12,160
Interest rate	10.5	2.7	9.0	10.7	12.5	77,895	10.8	2.7	9.5	10.7	12.7	31,823	11.1	3.1	9.5	11.1	13.0	40,831
Maturity	10.7	5.9	6.1	10.2	14.7	79,158	9.3	5.7	4.8	8.7	13.1	32,334	9.7	5.8	5.2	8.9	13.8	40,621
LTV	37.2	18.1	22.8	37.1	51.4	79,228	32.5	18.5	17.5	31.9	46.5	32,605	35.3	17.1	21.6	35.8	48.5	41,045
Rating	4.9	0.4	5.0	5.0	5.0	79,183	4.4	0.9	4.0	5.0	5.0	32,536	3.4	1.0	3.0	3.0	4.0	12,150
Short Term Loans																		
Delinquency probability	5.0	21.8	0.0	0.0	0.0	17,001	8.7	28.2	0.0	0.0	0.0	7,174	27.9	44.9	0.0	0.0	100.0	3,983
Outstanding debt	5.0	7.4	1.0	2.4	5.4	16,126	5.0	7.4	1.1	2.4	5.4	6,414	4.7	7.0	1.1	2.3	5.0	3,766
Repayment	1.2	3.3	0.0	0.2	1.0	17,001	1.4	4.0	0.0	0.3	1.2	7,174	0.7	2.2	0.0	0.0	0.5	3,983
Delinquency days	3.6	17.1	0.0	0.0	0.0	16,637	5.1	21.7	0.0	0.0	0.0	6,850	11.7	36.8	0.0	0.0	0.0	3,160
Interest rate	22.9	7.9	23.7	27.1	27.2	16,797	23.3	7.6	24.3	27.1	27.2	7,040	24.7	6.4	25.9	27.2	27.2	3,870
Maturity	7.2	8.9	2.9	4.3	5.0	16,853	7.1	9.1	2.7	4.2	5.0	7,097	9.1	11.3	2.1	3.9	5.6	3,903
Rating	4.7	0.9	5.0	5.0	5.0	17,001	4.6	1.1	5.0	5.0	5.0	7,174	3.5	1.8	1.0	5.0	5.0	3,983
Car Loans																		
Delinquency probability	17.7	38.2	0.0	0.0	0.0	2,082	31.8	46.6	0.0	0.0	100.0	1,484	81.6	38.7	100.0	100.0	100.0	621
Outstanding debt	28.6	26.1	11.1	22.1	37.2	2,048	25.6	27.1	5.9	18.3	35.2	1,448	22.5	24.2	4.3	16.0	30.4	609
Repayment	1.6	3.6	0.0	0.8	2.1	2,082	1.4	4.7	0.0	0.2	1.8	1,484	0.5	1.8	0.0	0.0	0.0	621
Delinquency days	16.7	42.8	0.0	0.0	2.0	1,968	26.7	52.2	0.0	0.0	22.0	1,293	97.1	78.0	5.0	104.0	174.0	327
Interest rate	12.3	6.4	10.3	13.0	15.9	1,990	12.7	5.7	10.7	13.2	15.7	1,231	15.1	6.1	11.8	14.6	18.1	459
Maturity	3.2	1.8	1.7	3.3	4.5	2,053	2.7	1.8	1.0	2.6	4.2	1,447	2.4	1.8	0.9	2.0	3.6	594
LTV	51.3	24.3	34.3	54.8	77.8	1,803	50.0	23.5	32.3	53.2	76.2	1,006	58.8	25.7	39.5	64.7	85.9	386
Rating	4.3	1.3	5.0	5.0	5.0	2,082	3.6	1.8	2.0	5.0	5.0	1,484	1.7	1.1	1.0	1.0	2.0	621

