The Impact of Relaxing Liquidity Constraints on Small Firm Performance: Evidence from South Africa *

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Abstract

We examine whether liquidity constraints are a barrier to firm growth in low-income countries, and study the role that credit policies can play in addressing them. We combine novel data on small business owners in South Africa's informal minibus industry with a cut-off rule that generated discontinuity in program eligibility providing immediate reduction in payments on the outstanding minibus loan. We find that relaxing liquidity constraints lead to: (i) higher repayments and lower defaults on minibus loan; (ii) an increase in labor supply; and (iii) better overall financial health. We do not find any evidence of increase in firm misconduct or risk to passenger safety, suggesting an improvement in overall welfare. We rationalize these findings using a framework where penalties arising from late payments in presence of liquidity constraints leads to future debt overhang, thereby, generating moral hazard in effort.

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1. Introduction

The past decade has witnessed a substantial increase in corporate debt in emerging markets (Alfaro, Asis, Chari, and Panizza 2019). In low- and middle-income countries (LMICs), firms operate in uncertain economic environment with weak bankruptcy protection, making small enterprises especially venerable to liquidity shortfalls and insolvency risks arising from high debt burdens (World Bank 2021). This was evident in the COVID-19 crisis when the slowdown in economic activity led to severe challenges for small and medium-sized enterprises (SMEs) to meet their financial obligations. Over two-thirds of SMEs in Africa and Asia reported falling behind on their loan payments during mid-2020.[1] While COVID-19 was indeed an unprecedented event, insolvencies have typically increased following periods of crises. In response, policymakers and creditors have often intervened in credit markets to provide some form of liquidity support to small firms.[2]

Despite their growing use as a policy tool, relatively little is known on how relaxing liquidity constraints impact performance of small firms and their owners, fueling an active debate on whether such interventions are justified.[3] This lack of empirical evidence likely arises from three challenges faced by a researcher when attempting to address the issue. First, debt restructuring programs typically reduce both the immediate payments as well as the principal outstanding. Thus, it is unclear whether the observed effects are driven by alleviating short-run liquidity constraints or changing long-run wealth. Second, firms that received a negative demand or cost shock are more likely to demand a reduction in payments. This negative selection biases any estimates of payment reduction on outcomes of interest. Third, lack of information on small firm outcomes and their business owners — especially for small firms in developing countries, majority of which operate in the informal sector — has limited making much progress on the question.

We work with the largest creditor of minibus taxis in South Africa (the "financier")

[1] 90% of surveyed SMEs in South Africa, the country in this paper, expected that they will fall behind on their outstanding liability in the next six months. High financial distress was also reported by SMEs in other developing countries including Kenya (75%), Sri Lanka (70%), and India (60%) (Apedo Amah, Avdiu, Cirera, Vargas Da Cruz, Davies, Grover, Iacovone, Kilinc, Medvedev, and Maduko 2020).

[2] More than 80 countries enacted some form of debt restructuring, either for firms or individuals, in response to the COVID-19 crisis (World Bank 2022). These programs were structured either as a one-time debt relief, or extended lines of credit (e.g. Payment Protection Program in the US), or temporary pause in monthly payments (e.g. debt moratorium program in India), or extension of loan maturity (considered in this paper), or some combination of them.

[3] The main criticism of debt restructuring policies, such as restructuring of bad old loans as new by lenders, has been its misuse by lenders to avoid recognizing loan losses and keeping inefficient firms alive. Caballero, Hoshi, and Kashyap (2008); Adalet McGowan, Andrews, and Millot (2018); Acharya, Eisert, Eufinger, and Hirsch (2019); Blattner, Farinha, and Rebelo (2023) provide evidence on how credit market distortions lead to "zombie" firms and its negative consequences for aggregate growth.

to overcome these challenges. The nation's minibus industry is populated by small firms where individuals typically finance these taxis secured by the minibuses. These firms operate in an uncertain environment, yet competition within the industry is fierce as it provides one of the few avenues of wealth generation in the nation. As a result, financial distress is common with half of the firms falling behind on their payments at least once during the life of their loan. Our setting exploits a natural experiment where the financier reduced short-term payments without changing the long-term obligations for a subset of its borrowers in late 2021. The restructuring was initiated in response to a sharp increase in its portfolio delinquencies following COVID-19 related travel restrictions and the riots in July 2021 sparked by the imprisonment of the former president.

Our natural experiment allows us to overcome the issue of negative selection by exploiting a cutoff rule that determines borrower eligibility to receive the payment reduction offer. Only borrowers that paid at least 50 percent of their previous three months of owed payments got a reduction in their monthly payments. We show that this rule indeed led borrowers above the payment threshold (treated firms) to be 40 percentage points more likely to receive the offer compared to firms below the threshold (control firms), allowing us to use a fuzzy regression discontinuity design to estimate the causal impact of relaxing liquidity constraints. The critical identification assumption for obtaining unbiased estimates for the effects of payment reduction on our outcomes of interest is that the assignment to the treatment is as good as random. This assumption might not hold if, for example, borrowers were aware of the threshold and accordingly adjusted their payments to become eligible for the offer. We address such selection concerns by documenting the absence of any jump in the distribution of borrowers around the treatment threshold. We also support this by documenting that the distribution of baseline characteristics of the borrowers as well as terms of the loan taken display continuity at the treatment threshold.

We combine the natural experiment with four data sources that provide information on borrowers' loan performance, driving effort, risk-taking behavior, and credit bureau records one year after the program roll-out. The first dataset contains administrative loan data for the universe of loans of the minibus financier. We utilize detailed account-level information to construct various proxies of loan performance including future delinquencies, defaults and amount of late payments. The second dataset provides rich information on driving decisions and performance — including daily information on vehicle's first ignition, the distance covered, the time driven, the route taken, and total instances of overspeeding — captured using GPS devices installed in all the financed vehicles. The third dataset provides information on the number of accidents that the vehicle was involved in, along with the description of the intensity of the accidents, available to us because the

financier requires the minibuses to be insured under their contracted insurance program. The fourth dataset matches borrowers' administrative data to their credit bureau records, allowing us to construct measures of financial health including alternative borrowings and consumption.

We begin our analysis by documenting that enrollment in the program had meaningful impact on borrowers' required monthly payments: receiving the restructuring offer reduced monthly payments needed to be made by the borrowers by 4 percent. These reductions are not small as they translate into eligible borrowers paying about 2.4 percentage points of the outstanding balance less on an annual basis and are equivalent to reducing the number of monthly installments to be made in a year by one month. As the program was structured such that the total outstanding loan principal did not change, it increased the remaining loan maturity for the treated firms by five months (over an average loan maturity of 51 months in our sample). Thus the restructuring offer effectively shifts the payments from the present to the future, keeping the interest rate and the loan balance outstanding at the time of enrollment unchanged.

We then estimate the effects of treatment eligibility on the borrower's performance of financiers' minibus loan. We find that a reduction in monthly payment reduced the probability of being delinquent or defaulting on the financier's loan. A 1 percent reduction in payment reduces the probability of delinquency by 10 percent for treated firms relative to control firms.[4] We find similar effects if we instead use alternative measures of loan performance including the number of missed payments or number of months of delinquency within the one year after enrollment in the program.

Next, we examine the effects of payment reduction on labor supply by firm owners. We find that a 1 percent payment reduction led to a 4 percent increase in distance covered using the minibus on a daily basis. We also find positive effects on the number of hours during the day driving the minibus and number of days in a month the bus was driven, although the effects are imprecisely estimated. We show evidence that support that the increase in number of hours is not driven by total number of hours spent outside of driving but is rather driven by an increase in the number of hours supplied towards operating the vehicle. This increase in work hours does not translate to an increase in firm's risk-taking, as evident by no changes in the number of alerts received for over-speeding and in the number of accidents reported. We also find that both treated and non-treated firms behaved similarly in their driving efforts, debt repayments, external borrowing and financial outcomes in the months leading up to the payment reduction. This suggests that the la-

[4]We define delinquency event using the standard definition from the literature, which is being 90 days late on the scheduled payment.

bor market effects are indeed driven by treatment effects rather than selection of borrowers into the program based on pre-treatment labor market performance.

Finally, we examine the effects of the payment reduction on borrowers' overall financial health. In theory, relaxing liquidity constraints for borrowers has ambiguous effect on their future borrowings. On the one hand, a payment reduction on one form of debt could improve overall financial health by allowing borrowers to increase repayment on other sources of borrowing. On the other hand, if a reduction in payment leads borrowers to increase their consumption by borrowing from other sources, it crowds in overall debt mitigating any positive effects from the payment reduction. We find a reduction in the number of late payments as well as the amount by which borrowers are behind on their payments on alternative debt sources. We also do not find any evidence of increased borrowings from other sources of debt. Overall, this points to a net improvement in financial health for the owners of the treated firms.

Our findings that labor supply increases in response to alleviation of short-run liquidity constraints appears to be at odds with canonical models on how debt burden affects labor effort, raising questions on the mechanisms. These models can be classified in two areas. The first set of papers, starting with Myers (1977), highlight that high debt levels *reduce* agents' effort. As agents are residual claimant on the earnings, high debt levels lowers their incentive to exert more effort. This is *static* debt overhang. In our context, this implies that the debt restructuring should not have any effect on labor supply because the program intended to keep the debt level unchanged. A second set of papers imply that an increase in debt payments induces households to work more, especially in presence of consumption commitments (Chetty and Szeidl 2007). This would predict that a relaxation of liquidity constraints should lead to lower labor supply.

We present a simple model that incorporates a salient features of debt contracts absent in the above papers: the incidence of penalties in the event of late payments. This simple modification to standard models of debt contracting can rationalize our findings. Intuitively, the inclusion of a penalty for late payment in debt contract generates *dynamic* debt overhang. Borrowers with same initial debt levels but different monthly payments will have different debt obligations in the future when liquidity constraints force borrowers with higher monthly payment to accumulate higher debt balance over time due to accrual of larger penalties. Higher debt balance in turn generates debt overhang, reducing the labor supply.

We present a number of additional results consistent with this framework. First, descriptive evidence suggests that the responses come primarily from deterioration of outcomes among borrowers that did not receive payment reduction (control firms), rather

than gains from firms that received payment reduction (treated firms). Second, we find that effects take time to materialize, consistent with the above model where late payments take time to accumulate into borrowers' debt balance. Third, we find that delinquent borrowers with lower baseline credit score and revenue, proxies in our data of being more liquidity constrained, are the most responsive to the payment reduction.

Overall, our findings suggests that payment reduction can provide creditors as well as policymakers with a low-cost tool to align borrower's incentive with those of the creditors and improve credit market efficiency. However, our results should be interpreted as short-run effects of such restructuring programs. The long-run effect will have to take into account both the short-run benefits and the long-run costs incurred by deferring defaults from the present to the future.

Contribution to the literature. Our study contributes to a number of literature. First, it relates to the literature analyzing firm growth in developing countries and the important role of credit interventions in this process. Work in this area has been primarily focused on increasing credit supply or access to finance among SMEs (Banerjee and Duflo 2014). Yet, firms in low income countries appear to stay small suggesting they face barriers to their growth. Recent work has, therefore, focused on identifying and relieving constraints faced by small firms in developing countries (Bloom, Mahajan, McKenzie, and Roberts 2010; McKenzie 2017; Kelley, Lane, and Schonholzer 2021). Our findings point to liquidity constraints as an important barrier to firm growth.

Our paper also relates to the literature on debt restructuring. Much of this literature has analyzed the impact of changes in consumer debt on household consumption. For example, Fuster and Willen (2017); Di Maggio, Kermani, and Palmer (2019) study consumption responses to changes in mortgage debt that affected both short-term payments and long-run principal. More recently, papers aiming to disentangle the role of liquidity versus debt overhang in the consumer credit market have arrived at mixed conclusions. Focusing on the unsecured credit card debt in the US, Dobbie and Song (2020) finds limited impacts of payment reduction on households' consumption and labor supply. Yet evidence from the secured loan market of US mortgages suggests an important role of liquidity constraints on households' balance sheet (Ganong and Noel 2020; Indarte 2023).[5] These contrasting results call for more evidence generation across different markets and

[5]In the context of developing countries, work analyzing debt restructuring includes Kanz (2016) which analyzes a debt relief programs for Indian farmers that waived outstanding debt and finds limited effects on consumption and investment but strong effects on moral hazard. Fiorin, Hall, and Kanz (2023) finds that a debt moratorium policy that paused payments for two months for borrowers improved loan repayments rates and their trust in the lender. Using experiment evidence from a consumer credit provider in Mexico, Castellanos, Jimenez-Hernandez, Mahajan, Alcaraz Prous, and Seira (2022) find large effects of unemployment shocks but little effects of changes in interest rate and minimum payments on consumer default.

settings. Our study takes a step in that direction and complements them by documenting the importance of liquidity effects in secured auto loan markets, where loan duration ranges between that of low-maturity credit card debt to longer-maturity mortgage debt.[6]

Our study also differs in two important ways from the above work, both of which are important in their own right. First, our focus is on small firms rather than households. Work by Field, Pande, Papp, and Rigol (2013) suggests that providing new borrowers with a grace period with no required payments after loan disbursement can increase investment, and that lowering the required frequency of payments leads to better consumer welfare without hurting the lender (Field and Pande 2008). We add to these works by documenting how contract modifications after loan disbursement, by extending maturity and reducing payments, for distress borrowers could prevent inefficient firm destruction. As avenues to file for bankruptcy are limited in developing countries which are also plagued by inefficiencies of the court system (La Porta, Lopez-de Silanes, Shleifer, and Vishny 1998), payment reduction presents a promising low-cost tool to alleviate constraints among distressed firms. Second, the granularity of our data allows us to study actual labor supply decisions, instead of relying on wages as is typical in these papers.