Authors' calculations. The Table presents the summary statistics for stressed households. We employ data of *existent* mortgage holders on credit cards, mortgages, short term loans, and car loans during Q2-2020. Credit card purchases (millions of COP) are computed following equation (1) and then aggregated across all credit cards held by each mortgage holder, and the growth rate (percentages) is computed as the log difference relative to Q4-2019. Repayment on mortgages (millions of COP) are calculated as the negative value of quarterly changes in outstanding balance principal and interests. Delinquency probability (percentages) is a dummy taking the value of one if loan is more than thirty days of later on payments at the end of the quarter, outstanding debt (millions of COP) represents the debt balance, interest rate is expressed in percentages, maturity represents remaining number of years until loan matures, Loan-to-Value (percentages) is the ratio of the collateral relative to the outstanding debt, credit rating takes values from 1-5 with 1(5) representing the lowest(highest) rating.

Appendix E Bank Level Analysis: Bartik Instrumental Variables Approach

In this section we proceed to explain in detail the Bartik-IV approach we employ to estimate the effect of exposure to debt moratoria on banks.

Let x_{jt} denote the bank's 'j' percentage growth in the portfolio size for eligible loans (i.e., loans with less than 60 days delinquency by February 2020) at time t. The main outcomes of interest are the growth rate of profits, equity, total assets, and liabilities at the bank level, which we represent by y_{jt}. Consider the following bank-level regression:

$$y_{jt} = \beta_0 + \delta_{j,t} + \beta_1 x_{jt} + \epsilon_{jt} \tag{E1}$$

where the coefficient of interest is β_1. However, y_{jt} and x_{jt} are determined simultaneously, meaning that the OLS estimate for β_1 in (E1) will be biased upwards or downwards depending on the correlation between x_{jt} and ϵ_{jt}.

To address the endogeneity problems, we estimate (E1) using a Bartik-IV approach that exploits the interaction between bank-level pre-policy variation in shares of eligible loans with ex-post aggregate time varying variation in growth of eligible loans portfolio. In particular, notice that the debt moratorium was not only available for existent mortgages but also for existent corporate and consumption loans (e.g., car loans). Therefore, banks' exposure to the debt moratorium policy differs depending on (a) the size of the portfolio of eligible loans and (b) the allocation of the loan portfolio into housing, commercial, and consumption loans. Notice that we can express x_{jt} as follows:

$$x_{jt} = \sum_{\kappa \in \mathbf{K}} \alpha_{jt}^{\kappa} \cdot x_{jt}^{\kappa} \tag{E2}$$

The identity in (E2) shows that bank exposure to the debt moratorium policy can be expressed as the inner-product of type $\kappa \in \mathbf{K}$ loan shares and the growth loan portfolio with $\mathbf{K} = \{\text{mortgages, consumption, corporate}\}$. On the other hand, we can also express x_{jt}^{κ} as the sum of a bank-idiosyncratic portion and an aggregate part:

$$x_{jt}^{\kappa} = \tilde{x}_{jt}^{\kappa} + X_t^{\kappa} \tag{E3}$$

Therefore, using identities (E2) and (E3), we can build a Bartik-type instrument for bank 'j' exposure to the debt moratorium policy as follows:

$$B_{jt} = \sum_{\kappa \in \mathbf{K}} \alpha_{jt_0}^{\kappa} \cdot X_t^{\kappa} \tag{E4}$$

where $\alpha_{jt_0}^{\kappa}$ denotes the share of κ loans with less than 60-days delinquency by Q4-2019 and X_t^{κ} represents the economy-wide growth of eligible κ loans portfolio according to eligibility rules defined by the debt moratorium policy.

We employ a conventional 2SLS procedure to obtain an estimate for β_1 using B_{jt} as an instrument for x_{jt}. The bank-level two-stage procedure is presented as follows:

$$1^{st} \text{ stage:} \qquad \arg\min_{\boldsymbol{\pi}_0} \sum_{j=1}^{J} \sum_{t=2020Q2}^{2020Q4} \left[x_{jt} - FE_{j,t}\pi_{0,0} + \pi_{0,1}B_{jt} \right] \tag{E5}$$

$$2^{nd} \text{ stage:} \qquad \arg\min_{\boldsymbol{\pi}_1} \sum_{j=1}^{J} \sum_{t=2020Q2}^{2020Q4} \left[Y_{jt} - FE_{j,t}\pi_{1,0} + \pi_{1,1}B_{jt} \right] \tag{E6}$$

where $FE_{j,t}$ are bank and time-quarter fixed effects. The 2SLS estimate is defined as follows:

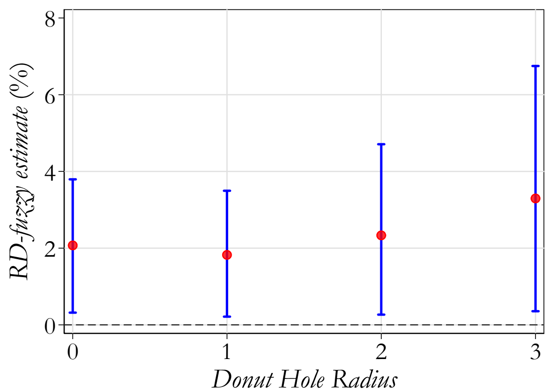
$$\hat{\beta}_{2SLS} = \frac{\hat{\pi}_{0,1}}{\hat{\pi}_{1,1}} \tag{E7}$$

Notice that we employ banks' variation in the growth of profits, equity, assets, and liabilities from the quarter right after the policy was implemented (i.e., Q2-2020) up to the end of 2020. However, our instrument in (E4) exploits variation coming from a single cross-sectional bank-level exposure before the policy shock starts, which should be uncorrelated with any bank unobservable factor determining the outcome variables after the implementation of the moratorium policy.

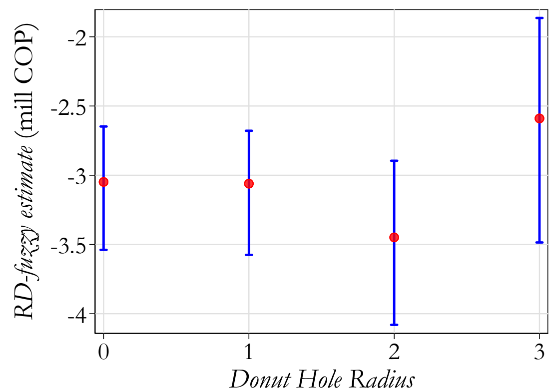
Appendix F Additional Robustness Checks

Appendix F.1 Donut-Hole Test

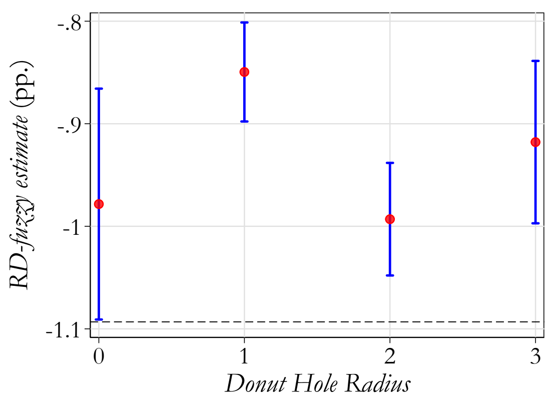
Figure F1: Donut-Hole Sensitivity Test: Credit Cards and *Existent* Mortgages



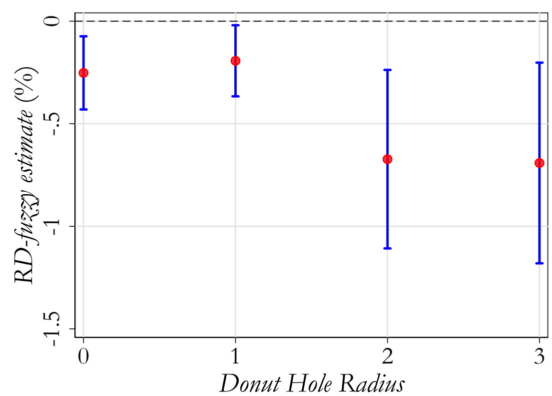
(a) Log(CC Expenditures)