Finally, our work relates to the literature in LMICs documenting a lack of separation between production and consumption decisions. Small enterprises in developing countries are owned by individual households, resulting in propagation of shocks to household spending on production decisions (LaFave and Thomas 2016; Kinnan, Samphantharak, Townsend, and Vera-Cossio 2023). We generate evidence on the other side — how relaxing liquidity constraint on production side have positive spillovers on overall financial health of households, consistent with recent evidence on the reliance on personal debt by SMEs in developed economies to mitigate impacts from a decline in corporate credit supply (Fonseca and Wang 2023).

The rest of this paper is organized as follows. Section 2 provides context our study, including the background of the South African informal transit sector, the financier loan portfolio and details on the debt restructuring program that we analyze. Section 3 describes the empirical strategy to analyze the impact of payment reduction on firm outcomes. Section 4 presents the results and discusses the mechanism. Section 5 presents a model which rationalizes our findings. Section 6 discusses alternative mechanisms and presents robustness, and Section 7 concludes.

[6] A related literature has studied how consumption and bankruptcy choices respond to short-run changes to liquidity (Johnson, Parker, and Souleles 2006; Agarwal, Liu, and Souleles 2007; Gross, Notowidigdo, and Wang 2014). We provide complementary evidence by showing that another margin of adjustment to liquidity provision, especially for highly indebted borrowers, is paying down other forms of debt.

2. Background and Data

South Africa's minibus industry provides an ideal setting to study debt restructuring for several reasons. First, it is representative of informal firms that contribute to the majority of employment in the developing world. Second, the loan contract we study is similar to the subprime auto loans in the US, allowing our findings to speak to the broad literature on borrower behavior in the collateralized loan market. Third, the setting allows us to exploit a natural experiment to overcome challenges associated with identifying the effects of payment reduction. Finally, this setting and collaboration with the financier allow us to overcome data constraints that have limited researchers' ability to study how changes to liquidity in small firms affect their performance and the labor supply decision of their owners.

2.1 The Minibus Industry in South Africa

Due to the lack of public transportation in South Africa as a result of Apartheid spatial planning, the minibus taxi industry has grown to become the primary mode of transport for the majority of the population. The industry provides a dense network of services, connecting city centers, suburbs, peri-urban, and rural areas across the country. The primary clientele is the historically disadvantaged population, Black Africans, Indians, and Coloureds, who were systematically excluded from state services during Apartheid. Approximately 40% of the population (15 million individuals) report using the industry daily, and 80% over the course of the year. The industry is privately run without public subsidy for passengers or operators. Estimates suggest that approximately 250,000 minibus taxi vehicles operate in the country, informally employing at least half a million people, generating an estimated R90 billion in annual revenue (2017), accounting for approximately 2-3% of annual GDP.

Each minibus taxi operator is part of a taxi association, which is the industry's de facto set of governing bodies. Minibus taxis operate an unscheduled service on pre-allocated routes, usually departing from fixed points and stopping anywhere along their route to pick up and drop off passengers. Passengers hail taxis using hand signals along these established routes. The taxi fare is determined by the associations that govern route entry. Taxi fares consider multiple factors, including the route length, time taken to cover the route, projected passengers, commuter affordability, and minimum profitability requirements for owners. Typical fares range from USD 0.5 to USD 4 for shorter routes and could exceed USD 25 for longer routes. The fares are overwhelmingly paid in cash and do not change, irrespective of where or what time a passenger enters the vehicle. As a result the sector has remained information with minibuses comprising less than 2% of registered

vehicles in the country.

A common complaint amongst passengers and observers of the industry is that the industry is plagued by violence. There have been many instances of "taxi wars" starting in the late 1970s until the present day. Given the lack of oversight of the government, taxi owners and associations regulate entry into the market and disputes amongst themselves, often at the barrel of a gun. In the last five years, it is estimated that over 500 individuals have been assassinated in taxi-related violence. This self-regulation also leads operators to take excessive risks leading to over 5,000 accidents annually. These challenges make operating a minibus taxi extremely dangerous, yet doing so can be lucrative. In a country with 40% unemployment rate, the minibus taxi industry provides one of the few avenues for income and wealth generation for the disadvantaged population.

The typical minibus taxi is a 16-seater minibus produced by Toyota. About one-third of operators have a single minibus. The remaining operators either operate a small fleet ranging from two to seven minibuses (50% of vehicles) or huge fleets (15% of vehicles). Our sample is more representative of single-owner firms, which comprise 75% of our sample. The remaining 25% are part of mostly smaller fleets. Therefore, our sample is more representative of firm size typical in developing countries, where firms with a labor size of 10 employees or less constitute a significant portion of the labor force.

2.2 The Minibus Financier

The minibus financier provides asset-backed financing for about 35,000 minibuses. The company has been operational since 2006 and makes up approximately 15% of the market for minibus loans in the country as of 2020. Along with providing credit for purchases of new and used minibuses, the financier also provides auxiliary services, including insurance, maintenance, and spare parts. Given the lack of reliable credit ratings on borrowers in South Africa, the financier conducts an extensive financial background check on each applicant. Specifically, the company collects demographic information, driving records, detailed business plans for the use of the taxi, the proposed route, and affiliated taxi association in addition to their credit scores. Once a client's request for a loan is approved and the client purchases a vehicle, the company installs a global positioning satellite (GPS) telemetric device in the vehicle, which provides the precise location of the vehicle every six seconds. The primary reason for installing these GPS devices is detection of fraudulent events and vehicle reclamation in the event of default.

Column 1 of Table II reports the average characteristics of the firms in our sample. The average minibus loan we analyze shares characteristics with a typical US subprime auto loan: the maturity of the loan varies between 60 to 72 months, and the loan is collater-

alized by the minibus. The price of a minibus is typically USD 30,000, which is much higher than the income of the average borrower (USD 20,000), according to the World Bank. Borrowers are typically required to pay 10 percent of the amount upfront, making the average principal of a minibus taxi loan of USD 26,000. The borrower's average credit score is 600, which typically ranges between 0 and 999. Borrower with credit score below 660 is considered as subprime, and hence, the minibus borrowers represent the distribution of population with higher default risk. The average annualized interest rate on the loan is 21 percent and ranges between 14 percent to 26 percent. These numbers reflect the underlying risk of the borrowers' pool due to both asymmetric information on borrowers' creditworthiness and inconsistent income streams in the industry. Indeed, at any point, about half of the loans are 90 days delinquent, and the overall default in the financier's portfolio is close to 30 percent.

2.3 The Debt Restructuring Program

The transportation sector in South Africa witnessed a significant drop in revenue after COVID-19 travel restrictions were enforced through strict lockdowns in the country. Political unrest followed these notoriously draconian lockdowns across major cities in July 2021, nominally ignited by President Zuma's arrest. As a result of the sustained impact of COVID, riots, and few other high-impact events on travel demand, delinquencies on minibus loans started increasing rapidly. These events led the minibus financier to initiate a debt restructuring program for a subset of its borrowers. The purpose of the restructuring was to limit losses on its portfolio by providing debt relief to the most financially distressed borrowers.

The debt restructuring program was conducted in two phases. The first phase was rolled out in September 2021 and the second phase in March 2022, and targeted borrowers who were late on their monthly payments. To ensure a lack of liquidity, rather than moral hazard, plausibly constrained the targeted borrowers, the program included those borrowers who did not accumulate too much or too few arrears. Moreover, the financier only aimed to reduce the borrowers' monthly payments without changing their outstanding principal amount owed. As the borrowers became delinquent on their payments, their monthly owed payments increased to amount for any arrears accumulated upto that point.[7] Under the debt restructuring offer, their updated monthly payments were restored to the monthly payment the borrower agreed to at contract origination. The accumulated arrears were added to their principal amount. This financier financed the program by ex-

[7]The borrowers learned of these delinquencies through the monthly bill statement they received, which showed their outstanding balance, the original contracted payments, and the accumulated late payments. The borrowers also received reminders via text about the late payments.

Table I: Example of the debt restructuring treatment

Principal Outstanding	Accumulated Arrears	Total Amount Outstanding	Interest Rate	Monthly Payment		Remaining Months	
				Before	After	Before	After
(1)	(2)	(3) = (1) + (2)	(4)	(5)	(6)	(7)	(8)
R 378,713.7	R 25,143.92	R 403,857.62	20.7%	R 11,970.23	R 11,224.97	51	57

Notes: The table illustrates how enrollment into debt restructuring treatment changes the payment for a hypothetical borrower. Column (1) shows the principal outstanding for an average loan from our sample. Column (2) shows the average accumulated debt for delinquent borrower. Column (3) shows the total amount outstanding which is the sum of original outstanding principal and accumulated arrears. Column (4) shows the annualized interest rate. Column (5) shows the monthly payments based on total amount outstanding. Column (6) is the original contracted monthly payments, which are the also payment post debt restructuring. Column (7) shows the original outstanding maturity and Column (8) shows the new maturity after the debt restructuring.

tending the maturity of the original loan and accomodating the accumulated arrears. The financier explicitly decided against any interest rate or insurance payment concessions.

Table I provides an illustrative example of how the schedule for an average borrower who received the payment reduction offer changed. In this example, we consider a hypothetical borrower with a monthly contractual payment of ZAR 11,224.97 which is the average . As the borrower has accumulated arrears of ZAR 25,144, her monthly payment increases to ZAR 11,970 (a 6.6% increase over the contracted amount). These values correspond to the average principal outstanding, accumulated arrears, and interest rate. Under the debt restructuring, the borrower receives an offer to reduce her monthly payments to the original contracted amount without changing the outstanding principal (including the accumulated arrears) and interest rate. This offer translates to increasing the remaining maturity of the loan by six months (from 51 months to 57 months).

Panel (a) of Figure I shows changes to monthly payments for the borrower. Thus the financier effectively shifts the payments from the present to the future, keeping the interest rate unchanged. This reduction could effectively lower defaults in the short run for liquidity-constrained borrowers but could increase defaults toward the end of the loan cycle. Panel (b) of the figure shows that borrowers received about ZAR 9,000 in payment reduction in the year following enrollment into the program. This reduction is equivalent one month of installments. Importantly, the figure shows that when discounted at average borrower's interest rate of 20.7% the net present value of debt outstanding does not change for the borrower.

The borrowers eligible to receive these offers had to satisfy a few criteria. First, they had to be active borrowers; that is, their loan must not be undergoing repossession or involved in any legal proceedings initiated by the financier. Second, they could have cu-

mulatively missed more than one and a half months but not more than three months of their installments. The lower limit was to ensure that the reduction amounted to at least a substantial amount to help those in need. The upper limit was arrived based on financier's belief that borrowers with more than three month of payments were less unlikely to respond to its simple debt modification offerings. Based on past experience in dealing with high delinquent borrowers, the financier concluded that borrowers with more than three months of payments in arrears were more likely to response to more aggressive debt relief offers. Third, their loan should have originated at least six months before the roll-out of the program. Fourth, the borrowers should have made at least 50% of their total cumulative payments that were due over the previous three months. We condition our sample of borrowers to satisfy the first three criteria and we exploit the fourth criteria in a regression discontinuity framework to assess the impact of enrollment into the program.

The process to determine eligible accounts based on the above criteria was automated using a computer code that runs daily with updated payment information on borrowers. These criteria would reflect payments by some borrowers that made an off-cycle payment. The accounts that fit the criteria were then passed along to the customer representatives for the financier, who either called or texted the eligible borrowers that they were enrolled in the restructuring. The borrowers then had the option to opt out of the program, but only two borrowers chose to do so. If they did not respond within five working days, their account was automatically enrolled into the program. In total, the offer was received by 2,655 borrowers in September 2021 and 1,139 borrowers in March 2022.

2.4 Data

We use two proprietary datasets. Our first dataset comes from the minibus financier and provides information on borrower characteristics, loan information and monthly performance, driving behavior, and accident reports. Our second dataset comes from the credit bureau, which we link to the financier data to examine the impact of payment reduction on alternative borrowings, credit performance and consumption.

We first obtain information on the (i) characteristics of all borrowers with outstanding loans with the financier for the month of August 2021 and February 2022; and (ii) list of borrowers that received the payment reduction offers in September 2021 and March 2022. The former provides us with the set of both eligible and ineligible borrowers, and the latter provides information on the firms that the eventually financier enrolled in the program. We combine this list of borrowers with information on baseline characteristics of the loan as well as the borrower, along with their loan performance, driving effort, risk-taking, and credit bureau outcomes. We describe the data sources for these next.

Data on baseline characteristics. Information on baseline characteristics for borrowers comes from a snapshot of the financier's loan portfolio for the months of August 2021 and February 2022. This information includes the total sample of firms with active loans with the financier in both these months. First, we obtain the characteristics — duration of the loan since origination, remaining maturity, number of overdue payments, and whether the loan was active — essential to construct the sample of eligible and ineligible firms for the offer. Second, the data provides us with numerous firm characteristics at baseline that we use to verify the identification assumptions of our empirical strategy. These include borrower's age, credit score, and gender, as well as loan-level information such as the amount of loan originated, the interest rate, the amount of loan outstanding, the cost of the collateralized vehicle, the remaining maturity of the loan, the number of missed payments on the loan, and the number of months spanned since loan origination.

Minibus loan performance data. Information on account performance comes from the financier. We obtain details on the payment history for all the loans from January 2021 to April 2023. The data includes both the monthly payment owed as well as the actual payment made by the borrower. It also provides information on accumulated arrears by each month. We use this information to construct the primary running variable used in the analysis, that is, the percent of the past three months owed payments by the borrower. In addition to using the pre-treatment information, the data is also used to construct a measure of loan performance in the year following borrower's enrollment in the restructuring program. We use the information on the number of on-time payments, the share of past payments due made, whether the borrower was ever 90 days delinquent, the number of months the borrower was 90 days delinquent, and whether the borrower had the vehicle repossessed by the financier.