(b) Mortgage Payment



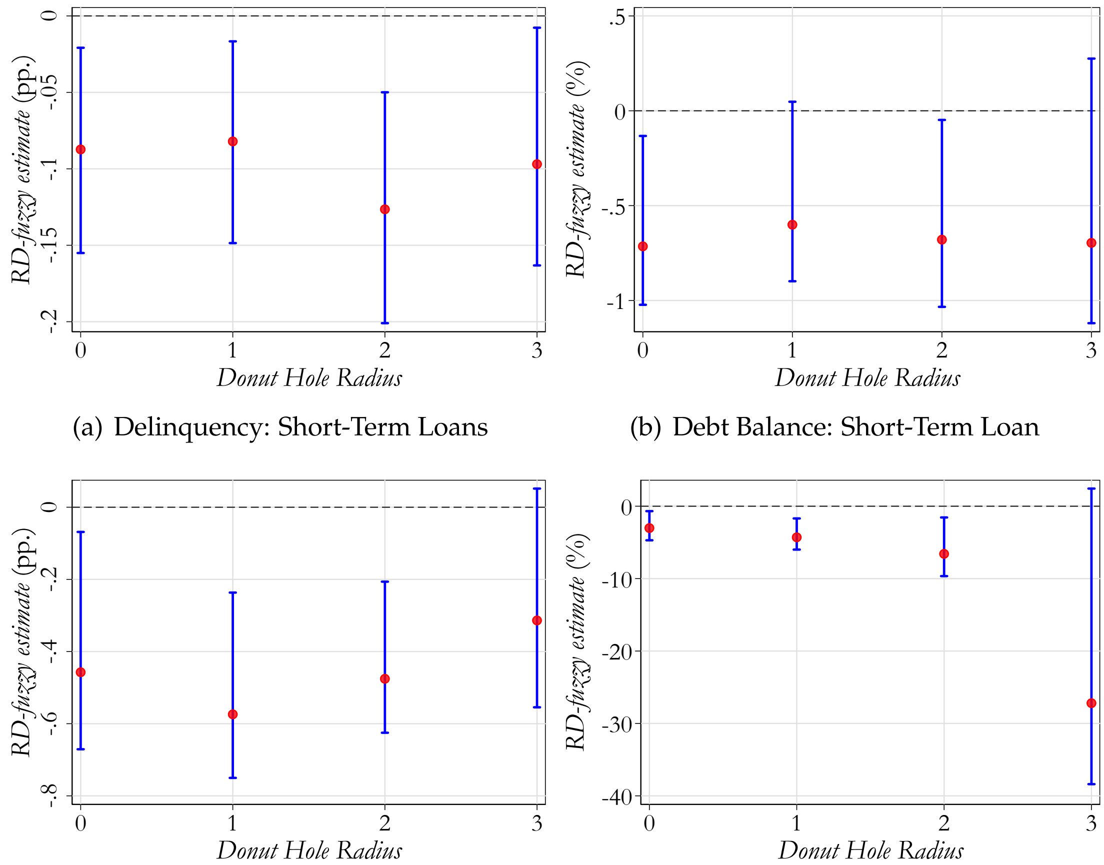
(c) Delinquency: Mortgages



(d) Debt Balance: Mortgages

The figure shows the Donut-hole sensitivity test, excluding 1, 2, and 3 days before/after the cutoff. We employ data on credit cards and *existent* mortgages. Red dots and vertical blue lines capture the point estimates and 95% robust confidence intervals, respectively. The estimates for zero-value radius (no holes) correspond to the Fuzzy-RD benchmark results for: (i) four quarters after treatment for debt balance on *existent* mortgages (log) and (ii) during the quarter of treatment for credit card purchases (log), *existent* mortgages re-payment (mill of COP) and delinquency probability. Panel (a) and (b) present the results for credit card expenditures and mortgage repayments, and panel (c) and (d) correspond to delinquency and debt balance on *existent* mortgages.

Figure F2: Donut-Hole Sensitivity Test: Other Household Debt



(a) Delinquency: Short-Term Loans

(b) Debt Balance: Short-Term Loan

(c) Delinquency: Car Loans

(d) Debt Balance: Car Loan

The figure shows the Donut-hole sensitivity test, excluding 1, 2, and 3 days before/after the cutoff. We employ data on short term loans and car loans for households. Red dots and vertical blue lines capture the point estimates and 95% robust confidence intervals, respectively. The estimates for zero-value radius (no holes) correspond to the Fuzzy-RD benchmark results for:(i) one quarter after treatment for debt balance on short term loans (log), and (ii) during the quarter of treatment delinquency probability on short term loans, car loans, and debt balance on car loans (log). Panel (a) and (b) correspond to for delinquency and debt balance on short term loans, and panel (c) and (d) is for delinquency and debt balance on car loans.

Appendix F.2 (Un)-Predictability of Treatment

Table F1: Falsification test: (Un)-Predictability of Treatment

	Entire sample	BW=40	BW=30	BW=25	BW=15
Running	0.0021***	0.0090***	0.0087***	0.011***	0.012***
	(0.0001)	(0.00005)	(0.0001)	(0.0001)	(0.0004)
Oustanding Debt	0.41***	0.15***	0.21***	0.19	0.13
	(0.041)	(0.042)	(0.071)	(0.123)	(0.108)
Expected Payment	-1.144e-08***	0.0012***	0.00015	0.00023	0.00072
	(0.000)	(0.0002)	(0.0003)	(0.0003)	(0.0006)
Maturity	-0.0001	-0.00006	0.0004	0.0004	0.0004
	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0005)
LTV	-1.919e-12***	-8.833e-07	1.048e-06	4.199e-06	7.932e-06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank FE	x	x	x	x	x
Origination Year	x	x	x	x	x
Social Interest Housing	x	x	x	x	x
Observations	822,876	28,513	20,289	14,916	10,348
R-squared	0.21	0.38	0.26	0.29	0.34
F-test all	403.59	8116.69	2853.01	2748.68	927.55
pvalue all	0.00	0.00	0.00	0.00	0.00

Each column reports a linear regression with the treatment dummy D_{ij} as dependent variable and with different bandwidth choices (entire sample, 40, 30, 25, and 15 days). Robust Bias-corrected standard errors clustered at the two-digit industry code reported by the mortgage holder in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. We employ loan level data for *existent* mortgages during Q1-2020, we exclude mortgages with less than two years of remaining maturity. All columns control for bank fixed effects, origination year fixed effects, and an indicator if the *existent* mortgage was used for a Social Interest Housing (SIH). Oustanding Debt includes the remaining balance for capital and interests, Expected Payment is expressed in percentages relative to the oustanding debt, LTV is the Loan-to-Value ratio (percentages) defined as the collateral relative to the outstanding debt.