Labor supply and driving behavior data. Information on driving performance comes from the data recorded through GPS devices installed by the financier in all loaned vehicles. The GPS is able to provide daily information on time of first and the last ignition of the vehicle, the total distance covered by the driver, and the total time vehicle was operational. These data allow us to construct measures of borrowers' daily labor supply. We also use a more detailed version of the GPS data that provides us information on the route taken by the driver. Given the routes for the minibuses are pre-allocated, we are able to use the information to determine total number of trips made and also construct measures of the efficiency of each trip by calculating the deviation from the pre-allocated routes.

We also construct two measures of risk-taking. For our first measure of risk-taking, we use the information on the number of daily warnings issued by the GPS for over-speeding,

defined as driving above the national legal limit of 120 kilometers per hour. Information on the number of accidents, our second measure of risk-taking, comes from the insurance claims filed with the insurance arm of the financier. As part of its lending philosophy, the financier insures all the vehicles present in our sample. The monthly premiums for the insurance are added to the monthly installment paid by the borrowers, an average of USD 70 per month. The insurance claims in the data capture claims of varying intensities, along with the date on which the claim was filed. These filings range from small repairs such as windscreen damage or minor dents (USD 50 to USD 150) to significant repairs resulting from major accidents, collisions, and violence against the owner (USD 2500 and above).[8] The richness of the data allows us to capture each of these occurrences separately.

Credit Bureau Data. Lastly, information on borrowings from alternative sources comes from individual-level credit bureau data. The financier sources information on its borrowers' borrowings and payments from other sources using these credit reports. The data contain information on new borrowing, including new credit card, debit card, auto loan, home loan, or personal loan.[9] The data also report whether the borrower had a negative flag reported on her credit report during a month. These negative flags include events such as previous defaults or overdue loans. We also see borrowers' accumulated late payments across these credit lines. Finally, the credit report data allows us to construct a measure of net borrowings based on borrowings made on credit cards. In particular, we calculate net borrowings in a month as the difference between the end of monthly balances between the current and the past month.[10] We use the data to construct proxies of consumption using the definition deployed in Ganong and Noel (2020) using information on spending and payments on various borrowings.[11]

3. Empirical Strategy

A cutoff rule determines borrowers' eligibility to receive the maturity extension: borrowers that made at least 50 percent of their owed installments during the last three months were eligible for the debt restructuring. Our empirical strategy exploits the quasi-experimental

[8]Insurance claims are prevalent in the industry given the intensity and frequency of violence described above.

[9]There are other types of borrowings in the data, such as student loans, but those constitute less than 5% of observations.

[10]Let b_t denote the outstanding balance, p_t be the payments made and e_t be the expenditure at the end of the month on the credit card. We define the net borrowings nb_t as $nb_t = e_t - p_t = b_t - b_{t-1}$. Similarly, we define the consumption by borrower as: $e_t = b_t - b_{t-1} + p_t$.

[11]Our credit bureau data currently is available from July 2021 September 2022. Therefore, we only use it to analyze one-year post-performance for the borrowers that received the payment reduction offer in September 2021. We are in the process of obtaining the data till mid-2023 for all set of borrowers.

variation generated by the assignment rule using a regression discontinuity framework. Specifically, the treatment effect of receiving a 1 percent payment reduction is determined by the jump in the outcome of interest divided by the jump in the percent payment reduction at the cutoff. Let Y be the outcome of interest (such as default) and ΔPay be the percent payment reduction. The fuzzy RD estimator is

$$\beta_1 = \frac{\lim_{p \downarrow 0.5} E[Y|P = p] - \lim_{p \uparrow 0.5} E[Y|P = p]}{\lim_{p \downarrow 0.5} E[\Delta Pay|P = p] - \lim_{p \uparrow 0.5} E[\Delta Pay|P = p]}$$

Under the assumption of continuity of borrower characteristics at the treatment threshold, the fuzzy RD estimator identifies the local average treatment effect of relaxing liquidity constraints of borrowers near the cutoff. We follow RD design recommendations from Lee and Lemieux (2010) and Imbens and Kalyanaraman (2011) to estimate β_1 using a local linear regression within a given bandwidth of the treatment threshold, while controlling for the running variable on either side of the threshold. Specifically, we use the following two-stage instrumental variables specification:

$$\begin{aligned} \Delta Pay_{ir} &= \alpha_0 + \alpha_1 \,.\, 1(P_i \geq 0.5) + \alpha_2 \,.\, (P_i - 0.5) \\ &\quad + \alpha_3 \,.\, 1(P_i \geq 0.5) \times (P_i - 0.5) + \gamma X_i + \nu_j + \nu_r + \eta_i \end{aligned} \tag{1}$$

$$\begin{aligned} Y_{ir} &= \beta_0 + \beta_1 \,.\, \Delta Pay_i + \beta_2 \,.\, (P_i - 0.5) \\ &\quad + \beta_3 \,.\, 1(P_i \geq 0.5) \times (P_i - 0.5) + \eta X_i + \nu_j + \nu_r + \epsilon_i \end{aligned} \tag{2}$$

Y_i is the outcome of interest for firm i enrolled in the maturity extension program round r (either Sep-21 or Mar-22), P_i is the percent of the past three months' payment made by the firm (the running variable), and X_i is a vector of firm controls measured at baseline. We include region-fixed, denoted by ν_j, in all specifications. Including region-fixed effects absorbs any aggregate changes within the region and ensures that we compare the outcomes (such as driving behavior) within the same region. The inclusion of cohort fixed effects implies that we compare the treated and non-treated firms within the same restructuring months. Firm-level controls include age, credit score, the amount of loan originated, interest rate, the amount of loan outstanding, probability of male firm owner, the remaining maturity of the loan, and the number of months since loan origination. While the inclusion of firm controls is not essential for identification, it improves the precision of estimates. Standard errors are clustered at the firm-level.

Two conditions must hold for the estimates of β_1 to be unbiased. First, the density of

the running variable P should be continuous around the treatment threshold.[12] Panel (a) of Figure II plots the distribution of the share of the last three months of payments made by borrowers when the value of the variable lies between 0 and 1. We focus our analysis on the 770 firms that fit the criteria described above and had made at least 30 percent and at most 70 percent of their last three months of owed payments. Panel (b) plots the distribution of the running variable in our final sample. The distribution is smooth around the threshold with no evidence of a jump. The McCrary test statistic testing for discontinuity in the distribution around the threshold is 0.018 with a standard error of 0.129 (Panel a) and 0.265 with a standard error of 0.193 (McCrary 2008). The absence of any discontinuity in the distribution of running variable rules out any sorting into the treatment.

The second identifying assumption that needs to hold is that the baseline covariates should be balanced across the treatment threshold. Figure III presents the graphical versions of balanced tests for variable borrower characteristics, including borrower's age, credit score, amount of loan originated, interest rate, amount of loan outstanding, probability of male firm owner, the remaining maturity of the loan, number of months since loan origination, and the number of missed installments, conditional on fixed effects and controls. Columns 2 and 3 of Table II show the average characteristics of firms above and below the treatment threshold, respectively. Columns 4 and 5 show the difference in the averages and their associated p-values. It is clear that while borrowers above and below the treatment threshold are similar across most characteristics, they still differ in the amount of loan outstanding with the firm and month on book. However, as Columns 6 and 7 of Table II present, the RD estimate of the cross-treatment threshold on baseline characteristics is not statistically different from zero. Consistent with the figure, we find that none of the baseline characteristics indicate a jump at the threshold.

Finally, a potential concern with our identification strategy is that the financier could have targeted the treatment offer to firms based on non-traditional information such as driving effort, risk-taking behavior, or financial information from the credit bureau. Even if the financier did not use this information for targeting the offer, one might still be concerned that borrowers around the threshold differ in their recent driving behavior or performance on the job. Figure IV shows evidence inconsistent with the presence of pretrends around the treatment threshold. We compute the averages across various covari-

[12] Discontinuity in running variable around the threshold could arise if borrowers sort into the treatment. Intuitively, this is unlikely for a few reasons. First, the debt restructuring program was a new initiative the financier took, and borrowers were unlikely to be aware of the program's existence or its logistics. Second, the lender provided the restructuring program to all the borrowers who met the eligibility criteria, and borrowers were then given the option to opt out of the offer. This approach differs from opt-in offers wherein the borrowers initiate or request restructuring and generate selection into treatment.

ates in the three months before the debt restructuring offer. Panel (a) of the figure shows that the average daily driving performance, as measure by the driving distance and duration for which vehicle was driven, before the offer roll-out does not differ at the treatment threshold. Similarly, there is no evidence of risky driving or passenger safety — there is no discontinuity in reported accidents or speeding alters at the treatment threshold (Panel (b)). We also do not find evidence that borrowers above and below the treatment threshold differ in their borrowings and payment behavior from other credit sources (Panel (c)).

Appendix Figure A.2 shows the probability of receiving the payment reduction offer across each band of running variable. The figure shows a significant discontinuity in the probability of receiving payment reduction at the threshold. Consistent with the structure of the offer, Panel (a) of Figure V shows that the payment reduction is associated with an increase in loan maturity right at the treatment threshold. Panel (b) of the figure shows that getting the offer led to a discontinuity in the monthly payments for the borrowers. The graphical evidence in the figure provides evidence for a strong first-stage treatment upon crossing the treatment threshold. Table III presents the first-stage estimates using equation 1 to better assess the magnitudes underlying the payment reduction offer. Consistent with the figure, Column (1) shows that borrowers making at least 50 percent of payment are 43 percentage points more likely to receive the debt restructuring offer. Column (2) shows that crossing the payment threshold leads to an increase in maturity of 6 months. The maturity extension effectively reduces payments by 3.5 percent more (Column (3)).

As Appendix Figure A.2 shows, the estimate of receiving the treatment does not jump to one above the threshold. The reason driving the non-compliance is the way the offer was implemented. As the process of determining eligible borrowers was automated, the data finally used to run the code was the one that was updated a day before the implementation date. However, the data that we received and eventually use was the one processed on the last date of August 2021. For these reasons, some borrowers who should be classified as eligible based on our data did not get the offer due to a change in their payment profile. Therefore, our empirical strategy uses a fuzzy regression discontinuity rather than a sharp regression discontinuity design.

4. Results

4.1 Main results

In this section, we examine the effects of the payment reduction program using the empirical strategy outlined above. We start by analyzing the effect of payment reduction on the loan outcomes with the taxi financier. We then discuss the impact on driving effort,

risk-taking, and overall financial outcomes.

Debt Repayment. Figure VI shows the effects of payment reduction on loan performance around the treatment threshold using various proxies of debt repayment. Panel (a) shows the number of delinquent months one year after the loan modification. However, because we define delinquent months as months in which the borrower was at least three months behind their payment, part of this effect is mechanically induced due to the payment reduction offer. This inducement resulted as enrollment into the offer meant that current arrears were transferred towards future balance, making any late payments immediately zero. We, therefore, study various other measures of loan performance. Panel (b) evaluates the effect on whether the borrowers were ever delinquent in the one year following the reduction. As the figure shows, loan performance measured through all these measures indicates that payment reduction increased repayment for the treated firms.

Table IV provides parametric effects of payment reduction on various measures of loan performance. Column 1 shows that a 1% percent reduction in payment reduces the number of missed payments by 0.3 months. This reduction is significant in magnitude — it is 7.2% lower than the control mean. Columns 2 and 3 show that the short-run payment reduction reduces the financial distress in the year following the reduction — it lowers the number of months the borrower was 90-days delinquent by 0.55 (about 10% reduction relative to the non-treated group) and reduces the chances of ever being 90-days late on the payments by 0.03 percentage point. While 90-day delinquency is the most reliable and standard proxy of financial distress used in the literature (Ganong and Noel 2020), we also examine the effects on the formal definition of default. We find no significant effects on the alternative measures of default (Columns 4 and 5). This result is most likely driven by the fact that we are only studying the outcomes one year after the program rather than longer-term default.

Overall, our results suggest that liquidity constraints are an important driver of financial distress in our sample. However, the results above do not speak on the channels driving these effects. We next provide evidence on two channels- effort and overall financial outcomes- through which payment reduction affects debt repayment.

Effort. Figure VII presents results for driving effort and firm performance. In Panel (a), we find that owners that received payment reduction have vehicles that drive more (i.e., covering more distance daily). In Panel (b), we also find their vehicles drive longer hours, although the effects here are imprecise. Panel (c) shows that the number of days in a month the drivers miss their jobs reduces upon receiving the payment reduction. Table V shows the magnitudes of these effects. A reduction in payments by 1% increases distance

covered by 7 km. This is a 4% increase relative to the control group.

Taken together, the evidence suggests that borrowers are increasing their effort in response to a reduction in their financial distress. Panel (d) suggests further support for this mechanism. It shows that the number of trips made by firms does not change in response to payment reduction. Given that competition for passengers can be extremely fierce among taxis operating on that route, drivers could circumvent this by making slight deviations from their routes and capturing off-route customers. Such deviations, however, are costly because their investment (including extra gas, plausible fines, and longer trip times for already boarded passengers) must be incurred upfront while the demand is uncertain. The results above suggest that the drivers are putting in more effort and undertaking this investment in response to a relaxation of their financial constraints.

In Appendix Figure A.3, we also test whether borrowers are increasing the overall time they are out with their vehicle versus only changing their driving time. Drivers usually head out for a passenger station in the morning. Over the day, however, they spend time in alternative activities, including leisure, waiting for their minibus to fill up with passengers. Our data captures the first time the vehicle ignition was switched daily and the last time it was switched off, allowing us to capture the total time the borrower was out on the job that day. In the figure, we do not find any effect on the total time spent between the vehicle's first and last ignition of the day. This result suggests that the vehicles of the treated owners spend more time in use.

An increase in distance traveled and hours in operation could be driven by greater firm destruction for firms that did not receive debt restructuring. If more delinquencies among the firms not receiving restructuring, as discussed above, led to a higher rate of vehicle repossession, then our estimates on distance and time driven might be biased upwards. Two results show that this is unlikely to be the case. First, we re-estimate the effects using only the sample of active accounts. We find that the effects persist even among the firms that are operating. Second, we calculate the effects of payment reduction on vehicle repossession. Appendix Figure A.5 shows that while the number of vehicle repossessions was lower in the treated group, there was no apparent discontinuity near the treatment threshold. Together, these results suggest that payment reduction led to increased effort and firm performance

Risk-taking. The increase in daily distance documented above might result from faster driving, which generates negative externalities for passengers and pedestrians. Consistently driving the minibus at a fast speed also leads to higher maintenance costs and reduces the vehicle's lifespan. In Panel (a) of Figure VIII, we measure whether the treatment is associated with rash driving by analyzing whether the treated firms receive more warn-

ings for driving greater than 120 kilometers per hour. We do not find any evidence that treatment led to faster driving. This evidence is also consistent with the previous finding, which shows that an increase in driving distance is also associated with an increase in the number of hours driven.

The results in the driven time above, although imprecisely estimated, suggest that drivers are working an additional half-hour over the already long work day of 12 hours before receiving the offer. This result might raise concerns about the negative consequences for passenger and road safety. We examine whether drivers are trading off safety by working longer hours by analyzing the number of accidents. Panel (b) of Figure VIII documents the findings. We find evidence inconsistent with worse safety outcomes following the payment reduction.

Alternative Borrowings. Figure IX presents results on alternative financial outcomes in the first year following the payment reduction. In theory, relaxing liquidity constraints for borrowers has an ambiguous effect on their future borrowings. On the one hand, a payment reduction could improve overall financial health by allowing borrowers to increase debt repayment on other forms of borrowing. On the other hand, a reduction in payment could lead borrowers to borrow more from alternative sources.

We start by analyzing how borrowers fare on their payments made on other credit lines. For this, we consider two proxies of their credit performance that excludes the debt with the financier. First, we consider the total amount outstanding in late payments in the year following the payment reduction (Panel a of Figure IX). Second, we consider the number of late payments reported on the borrower's credit file during the year (Panel b). We find that borrowers receiving the payment reduction have a significant decline in both the total amount in arrears and the number of late payments reported. Next, we start by examining the effects on new borrowing. We consider the amount of total borrowings (Panel c) and the borrowings on credit cards (Panel d). As both figures show, borrowers do not seem to increase their borrowing from other sources of credit. The difference in both total borrowings and credit card debt above and below the treatment threshold is precisely estimated zero.

Together the evidence strongly suggests that the payments reduction on the minibus loan generated spillovers on other forms of debt and improved borrowers' financial health. These results are driven by borrowers lowering their delinquencies and defaults on other loans rather than a decrease in their borrowings.

5. Model and Supporting Evidence

Our main findings, particularly that the relaxation of short-run liquidity constraints increases effort, may seem surprising. This particular result is inconsistent with canonical models in the literature that study the effect of debt payments on labor supply. These models can be classified in two areas. The first set of papers, starting with Myers (1977), highlight that high debt levels *reduce* agents' effort. As agents are residual claimant on the earnings, high debt levels lowers their incentive to exert more effort. This is *static* debt overhang. In our context, this implies that the debt restructuring should not have any effect on labor supply because the program intended to keep the debt level unchanged. A second set of papers imply that an increase in debt payments induces households to work more, especially in presence of consumption commitments (Chetty and Szeidl 2007). This would predict that a relaxation of liquidity constraints should lead to lower labor supply.

In this section we argue that our results are in line with these models when we combine two reasonable assumptions: (i) imposition of late fees in the event of incomplete payment; (ii) binding liquidity constraints. This simple modification to standard models of debt contracting can rationalize our findings. Intuitively, the inclusion of a penalty for late payment in debt contract generates *dynamic* debt overhang. Borrowers with same initial debt levels but different monthly payments will have different debt obligations in the future when liquidity constraints force borrowers with higher monthly payment to accumulate higher debt balance over time due to accrual of larger penalties. Higher debt balance in turn generates debt overhang, reducing the labor supply. Because late fees are a feature of most real-world contracts, we believe that our findings are likely to hold broadly.

5.1 Model

We now describe a model of debt contracting. The main distinction of this model to the existing framework is the presence of a late fees/penalties imposed on the borrower in the case of a late payment. The presence of late fees allows the borrower to keep ownership of the asset and operate it for another period, instead of lender repossessing the asset and liquidating it. This defining feature of debt contract is not unique to our setting — in fact, most borrowing contracts incorporate the late fees feature and allow the borrower to keep possession of the asset for a while instead of resorting to liquidation. The model allows us to derive specific empirical predictions about the effect of liquidity constraints on labor market effort for the borrowers. We describe the model next.

More formally, let the risk-neutral agent owe the lender a total amount of D and is required to make the payment over two time periods. She is required to make a payment of D_1 at time 1, and the remainder amount, $D_2 = D - D_1$ at time 2. She discounts the

future with β. We model liquidity constraints in a simple form — through their effect on β. Intuitively, we follow the literature and assume that the liquidity constraints make agents myopic and they discount the future more. The agent chooses labor l_1 and l_2 across the two periods, which has a disutility $c(l)$. For simplicity, we assume that effort across the periods are independently chosen to one another. On the basis of labor supply, nature draws revenue y_t from the revenue distribution $F(y_t, l_t)$ with probability density $f(y_t, l_t)$. We assume first-order stochastic dominance for $F(.,.)$ i.e. $F(y, l'') < F(y, l')$ for $l'' > l'$ (which implies that $F_l(., l) < 0$).

In period 1, if $y_1 \geq D_1$ the agent makes the payment. However, if $y_1 < D_1$ the lender does not repossess the vehicle but rather imposes a penalty on the borrower. Specifically, if $y_1 < D_1$ the borrower pays y_1 to the lender at time 1 but is required to pay $\gamma(D_1 - y_1)$, where $\gamma > 1$, to the lender at time period 2. In return, she is allowed to keep operating the asset for another period. In period 2, the agent is allowed to keep the vehicle if $y_2 \geq D_2$, otherwise the vehicle is repossessed by the lender. The agents selects effort that maximizes the the expected sum of current profits, which is the expected sum of cash flow today and future discounted value of contract minus the cost of effort:

$$G(D_1, l_1) = \Big[\int_0^{D_1} \beta(V_2 - \gamma(D_1 - y_1)) f(y_1, l_1) dy_1 + \int_{D_1}^{\infty} (y_1 - D_1 + \beta V_2) f(y_1, l_1) dy_1 \Big] - c(l_1)$$

where V_2 is the continuation value given by:

$$V_2(D_2) = \max_{l_2} \int_{D_2}^{\infty} (y_2 - D_2) f(y_2, l_2) - c(l_2)$$

The objective is to analyze how the agent changes her effort l_1 in response to initial debt payment D_1. We utilize the robust comparative statics which implies:

$$\text{sign}\left(\frac{dl_1^*(D_1)}{dD_1}\right) = \text{sign}\left(\frac{d^2G(D_1, l_1)}{dl_1\, dD_1}\right)$$

where

$$\frac{d^2G(D_1, l_1)}{dl_1\, dD_1} = (1 - \gamma\beta) F_e(D_1, l_1) - F_e(D_2, l_2^*) \frac{dl_2^*}{dl_1}$$

Because the efforts across the two periods are assumed to be independent, the sign of first term on the right hand side of the above equation depends on discount rate β^{-1}. If $\beta < \frac{1}{\gamma}$, i.e. for high discount rate, effort decreases in the initial amount of payment D_1. Thus liquidity constrained borrowers, that is those with high discount rate, will reduce their effort when facing more upfront payment D_1 because the presence of late fees in the

contracts increases their future debt levels and generates *dynamic* debt overhang.

5.2 Additional supporting evidence

This simple model described above is consistent with the main empirical results presented in the previous section. In this section, we present additional supporting evidence for the model described above. First, we show that indeed the borrowers that did not receive payment reduction have higher debt levels and have missed more payments a year after the program initiation. This increase in debt levels is generated as a result of the accumulation of late fees. Second, we show treatment effects by each month and find that both labor market and credit market effects materialize after two to three quarter after enrollment into the program. Third, we show that the effects are primarily from the deterioration of outcomes among non-treated borrowers, and not from gains for the borrowers that received payment reduction. Fourth, we show that the effects are more prominent in borrowers that face stronger liquidity constraints as proxied by their credit scores and past driving performance.

Results on debt levels. We start by analyzing whether the level of debt and number of missed performance are affect by the payment reduction offer. Appendix Figure A.4 shows that the treated firms were 5% less number of months late on their payments. This affirms well our setup outlined in the model above that the payment reduction reduces the likelihood that firms will be late on their payments and incur additional penalties on those late payments. This is reflected in the lower total balance outstanding for the borrowers that received payment reduction, even when both the treated and control firms had the same total balance outstanding at the program initiation (as documented in panel (d) of Figure III).

Effects over time. The model suggests that payment reduction reduces moral hazard in effort once the benefits of avoiding the accrual of late fees are realized. This implies that we should see most of the effects on efforts as well as alternative borrowings which would materialize after few months into program enrollment. We test for this by analyzing the regression discontinuity estimate by every month following program roll-out in Appendix Figure A.6. The results corroborate this hypothesis and the differences in effort and alternative debt repayment arises only after eights months of program initiation.

Heterogeneity by degree of liquidity constraints. The model also generates prediction that the effects should be more pronounced for borrowers that are more liquidity constrained. To provide evidence on this, Appendix Table A.3 and Appendix Table A.4 present the main results by baseline credit score and baseline monthly distance covered. We interpret the former as a proxy for baseline liquidity and the latter for baseline revenue.

If financial constraints are driving our effects, then we should find a stronger response under borrowers with lower baseline credit scores and lower recent revenue. We split the sample above and below the third quartile of these baseline characteristics. As Appendix Table A.3 shows, borrowers with lower credit scores at baseline are less likely to default, cover more distance, and have lower arrears on other credit lines after the payment reduction. Similarly, Appendix Table A.3 shows that borrowers with lower past revenue gain the most from payment reduction, although the effects are imprecise here. In both cases, we find no effect on total borrowings across either sub-sample.

6. Alternative Mechanisms and Robustness

6.1 Alternative Mechanisms

A reduction in short-run payments could affect labor market effort through several different channels. In this section, we first discuss whether other potential mechanisms put forward in the existing work could explain our findings.

Effects on credit score. First, the reduction could impact effort through its effects on credit scores (Bos, Breza, and Liberman 2018; Herkenhoff, Phillips, and Cohen-Cole 2016; Dobbie, Goldsmith-Pinkham, Mahoney, and Song 2020). Improved credit scores could provide a better signal to employers about the employees' ability. For borrowers in our sample, enrollment in the restructuring program also comes with the advantage of not getting a default flag reported on their report. However, driving buses is the primary occupation for these borrowers, so an increase in credit score being considered a signal in the job market is an unlikely scenario.

Cognitive channels. Second, it could be that reduction in financial distress could reduce cognitive costs for performing a job. For example, Kaur, Mullainathan, Oh, and Schilbach (2021) find that providing wages early to workers in a factory during a financially constrained period increased their consumption and productivity. If these results were the case here, we would expect the effects to materialize in the months following the restructuring. However, as Appendix Figure A.6 shows, the effects on efforts do not materialize until three quarters after the change in payments. We also do not find any effects on borrowings and consumption in the either short- or long-run. While we cannot completely rule out this channel, primarily due to data limitations, these evidence suggests limited role of reduction in cognitive costs in our setting.

Wage garnishment. Third, the payment reduction could affect labor supply by reducing the amount of wages that court orders under a bankruptcy filing could have garnished. We do not think this is the channel behind increasing effort in the informal sector we study.

The minibus sector largely relies on cash payments for revenue, making any income non-verifiable and not subject to legal garnishment.

6.2 Robustness

We now conduct two exercises to document the robustness of our results.

Given the limited number of observations we had to employ for our fuzzy RD empirical design, we ended up imposing two restrictions. First, we did not impose the optimal bandwidth selection criteria followed in Imbens and Kalyanaraman (2011) (see Cattaneo and Titiunik (2022) for an associated discussion). However, in Appendix Table A.1 we perform sensitivity checks on our estimates across choice of alternative bandwidths. While our effects on distance covered is the most sensitive to choice of alternative bandwidth in terms of statistical significance, the magnitude is stable. Moreover, estimates on first stage, debt repayment and alternative borrowings are robust in their economic and statistical significance across multiple bandwidth choices.

The second restriction we imposed was on the underlying function form in our main specification, for which we resorted to local linear models. We relax this assumption in Appendix Table A.2 which assumes the underlying functional form to be quadratic (polynomial of degree two). Considering a quadratic polynomial regression across the original bandwidth of [0.3,0.7] makes no impact on our results. We also conduct our analysis across multiple bandwidth choices similar to those discussed above. Our findings remain robust across most of these bandwidth choices. We only start losing statistical significance as our bandwidth becomes more narrower and our sample size becomes smaller to allow for precise estimation.

7. Conclusion

This paper uses information from a debt rehabilitation program to estimate the effects of short-run liquidity constraints on firm performance. Employing a fuzzy regression discontinuity design, we find that short-term financial relief improves firm performance one year later. Firms receiving short-term relief have higher repayments and lower defaults on debt, drive for longer distances and more hours, and have better financial outcomes one year later. Using quantitative and qualitative analysis to examine potential mechanisms, we find that temporary debt relief can alleviate moral hazard and assist in overcoming high-impact events that small firms in volatile and uncertain markets regularly experience. We overcome previous estimation challenges by leveraging a comprehensive proprietary dataset from a minibus taxi financier in South Africa.