Appendix F.3 Pre-existing differences Household Debt

Table F2: Testing for pre-policy differences in Household Debt and Consumption

Variable	RD Estimator	Robust Inference		Bandwidth (in days)	Observations
		p-value	95% Conf. Int.		
Credit Cards					
Log(Expenditure)	-0.68	0.71	[-3.70, 2.35]	49.56	17,252
Delinquency Prob.	-0.05	0.11	[-0.11, 0.00]	20.71	58,303
Log(Outstanding Debt)	-0.14	0.68	[-0.67, 0.40]	32.91	53,469
Interest Rate	0.04	0.85	[-0.29, 0.37]	18.33	66,581
Existing Mortgages					
Repayment	-0.06	0.71	[-0.32, 0.20]	30.84	149,556
Delinquency Prob.	-0.05	0.52	[-0.19, 0.08]	14.81	119,817
Log(Outstanding Debt)	-0.17	0.28	[-0.44, 0.09]	24.57	152,734
Interest Rate	-0.30	0.52	[-1.07, 0.47]	48.99	155,970
Maturity	-0.98	0.29	[-2.49, 0.53]	52.19	155,551
LTV	-1.45	0.64	[-6.52, 3.62]	24.28	155,985
Rating	0.20	0.17	[-0.04, 0.44]	8.83	119,802
Short Term Loans					
Delinquency Prob.	-0.02	0.50	[-0.08, 0.03]	30.34	27,158
Log(Outstanding Debt)	0.05	0.83	[-0.36, 0.47]	27.87	24,971
Interest Rate	0.08	0.92	[-1.33, 1.49]	19.02	26,830
Maturity	-0.36	0.35	[-0.99, 0.27]	35.76	26,522
Rating	0.24	0.26	[-0.11, 0.59]	40.45	27,158
Car Loans					
Delinquency Prob.	-0.11	0.63	[-0.49, 0.27]	38.28	5,489
Log(Outstanding Debt)	-1.57	0.19	[-3.52,0.38]	27.07	5,362
Interest Rate	0.55	0.65	[-1.44, 2.53]	33.36	4,878
Maturity	-0.22	0.80	[-1.63, 1.20]	35.12	5,379
LTV	5.15	0.58	[-10.19, 20.49]	33.94	5,489
Rating	0.52	0.09	[0.02, 1.02]	30.50	5,489

Authors' calculations. The table shows the RD estimates (Sharp) in equation (5) for credit cards, *existing* mortgages, short term loans, and car loans before the implementation of the debt moratorium policy. We employ data of *existent* mortage holders on credit cards, mortgages, short term loans, and car loans during Q4-2019. Robust bias-corrected standard errors are employed for computing the confidence intervals and p-values. Standard errors are clustered at the two-digit industry code reported by the mortgage holder (except for estimates on mortgage repayment and credit card expenditures). In all rows we control for an indicator if the *existent* mortgage was used for a Social Interest Housing (SIH) and fixed effects: (i) of bank issuing the loan if dependent variable is delinquency, interest rate, maturity, LTV and rating, or (ii) of bank issuing the *existent* mortgage when outcome variable is credit card expenditures, repayment *existing* mortgages, and outstanding debt. Credit card purchases are computed following equation (1) and then aggreagated across all credit cards of mortgages holders. We measure repayment on mortgages as the negative value of quarterly changes in outstanding balance principal and interests. Delinquency probability is a dummy taking the value of one if loan is more than thirty days of later on payments at the end of the quarter, outstanding debt (in logs of COP) represents the debt balance, interest rate is expressed in percentages, maturity represents remaining number of years until loan matures, Loan-to-Value is the ratio of the collateral relative to the outstanding debt, credit rating takes values from 1-5 with 1(5) representing the lowest(highest) rating. We exclude any individual receiving moratoria on other type of loans except for mortgages in 2020.

Appendix G Consumption Elasticity for Non-Stressed Households

$$Y_{ij,t} = \lambda_{i,t} + \delta D_{ij} + \phi_T D_{ij} \times D_T + \sum_{\tau=T-2}^{T-3} \phi_\tau D_{ij} \times D_\tau + \sum_{\tau'=T+1}^{T+6} \phi_{\tau'} D_{ij} \times D_{\tau'} + \epsilon_{ij,t} \quad \text{(G8)}$$

Table G1: Effect of Moratoria on Non-Stressed Households

	CC Expenditure (COP)	Mortgage Payment (COP)
DID	0.043	-0.641***
	(0.056)	(0.008)
Observations	1 329,582	4 218,109
$\bar{R}^2$	0.11	0.12