Our results are significant in light of the ongoing debate on the relative merits of dif-

ferent types of debt relief for SMEs. For example, it is unclear whether providing comprehensive debt relief (reducing principal, term, and payments) increases firm performance by reducing short-run liquidity constraints or changing long-run wealth. Our evidence suggests that alleviating short-run liquidity constraints might improve firm performance for SMEs, thereby service delivery for more marginalized communities, employment outcomes, and the financial performance of the loan provider. Based on our findings, policymakers interested in improving SME performance should consider encouraging short-run debt relief as a potential lower-cost tool than more comprehensive relief. The evidence we document on spillover effects is particularly instructive. It seems targeted debt relief might generally improve firm repayment over a variety of loans beyond the focal financier.

Our findings must be interpreted with few a limitations in mind. Our experiment provided immediate debt relief and thus the findings only primarily speak to the short-run effects of the program. The long-run effect will have to take into account both the short-run benefits and the long-run costs incurred by deferring potential defaults from the present to the future. Another potential limitation is that any perennial roll-out of such targeted debt relief program could affect ex-ante borrower behavior. These factors limit our capability to derive any welfare implications arising from our findings.

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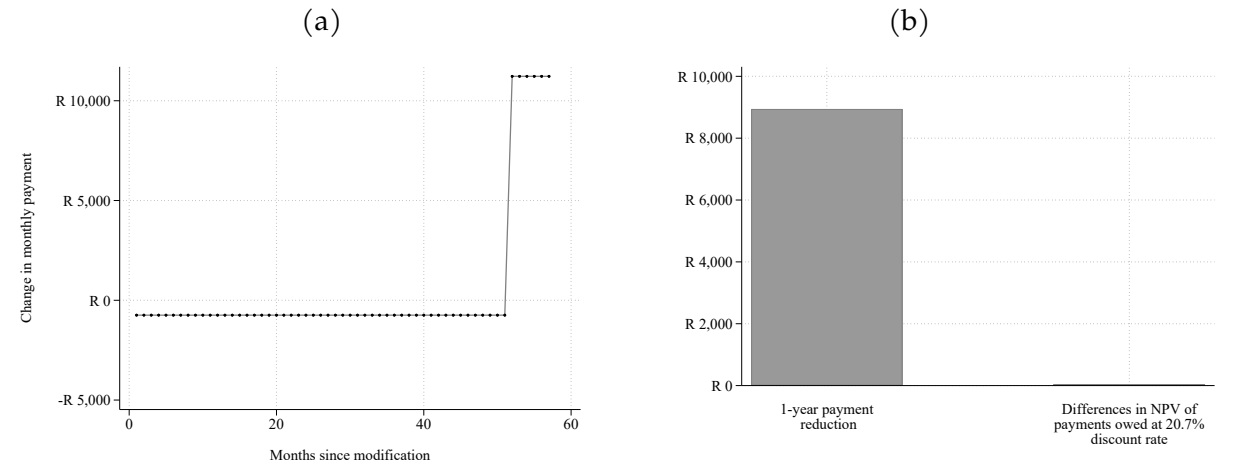
Figures and Tables

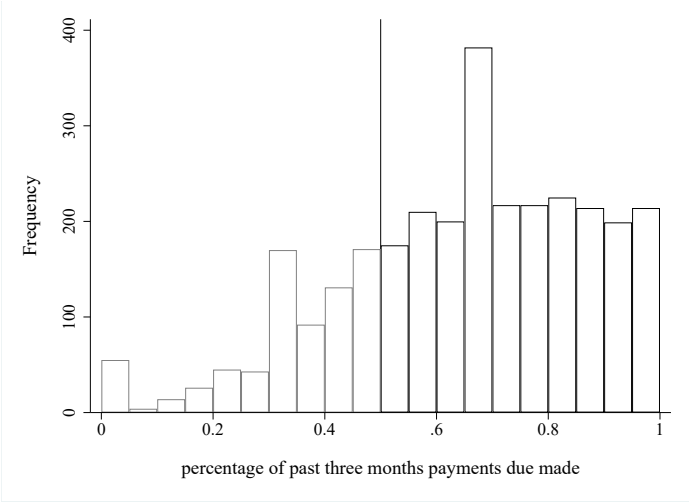
Figure I: Financial impact of the debt restructuring program



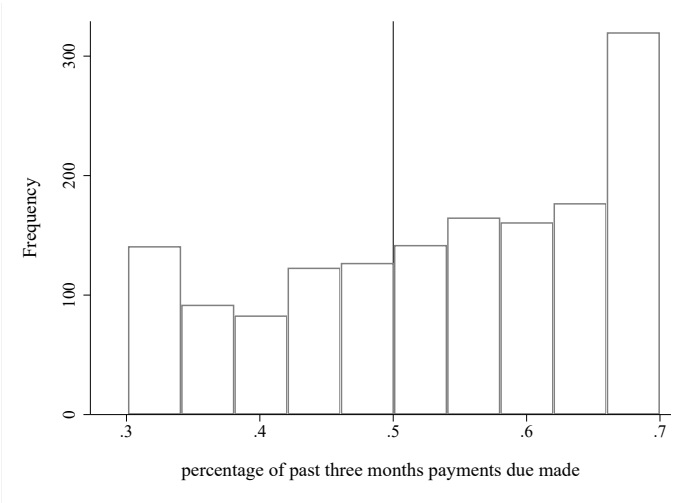
Notes: Panel (a) plots the financial impacts of the debt restructuring on the monthly payments of an average borrower. Panel (b) plots the one year payment reduction through the debt restructuring and the differences in net present value before and after the debt restructuring for the average borrower at 20.7% interest rate.

Figure II: Distribution of running variable

(a) full sample

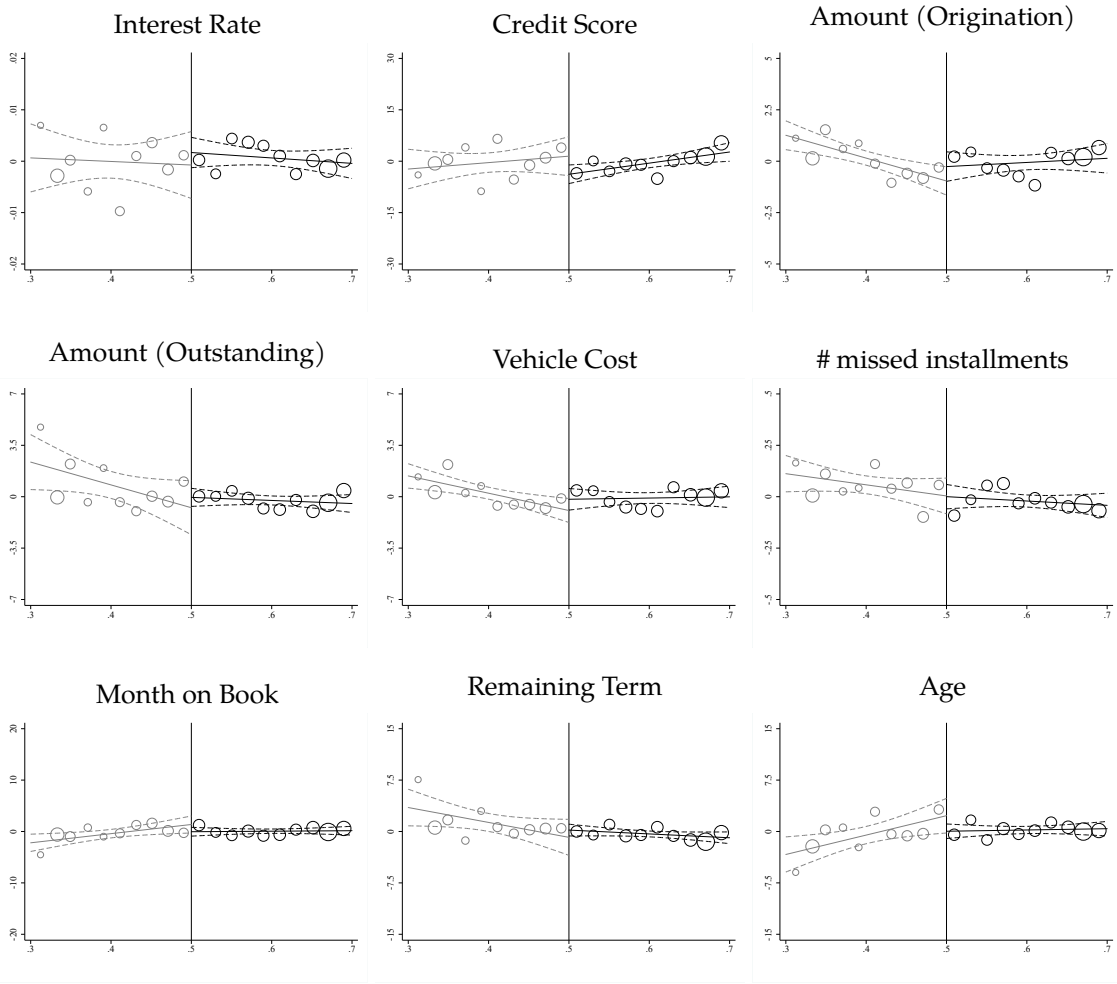


(b) main analysis sample



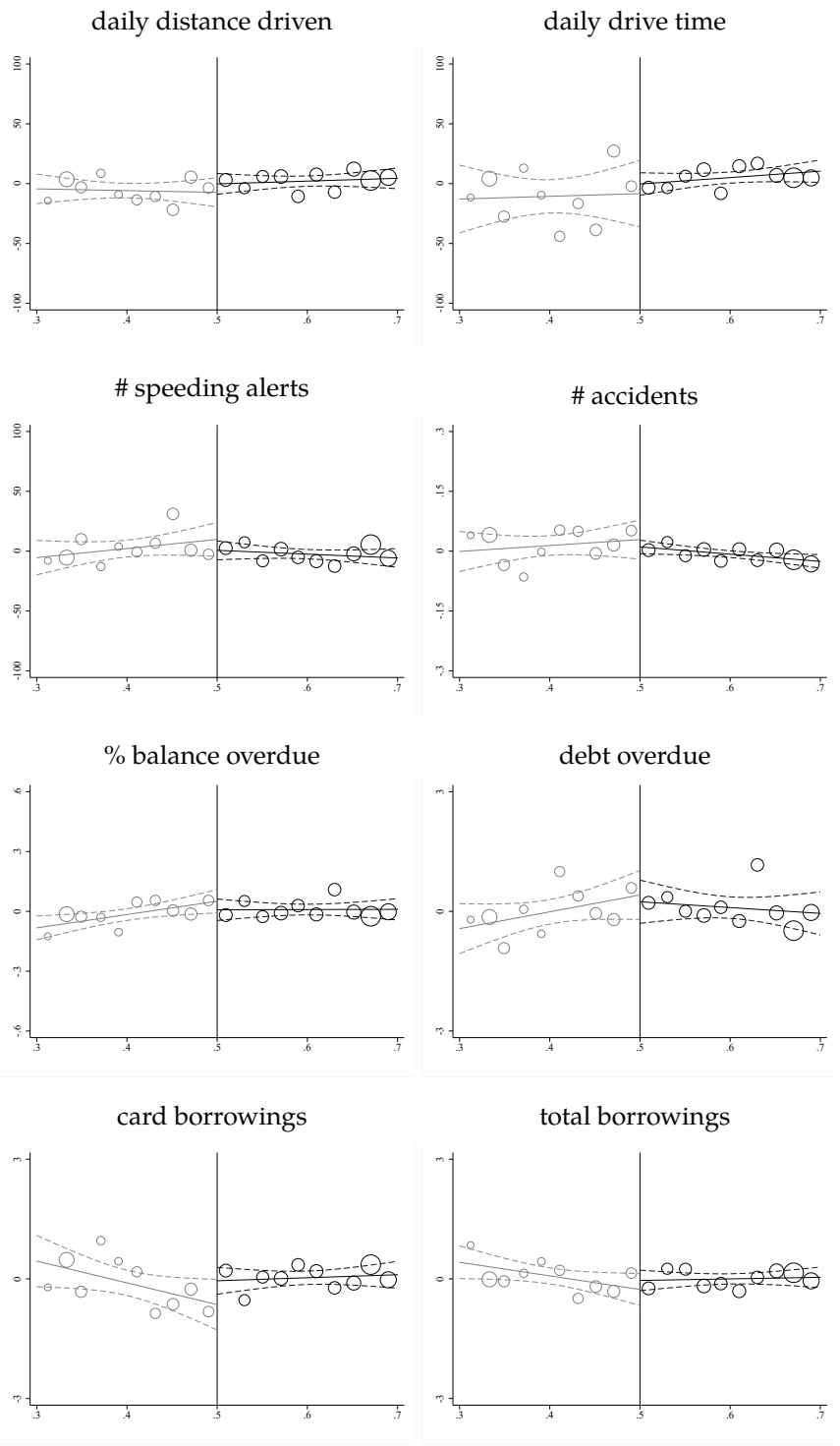
Notes: Panel (a) plots the distribution of running variable around a wider threshold between 0% and 100% of last three months payments made. Panel (b) plots the distribution of running variable around the treatment threshold of final sample used in our analysis which are borrowers that made more than 30% but less than 70% of last three months payments.

Figure III: Balance of baseline loan characteristics



Notes: The figure plots the distribution of baseline loan characteristics around the cut-off we have constructed described in detail above. Panel (a) plots the interest rate assigned at time of financing, Panel (b) the credit score at financing, Panel (c) the loan amount at financing, and Panel (h) age at time of financing. Panels (d) through (g) plots characteristics of borrowers at time of the debt rehabilitation program with Panel (d) showing outstanding loan amount, Panel (e) showing outstanding loan amount Panel (f) showing missed instalments, Panel (g) showing total months on book, and Panel (h) showing the remaining term.

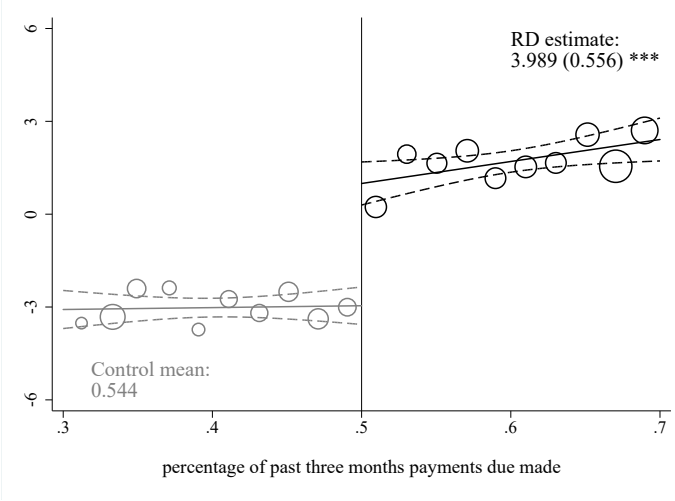
Figure IV: Reduced form: effect on pre-period outcomes



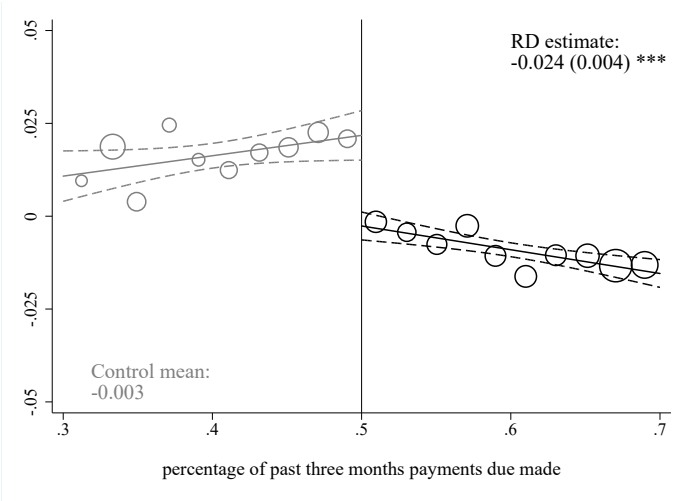
Notes: This figure plots pre-trends around the threshold for our primary outcome variables. The various panel demonstrate no trends over the treatment threshold. Panel (a) shows effort through distance and time driven respectively. Panels (b) shows risk-taking graphing the number of accidents and speeding alerts in the six months prior to the rehabilitation program. Panel (c) shows there is no evidence that borrowers differ in the borrowing and repayment behavior from other credit sources.

Figure V: First stage treatment

(a) Change in loan maturity



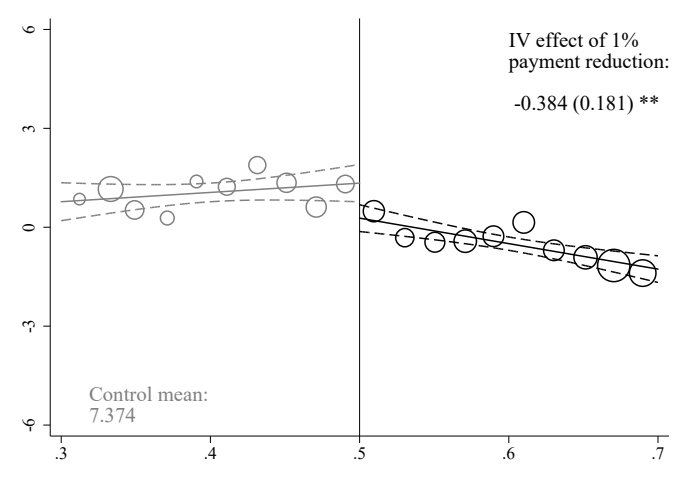
(b) % reduction in monthly payments



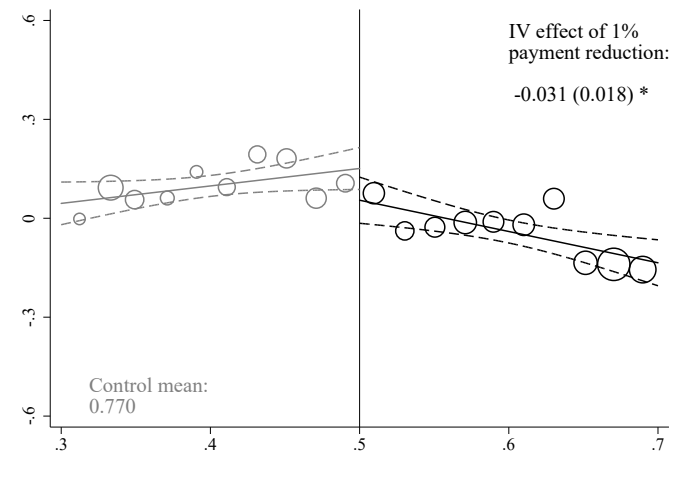
Notes: The figure plots the probability of receiving treatment across each band of the running variable. Panel (a) shows there is a large discontinuity in receiving the term extension, Panel (b) shows there is a large discontinuity in loan maturity, and Panel (c) shows that receiving the offer led to a discontinuity in monthly payments for the borrowers around the threshold.

Figure VI: Reduced-form: effect on loan performance

(a) number of months 90-days delinquent

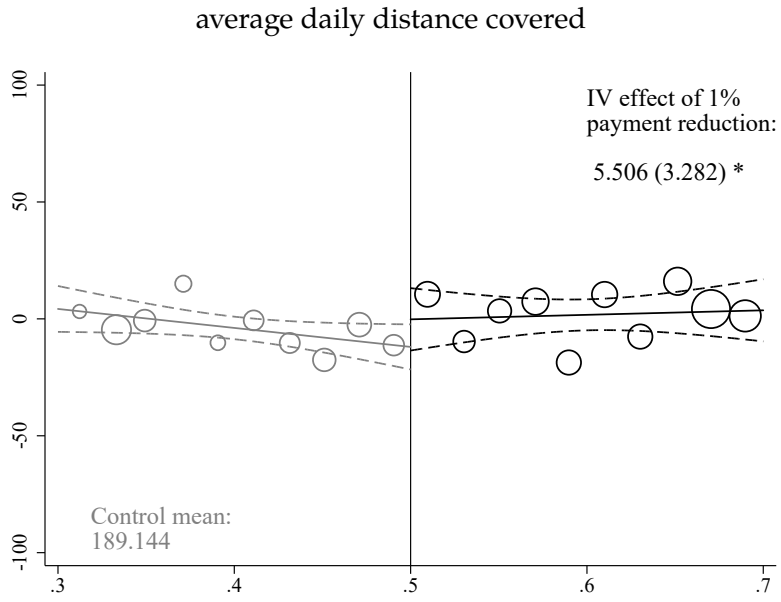


(b) ever 90-days delinquent



Notes: The figure plots the effect of payment reduction on loan performance around the treatment threshold. Panel (a) shows the number of delinquent months in one year after the loan modification. Panel (b) shows the impact on whether borrowers were ever delinquent in one year following the program.

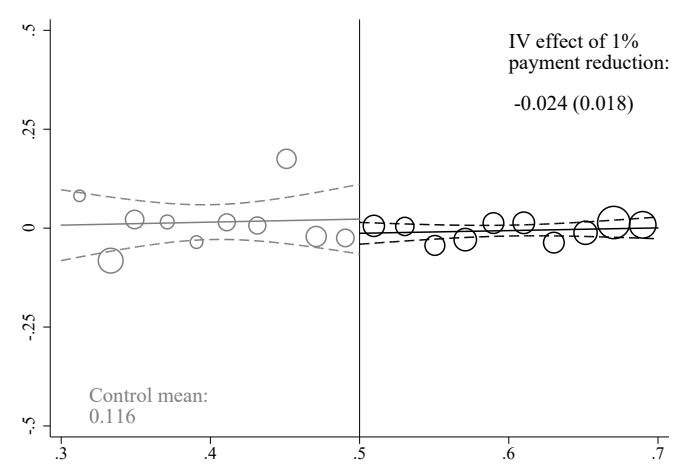
Figure VII: Reduced form: effect on labor effort



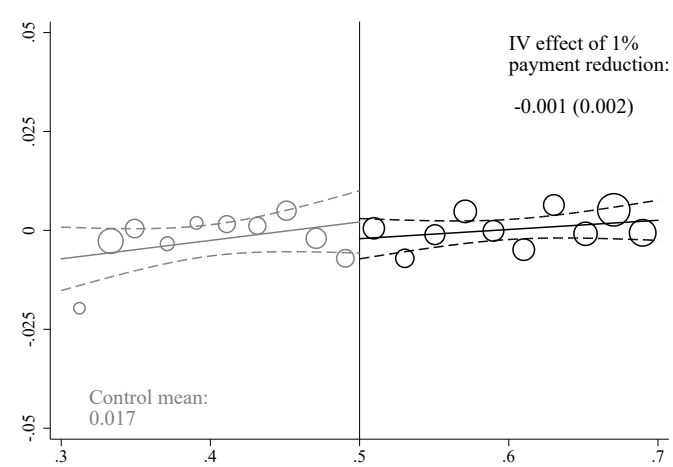
Notes: This figure plots the results for driving effort and firm performance. Panel (a) shows that those receiving debt relief drive longer distances, Panel (b) shows that they drive more hours, and Panel (c) shows they are less likely to miss days of work. These results suggest operators increase effort in response to a reduction in financial distress.

Figure VIII: Reduced form: effects on risk-taking

(a) number of of over-speeding alerts

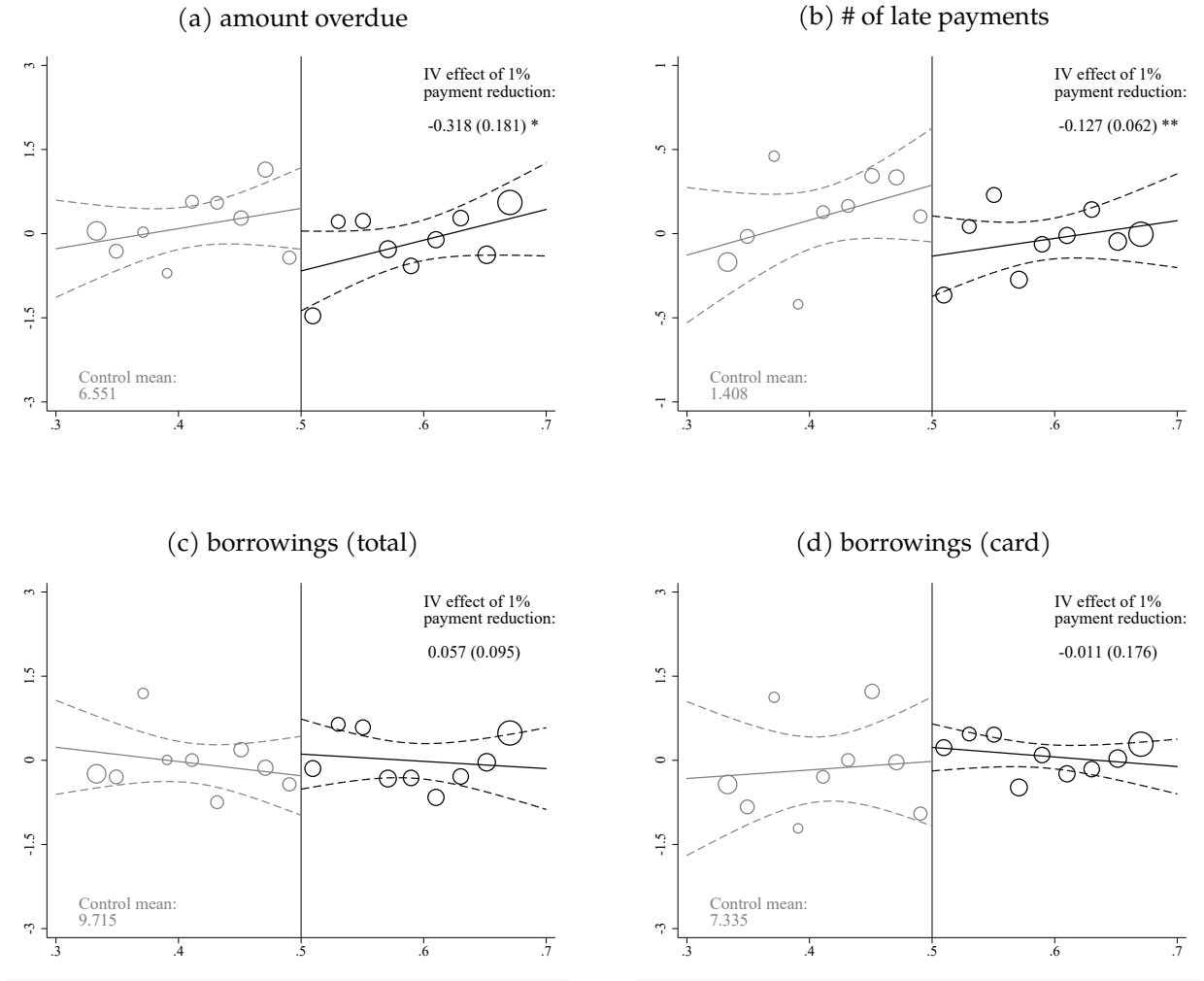


(b) number of accidents



Notes: This figure examines the impact of reduction of financial constraints on different measures of risk-taking. Panel (a) and (b) demonstrate that there is no appreciable change in the number of accidents or speeding alerts as a result of the debt rehabilitation program.