Authors' calculations. The table shows the main estimates for the contemporaneous effect of debt moratoria on non-stressed households' consumption. Non-stressed households have none delay on *existent* mortgages by Q1-2020. Estimates correspond to DID coefficient ϕ_T in equation (G8). The first column present the estimates for credit card expenditures in millions of COP. The second column shows the results for mortgage payments in millions of COP. Standard errors in parentheses, *, **, ***, indicate significance at the 10% 5% and 1% level, respectively. In all columns we control for *existent* mortgage bank fixed effects and an indicator if the *existent* mortgage is for Social Interest Housing (SIH). To estimate the contemporaneous effect, we define Q2-2020 as the quarter of treatment. We employ loan-level data for credit cards and mortgages during 2019Q3-2021Q4.We exclude any individual receiving moratoria on other type of loans except for *existent* mortgage in 2020.

Table G1 shows the DID estimates of the contemporaneous effect of moratoria on credit card expenditure and mortgage repayment. Next, we compute the average ratio of mortgage payment-to-credit card expenditures during for 2019Q4-2020Q1 for non-stressed households, which is equal to 0.21. This implies that the elasticity of credit card expenditure out of mortgage moratoria for non-stressed households is 0.014 (i.e. $(0.043/0.64) \times 0.21$).

Finally, we compute the weighted average elasticity for households using the elasticity for stressed and non-stressed households. We employ the total outstanding balance value for *existent* mortgages across both groups at the end of Q1-2020 as weight. In particular, the share of outstanding mortgages is 0.22 and 0.78 for stressed and non-stressed households, respectively.

Therefore, the weighted average elasticity is equal to 0.0373, which is the result of the following computation:

$$0.12 \times 0.22 + 0.014 \times 0.78$$

Appendix H Household Value Functions

Appendix H.1 Active Renters

An active renter has two choices: to continue to rent or purchase a house, that is, $V^r = \max\{V^{rr}, V^{rh}\}$ where V^{rr} is the value function if she decides to continue renting and V^{rh} is the value function if she decides to purchase a house. If she decides to continue to rent, she chooses rental unit size s at price p_r per unit, makes her consumption and saving choices, and remains as an active renter in the next period. After purchasing a house, she begins the next period as a homeowner. The value function of an active renter who decides to remain as a renter is given by

$$V_j^{rr}(a,z) = \max_{c,s,a' \geq 0} \left\{ u(c,s) + \beta E V_{j+1}^{r}(a',z') \right\} \tag{H9}$$

subject to

$$c + a' + p_r s = w\,(1-\tau)\,y(j,z) + a\,((1+r_k)\,,$$

where a is the beginning-of-period financial wealth, $p_r s$ is the rental payment, r_k is the return to savings, and w is the wage rate per efficiency unit of labor. The expectation operator is over the income shock z'.

Appendix H.2 Inactive Renters

Inactive renters are not allowed to purchase a house because of their default in previous periods. However, they can become active renters with probability π. Since they cannot buy a house, they only make rental size, consumption, and saving decisions. The value function of an inactive renter is given by

$$V_j^{e}(a,z) = \max_{c,s,a' \geq 0} \left\{ u(c,s) + \beta \left[\pi E V_{j+1}^{r}(a',z') + (1-\pi) E V_{j+1}^{i}(a',z') \right] \right\} \tag{H10}$$

subject to

$$c + a' + p_r s \;=\; w\,(1-\tau)\,y(j,z) + a\,((1+r_k)\,.$$

Appendix H.3 Homeowners

The options of a homeowner are: 1) stay as a homeowner, 2) refinance, 3) sell the current house (become a renter or buy a new house), or 4) default. The value function of an owner is given as the maximum of these four options, that is, $V^h = \max\{V^{hh}, V^{hf}, V^{hr}, V^{he}\}$, where V^{hh} is the value of staying as a homeowner, V^{hf} is the value of refinancing, V^{hr} is the value of selling, and V^{he} is the value of defaulting (being excluded from the ownership option). A stayer makes a consumption and saving decision given his income shock, housing, mortgage debt, and assets. Therefore, the problem of the stayer can be formulated as follows:

$$V_j^{hh}(a,h,d,z) = \max_{c,a' \geq 0} \left\{ u(c,h) + \beta E V_{j+1}^{h}(a',h,d',z') \right\} \tag{H11}$$

subject to

$$\begin{aligned} c + \delta_h p_h h + a' + m &= w(1-\tau)\, y(j,z) + a\,((1+r_k) \\ d' &= (d-m)(1+r^*), \end{aligned}$$

where m is the mortgage payment following the amortization schedule determined in equation 7.