Figure IX: Reduced form: effects on other financial outcomes



Notes: The figure plots the results of alternative financial outcomes in the first year following the debt rehabilitation program. Panel (a) shows that borrowers with lower financial distress have a significant decline in arrears. Panel (b) similarly shows that they decline in number of late payments. Panels (c) and (d) show that borrowers do not seem to increase borrowing from other sources of credit.

Table II: Summary Statistics and balancedness

Panel A. Loan and borrower characteristics

	Full Sample	Below Threshold	Above Threshold	Δ (means)	p-value on Δ	RD estimate	p-value on RD estimate
Loan amount ('1000)	45.54	45.65	45.47	-0.181	0.625	0.630	0.331
Amount outstanding ('1000)	41.87	42.67	41.4	-1.274	0.050	0.293	0.753
Cost of Vehicle (R '1000)	46.89	47.04	46.81	-0.239	0.512	0.706	0.275
Credit Score	636.11	632.11	638.44	6.328	0.165	3.291	0.681
Interest Rate	0.21	0.21	0.21	0.001	0.643	0.002	0.545
# Missed Installments	2.18	2.22	2.16	-0.054	0.012	-0.007	0.894
Month on Book	22.3	21.57	22.72	1.150	0.199	-1.097	0.328
Remaining Term	52.57	53.98	51.75	-2.227	0.011	0.505	0.683
Age	49.58	49.19	49.8	0.613	0.283	-1.718	0.146
1(male)	0.77	0.76	0.78	0.012	0.605	-0.022	0.641
Number of observations	1529	563	966				

Panel B. Pre-program outcomes

	Full Sample	Below Threshold	Above Threshold	Δ (means)	p-value on Δ	RD estimate	p-value on RD estimate
Daily Distance (kms)	197.26	192.37	200.11	7.747	0.048	10.112	0.180
Daily Drive Time (mins)	456.55	447.74	461.7	13.956	0.072	8.530	0.571
# speeding alerts	30.7	32.68	29.54	-3.137	0.530	-10.303	0.322
# accidents	0.08	0.1	0.07	-0.032	0.039	-0.015	0.630
% balance overdue	0.28	0.27	0.29	0.015	0.482	-0.024	0.588
Total amount overdue	5.77	5.74	5.79	0.048	0.842	-0.043	0.930
Borrowings (Card)	7.55	7.43	7.62	0.181	0.452	0.713	0.149
Borrowing (Total)	9.79	9.78	9.8	0.018	0.884	0.133	0.613
Number of observations	1529	563	966				

Notes: The table presents the mean values for borrower characteristics as measured in the month before debt restructuring (September 2021). Columns (1) shows the unconditional mean for the sample; Column (2) shows the unconditional mean for borrowers below the treatment threshold; Column (3) shows the unconditional mean for borrowers above the treatment threshold. Column (4) shows the differences in mean between the sample above and below the threshold. Column (5) shows the p-value on the threshold. Column (6) shows the effect of crossing the treatment threshold on the covariate using the regression discontinuity estimate from the main estimating equation. Column (7) shows the p-value on the estimate.

Table III: First stage: effect of eligibility on receiving payment reduction

			Reduction in ...	
	Prob(treated)	Δ Maturity	Payments (%)	$\frac{\text{Payments}}{\text{Balance}}$
	(1)	(2)	(3)	(4)
$(P \geq 0.5)$	0.309***	3.989***	-0.024***	-0.002**
	[0.039]	[0.556]	[0.004]	[0.001]
Control mean	0.04	0.54	-0.003	-0.000
Observations	1,526	1,526	1,526	1,526
R-squared	0.302	0.252	0.203	0.082
Region f.e.	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓

Notes: The table presents first stage estimates of the effects of being above the treatment threshold on the firm's probability to receive the debt restructuring offer. Column 1 shows the effect on probability on being treated; Column 2 shows the effect on change in loan maturity; Column 3 shows the effect on reduction in monthly payments; Column 4 shows the effect on reduction in share of payments out of outstanding balance. All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table IV: Effect of payment reduction on debt repayment

	# Missed Installments	# months Delinquent	Ever Delinquent	Vehicle Repossessed
	(1)	(2)	(3)	(4)
Δ Payment (%)	-0.210*	-0.384**	-0.031*	-0.015
	[0.127]	[0.181]	[0.018]	[0.012]
F-stat		35.54		
Control mean	4.51	7.37	0.77	0.10
Observations	1,526	1,526	1,526	1,526
Region f.e.	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓

Notes: The table presents the regression discontinuity estimates from the main estimating equation of the effect of payment reduction on debt repayment one year after the treatment. Column 1 shows the effect on number of missed installment; Column 2 shows the effect on number of 90-days delinquent months; Column 3 shows the effect on whether the firm was ever 90-day delinquent in the one-year period; Column 4 effect on probability of a liquidation event (i.e, vehicle repossesssion). All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table V: Effect of payment reduction on effort and risk-taking

	Distance Covered (in kms)	Time Driven (in mins)	Share of Days Missed per month	# speeding alerts in past year	# accidents reported in past year
	(1)	(2)	(3)	(4)	(5)
Δ Payment (%)	5.506*	9.005	-0.008	-0.201	-0.010
	[3.282]	[6.397]	[0.015]	[0.159]	[0.019]
F-stat			35.54		
Control mean	189.14	445.33	0.41	26.81	0.19
Observations	1,370	1,370	1,526	1,526	1,526
Region f.e.	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓

Notes: The table presents the regression discontinuity estimates from the main estimating equation of the effect of payment reduction on effort and risk-taking by firms. Column 1 shows the effect on average total daily distance covered; Column 2 shows the effect on total daily operational time; Column 3 shows the effect on share of days in a month the vehicle was not operated; Column 4 shows the effect on number of over-speeding (i.e. driving at greater than 120 km/hr) alerts received; and Column 5 shows the effect on number of reported accidents. All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table VI: Effect of payment reduction on alternative borrowings

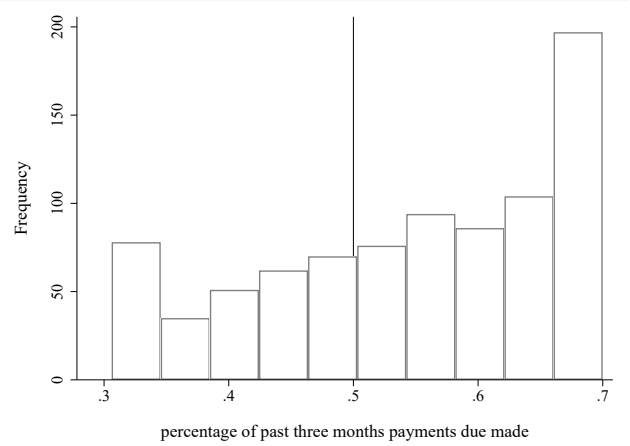
	(log) overdue amount	% of balance overdue	# late payments	(log) total borrowings	(log) card debt
	(1)	(2)	(3)	(4)	(5)
Δ Payment (%)	-0.318*	-0.016	-0.127**	0.058	-0.011
	[0.182]	[0.016]	[0.062]	[0.095]	[0.176]
F-stat			34.19		
Control mean	6.40	0.36	1.33	9.82	7.47
Observations	605	605	605	605	605
Region f.e.	✓	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓	✓

Notes: The table presents the regression discontinuity estimates from the main estimating equation of the effect of payment reduction on financial outcomes from other credit sources. Column 1 shows the effect on (log) total amount of late payments; Column 2 shows the share of balance that is classified as late; Column 3 shows the effect on number of late payments; Column 4 shows the effect on (log) total borrowings; and Column 5 shows the effect on (log) borrowings on credit card and store cards. All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

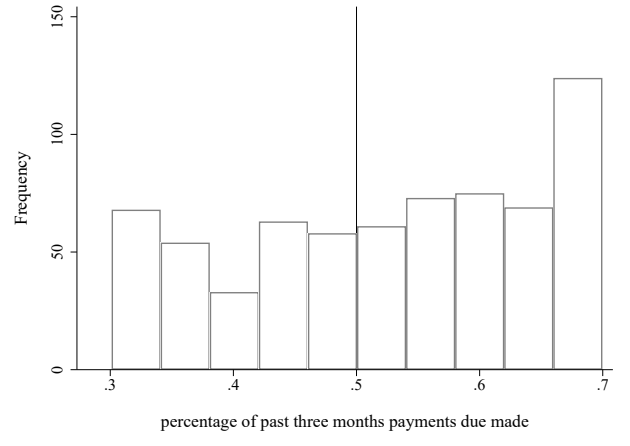
A Appendix Figures and Tables

Figure A.1: Distribution of running variable (by treatment months)

(a) September 2021

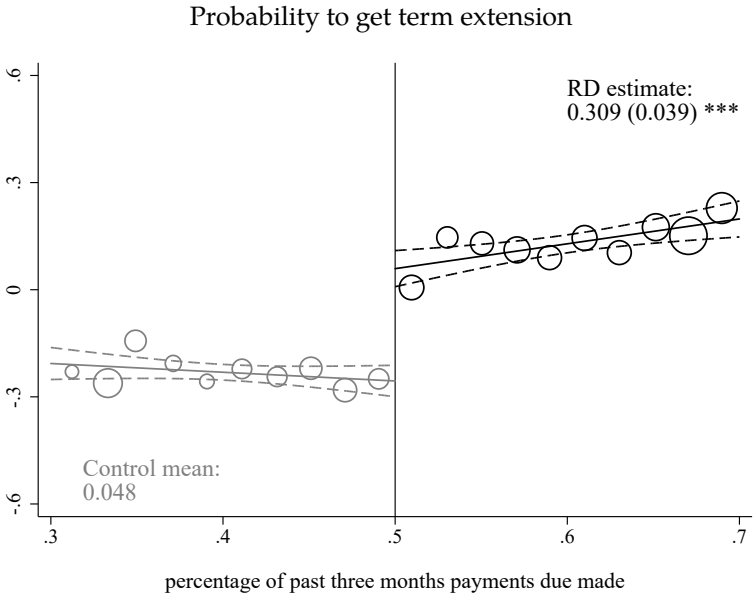


(b) March 2022



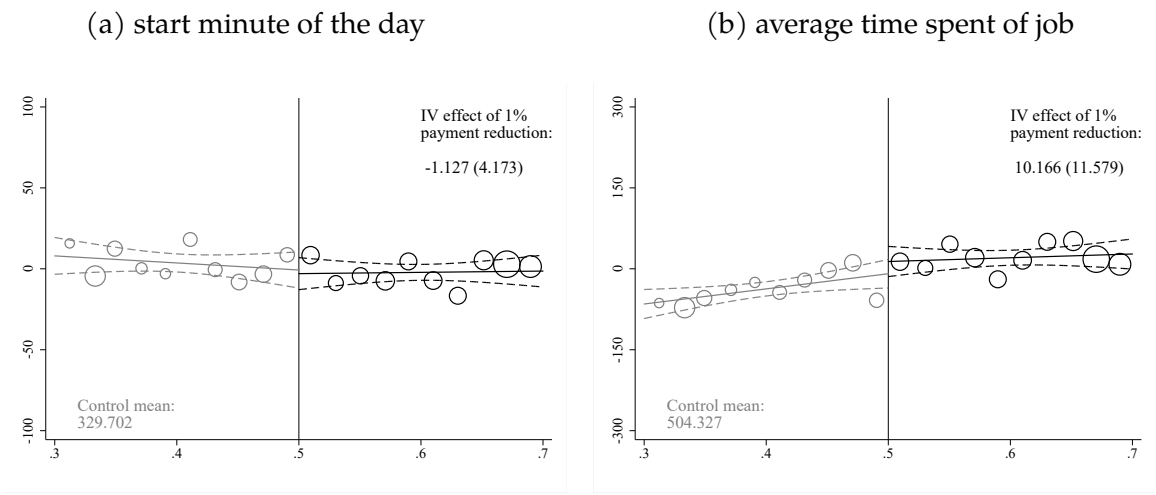
Notes: Panel (a) plots the distribution of running variable around the treatment threshold of borrowers in September 2021 in our analysis which are borrowers that made more than 30% but less than 70% of last three months payments. Panel (b) plots the distribution of running variable around the treatment threshold of borrowers in March 2022 in our analysis which are borrowers that made more than 30% but less than 70% of last three months payments.

Figure A.2: First stage treatment



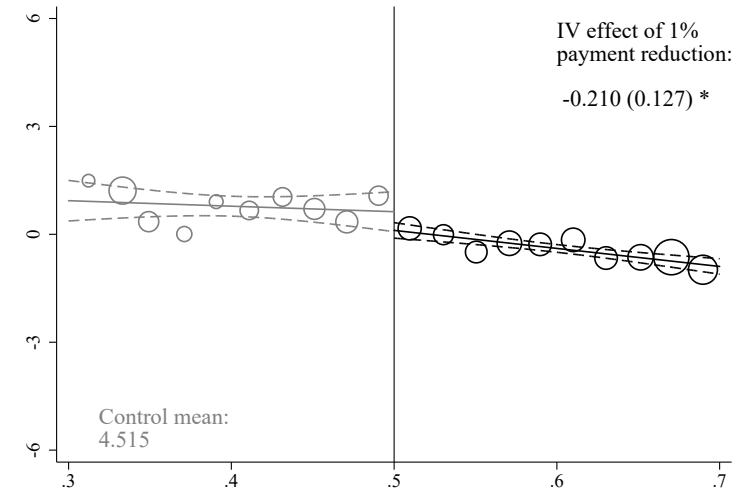
Notes: The figure plots the probability of receiving treatment across each band of the running variable. Panel (a) shows there is a large discontinuity in receiving the term extension, Panel (b) shows there is a large discontinuity in loan maturity, and Panel (c) shows that receiving the offer led to a discontinuity in monthly payments for the borrowers around the threshold.

Figure A.3: Effect on total time between taxi's daily first and last ignition



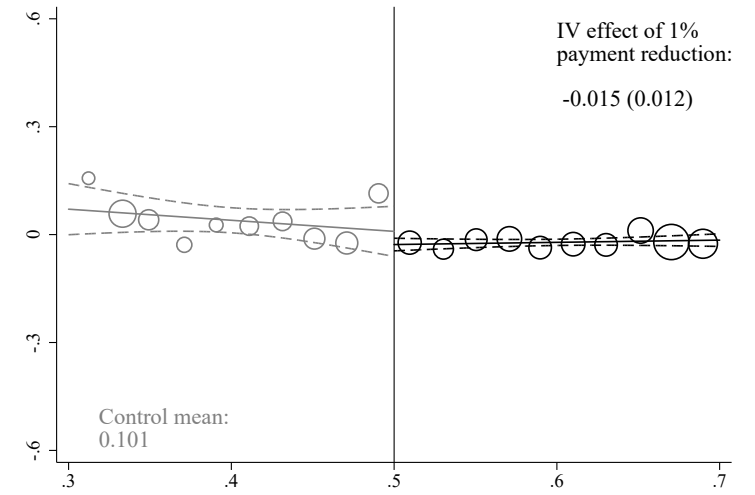
Notes: The figure plots the effect of average number of daily time spent on the job (defined as the total daily time between the vehicle's first ignition time and the time when the last ignition was turned off) around the treatment threshold.

Figure A.4: Reduced-form: effect on loan performance



Notes: The figure plots the effect of payment reduction on total number of missed installment around the treatment threshold after a year of program roll-out.

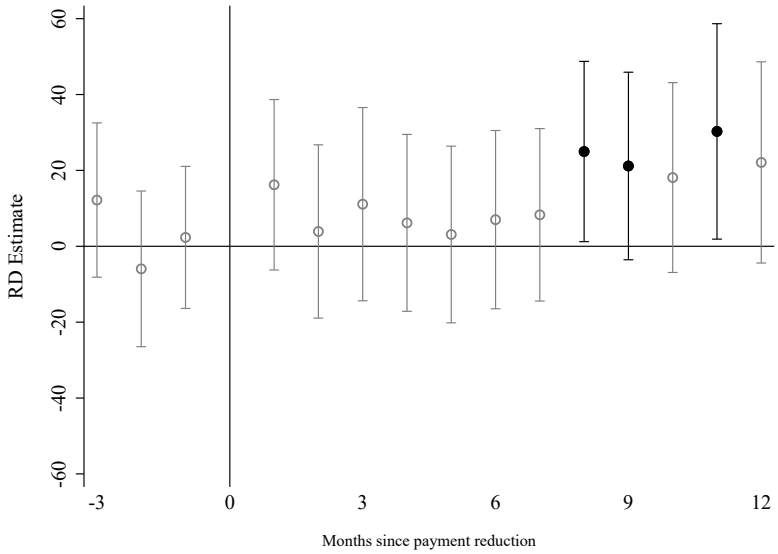
Figure A.5: Effect on vehicle repossession



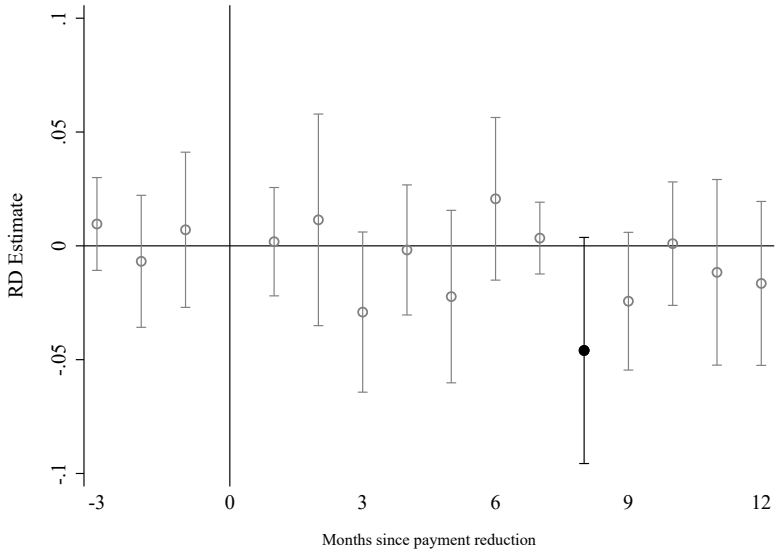
Notes:The figure plots the effect on the probability of vehicle possession by the financier around the treatment threshold one year after the payment reduction.

Figure A.6: Effect on outcomes over time

(a) daily distance driven



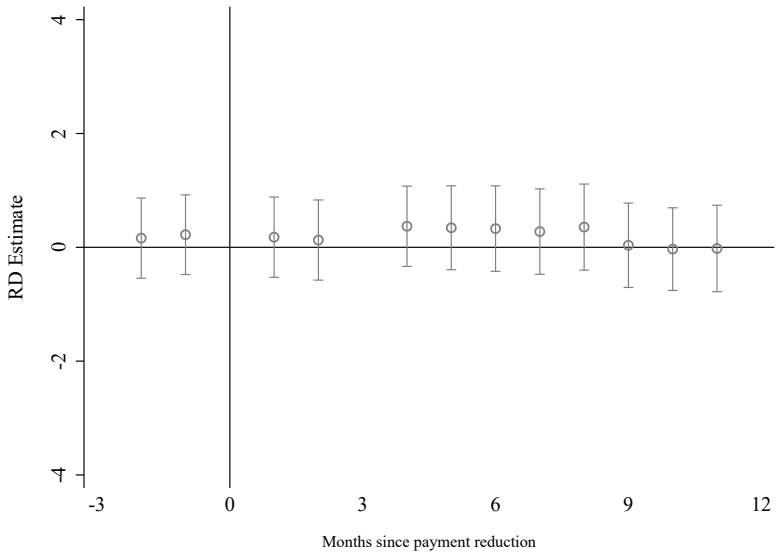
(b) number of accidents



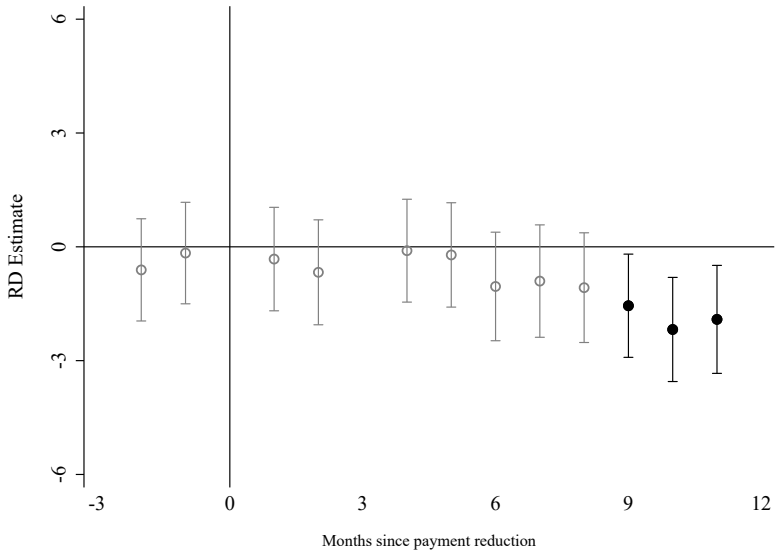
Notes: The figure plots the RD effects of payment reduction on the outcomes of interest in six months before and twelve months after the payment reduction. Panel (a) shows the effect on daily distance driven; Panel (b) shows the effect on borrowings on credit and store cards; Panel (c) shows the effect on share of balance overdue on alternative borrowings reported on the credit reports.

Figure A.6 (Continued): Effect on outcomes over time

(c) credit card borrowings



(d) share of balance overdue on alternate borrowings



Notes: The figure plots the RD effects of payment reduction on the outcomes of interest in six months before and twelve months after the payment reduction. Panel (a) shows the effect on daily distance driven; Panel (b) shows the effect on borrowings on credit and store cards; Panel (c) shows the effect on share of balance overdue on alternative borrowings reported on the credit reports.

Table A.1: Robustness to alternative bandwidth selection

	Δ Payment (%)	# months delinquent	Distance Covered (kms)	# late payments (alt. debt)	(log) total borrowings
	(1)	(2)	(3)	(4)	(5)
$P \in [0.1, 0.9]$	-0.025***	-0.325*	4.469	-0.073	0.029
	[0.005]	[0.196]	[3.676]	[0.069]	[0.112]
$P \in [0.15, 0.85]$	-0.022***	-0.424*	4.332	-0.078	0.065
	[0.004]	[0.234]	[4.344]	[0.079]	[0.125]
$P \in [0.2, 0.8]$	-0.022***	-0.422*	3.585	-0.083	0.066
	[0.005]	[0.248]	[4.744]	[0.083]	[0.131]
$P \in [0.25, 0.75]$	-0.023***	-0.418	6.469	-0.049	0.051
	[0.005]	[0.268]	[5.680]	[0.089]	[0.143]
$P \in [0.35, 0.65]$	-0.024***	-0.200	8.047	-0.093	0.064
	[0.007]	[0.316]	[7.754]	[0.111]	[0.168]
$P \in [0.4, 0.6]$	-0.026***	-0.136	3.049	-0.313*	-0.270
	[0.008]	[0.367]	[6.935]	[0.184]	[0.251]

Notes: The table presents the regression discontinuity estimates from the main estimating equation across various choices of bandwidth ranging from running variable between 10% and 90% (first row) to running variable between 40% and 60% (last row). Column 1 shows the effect on first stage; Column 2 shows the effects on debt repayment; Column 3 shows the effects on effort; Column 4 and 5 shows the effect on other financial outcomes. All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Robustness to quadratic polynomial specification

	Δ Payment (%)	# months delinquent	Distance Covered (kms)	(log) overdue amount	(log) total borrowings
	(1)	(2)	(3)	(4)	(5)
$P \in [0.1, 0.9]$	0.036***	-0.499***	6.241	-0.380**	-0.014
	[0.006]	[0.144]	[3.906]	[0.186]	[0.101]
$P \in [0.15, 0.85]$	0.033***	-0.593***	8.071*	-0.468**	-0.006
	[0.006]	[0.175]	[4.531]	[0.212]	[0.113]
$P \in [0.2, 0.8]$	0.035***	-0.506***	8.743*	-0.441*	0.006
	[0.007]	[0.169]	[4.829]	[0.227]	[0.119]
$P \in [0.25, 0.75]$	0.037***	-0.570***	11.135**	-0.615**	-0.012
	[0.007]	[0.182]	[5.055]	[0.259]	[0.125]
$P \in [0.3, 0.7]$	0.035***	-0.490**	12.796**	-0.553**	0.034
	[0.008]	[0.196]	[6.285]	[0.280]	[0.140]
$P \in [0.35, 0.65]$	0.039***	-0.363*	11.981	-0.487	-0.020
	[0.011]	[0.203]	[7.814]	[0.328]	[0.162]
$P \in [0.4, 0.6]$	0.030***	-0.628*	14.768	-0.716	-0.212
	[0.011]	[0.324]	[10.582]	[0.490]	[0.239]

Notes: The table presents the regression discontinuity estimates from the main estimating equation for quadratic polynomial specification instead of linear polynomial specification. We also perform the exercise across various choices of bandwidth ranging from running variable between 10% and 90% (first row) to running variable between 40% and 60% (last row). Column 1 shows the effect on first stage; Column 2 shows the effects on debt repayment; Column 3 shows the effects on effort; Column 4 and 5 shows the effect on other financial outcomes. All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Effect of payment reduction, by baseline credit score

	# months delinquent	Distance Covered (in kms)	(log) overdue amount	(log) total borrowings
	(1)	(2)	(3)	(4)
	A. Low Credit Score ($< 75^{th}$ percentile)			
Δ Payment (%)	-0.457**	6.574	-0.116	0.036
	[0.229]	[4.615]	[0.272]	[0.146]
Observations	1,144	1,014	848	848
Region f.e.	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
	B. High Credit Score ($\geq 75^{th}$ percentile)			
Δ Payment (%)	-0.229	8.370	0.077	0.199
	[0.328]	[6.071]	[0.276]	[0.166]
Observations	382	356	309	309
Region f.e.	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓

Notes: The table presents the regression discontinuity estimates from the main estimating equation of the effect of payment reduction on main outcomes across firms with low baseline credit scores (Panel A) and high baseline credit scores (Panel B). Column 1 shows the effect on debt repayment; Column 2 shows the effects on effort; Column 3 and 4 shows the effect on other financial outcomes. All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Effect of payment reduction, by baseline income

	# months delinquent	Distance Covered (in kms)	(log) overdue amount	(log) total borrowings
	(1)	(2)	(3)	(4)
	A. Low Distance Covered ($< 75^{th}$ percentile)			
Δ Payment (%)	-0.215	5.547*	-0.213	0.064
	[0.207]	[2.907]	[0.199]	[0.111]
Observations	1,048	1,002	790	790
Observations	540	439	368	368
Region f.e.	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
	B. High Distance Covered ($\geq 75^{th}$ percentile)			
Δ Payment (%)	-0.662	10.706	0.396	0.196
	[0.418]	[11.149]	[0.555]	[0.290]
Observations	478	368	367	367
Region f.e.	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓

Notes: The table presents the regression discontinuity estimates from the main estimating equation of the effect of payment reduction on main outcomes across firms with low baseline performance (Panel A) and high baseline performance scores (Panel B). Column 1 shows the effect on debt repayment; Column 2 shows the effects on effort; Column 3 and 4 shows the effect on other financial outcomes. All columns include region fixed effects and firm baseline controls as described in the main text. Standard errors clustered by district level are reported in parentheses. Standard errors clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.