The second choice for the homeowner is to refinance, which also includes prepayment. Refinancing requires paying the full balance of any existing debt and getting a new mortgage. We assume that refinancing is subject to the same transaction costs as new mortgage originations. So, we can formulate the problem of a refinancer as

$$V_j^{hf}(a,h,d,z) = \max_{c,d',a' \geq 0} \left\{ u(c,h) + \beta_i E V_{j+1}^{h}(a',h,d',z') \right\} \tag{H12}$$

subject to

$$\begin{aligned} c + d + \delta_h p_h h + \varphi_f + a' &= w(1-\tau)\, y(j,z) + a\,((1+r_k) + d'\left(q^m(d';a,h,z,j) - \varphi_m\right) \\ d' &\leq p_h h(1-\varrho). \end{aligned}$$

The third choice for the homeowner is to sell the current house and either stay as a renter or buy a new house. Selling a house is subject to a transaction cost that equals fraction φ_s of the selling price. Moreover, a seller has to pay the outstanding mortgage debt, d, in full to the lender. A seller, upon selling the house, can either rent a house or buy a new one. Her problem is identical to a renter's problem. So, we have

$$V_j^{hr}(a,h,d,z) = V_j^{r}(a + p_h h(1-\varphi_s) - d, z).$$

The fourth possible choice for a homeowner is to default on the mortgage, if she has one. A defaulter has no obligation to the bank. The bank seizes the house, sells it on the market, and returns any positive amount from the sale of the house, net of the outstanding mortgage debt and transaction costs, back to the defaulter. For the lender, the sale price of the house is assumed to be $(1-\varphi_e)\, p_h h$. Therefore, the defaulter receives $\max\{(1-\varphi_e)\, p_h h - d, 0\}$ from the lender. The defaulter starts the next period as an active renter with probability π. With probability $(1-\pi)$, she stays as an inactive renter. The problem of a defaulter becomes the following:

$$V_j^{h}(a,d,z) = \max_{c,s,a' \geq 0} \left\{ u(c,s) + \beta_i E\left[\pi V_{j+1}^{r}(a',z') + (1-\pi)\, V_{j+1}^{i}(a',z') \right] \right\} \tag{H13}$$

subject to

$$c + a' + p_r s \quad = \quad a\left((1 + r_k) + w(1 - \tau) y(j, z) + \max\left\{(1 - \varphi_e) p_h h - d, 0\right\}\right.$$

The problem of a defaulter is different from the problem of a seller in two ways. First, the defaulter receives $\max\{(1-\varphi_e) p_h h - d, 0\}$ from the housing transaction, whereas a seller receives $(1-\varphi_s) p_h h - d$. We assume that the default cost is higher than the sale transaction cost, that is, $\varphi_e > \varphi_s$, the defaulter receives less than the seller as long as $(1-\varphi_s) p_h h - d \geq 0$ (i.e., the home equity net of the transaction costs for the homeowner is positive). Second, a defaulter does not have access to the mortgage in the next period with some probability. Such an exclusion lowers the continuation utility for a defaulter. In sum, since defaulting is costly, a homeowner will choose to sell the house instead of defaulting as long as $(1-\varphi_s) p_h h - d \geq 0$ (i.e., net home equity is positive). Hence, negative equity is a necessary, but not sufficient, condition for default in the model. Therefore, in equilibrium, a defaulter gets nothing from the lender.