Working it out: Randomized restructuring and entrepreneurial effort in a collateralized debt market*

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Abstract

Loan modification is increasingly important as advances in lending technology facilitate greater risk-taking. We examine how liquidity constraints and moral hazard shape borrower responses to modifications, and their implications for contracting, using an RCT on vehicle-collateralized debt, unusually rich administrative data on entrepreneurial effort, and an enriched workhorse model. The RCT randomizes the near-universe of a publicly-traded lender's poorly performing loans to either payment reduction (liquidity relief) or debt reduction (debt overhang relief). The borrowers are small businesses providing minibus taxi services that are essential to the functioning of the South African economy. GPS devices installed to facilitate vehicle repossession also measure borrower effort, in the form of driving activity. Our model accounts for liquidity constraints and repossession risk and their effects on effort—in contrast to standard models, which define debt overhang assuming full repayment—and predicts that: a) debt reduction will not improve repayment performance or effort for liquidity constrained borrowers; b) payment reduction will generate improvements, for borrowers with sufficient equity in their vehicle; c) payment reduction will often induce payment increases before effort increases. Our results thus far are consistent with these predictions.

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1 Introduction

Loan modification has long been important for lenders, policymakers, and courts — and is increasingly so as technological advances facilitate riskier lending. Effective and optimal modification depends on the nature and extent of liquidity constraints, moral hazard, and externalities, yet identification challenges and data limitations have constrained attempts to generate pertinent empirical evidence.

Most existing studies concern households, leaving the effects of business loan modifications largely unexplored despite decades of corporate finance research on debt overhang (Myers 1977; Kalemli-Özcan, Laeven and Moreno 2022; Jordà, Kornejew, Schularick and Taylor 2022). Existing studies largely concern policy-driven modifications in response to large aggregate shocks (e.g., Ganong and Noel (2020); Indarte and Kanz (2024); Gyongyosi and Verner (2024)), despite most modifications occurring in the normal course of lending business (Bidder, Crouzet, Jacobson and Siemer 2024). These studies tend to rely on quasi-experimental variation from policies that exclude borrowers deemed to have the strongest incentives for strategic default (Ganong and Noel 2023, p.1060), even though lenders must reckon with such borrowers. The two existing randomized control trials (RCT) on loan modifications concern unsecured consumer lending (Dobbie and Song 2020; Aydin 2024), but collateralized lending is contractually distinct (e.g., Bester (1987); Berger and Udell (1990); Gertler, Green and Wolfram (2024)) and economically important in most settings.[1]

We address these gaps by combining a collateralized debt modification RCT with rich administrative data on entrepreneurial effort and borrower incentives. Our RCT design and analysis are guided by a theoretical model that enriches the standard debt overhang framework with liquidity constraints and repossession risk.

The RCT is implemented by a publicly-traded lender on a near-universe of its delinquent loans, and compares three common approaches to loan modification. Our control arm implements the lender's standard modification: capitalizing arrears by extending maturity, keeping monthly payment unchanged. Our treatment arms start by administering the lender's standard "mod" and then further implement payment reduction (via maturity extension that lowers the monthly installment amount) or debt reduction (an interest write-down that leaves monthly payment unchanged).

The loans finance activity in an economically vital product market— minibus taxi services, the primary form of transit in many low- and middle-income countries—where borrowers pledge their business' primary productive asset as collateral.[2] GPS data on driving activity, from devices embedded in the financed vehicles per loan covenants, provides unusually granular and accurate

[1] More than $14.7 trillion (out $18 trillion) of household debt (Federal Reserve Bank of New York 2024), and more than $1 trillion (out of $1.3 trillion) of small business debt in the US is secured by a physical asset in 2023 (Federal Deposit Insurance Corporation 2023). In South Africa, $100 billion of household debt and $20 billion of small business debt is estimated to be secured by a physical asset, making secured debt approximately 75% to 80% of total debt outstanding in each category (World Bank 2022).

[2] Prior work estimating effects of vehicle loan modifications uses non-randomized sources of variation, and focuses on consumer credit and bankruptcy provisions therein (Chakrabarti and Pattison 2019), with some incidental coverage in work on COVID-era forbearance (Cherry, Jiang, Matvos, Piskorski and Seru 2021).

measures of entrepreneurial effort.[3] Together with data on repayments to our partner lender and outside lenders, our study paints an unusually complete and dynamic picture of how contract terms shape borrower behavior over a 12-month horizon.

Our conceptual framework examines how liquidity constraints and strategic incentives *jointly* influence borrower behavior under collateralized debt. Standard models of debt overhang focus on how high debt burden prevents the borrower from fully capturing the long-run returns to exerting effort (Myers 1977). These models predict that a reduction in the overall debt burden is sufficient to restore repayment incentives and effort. However, we show that once liquidity constraints are incorporated in the standard model, this logic no longer holds. For liquidity-constrained borrowers unable to meet short-run obligations, even a reduction in total debt may fail to avert liquidation, leading to an inefficient shutdown of the business ex-post and dampening effort ex-ante. Instead, policies that alleviate short-run cash flow pressures—such as lowering monthly payments—can have a more immediate effect on repayment. This issue is particularly acute for collateralized debt: if a borrower cannot meet immediate cash flow needs, they risk losing access to the income-generating asset that secures the loan. Hence, by reducing repossession risk, policies targeted at improving short-run liquidity may also increase borrower's incentives to exert effort.

Our model also highlights the crucial interaction between liquidity constraints and strategic incentives: even for liquidity-constrained borrowers, the overall impact of lowering payments depends on the extent to which strategic considerations drive decisions to reduce effort. For example, if the borrower's debt burden was already too high ex-ante, relaxing liquidity constraints alone may not significantly improve effort or repayment behavior. The model motivates our experimental design, our focus on entrepreneurial effort as well as repayment behavior, and pre-registered heterogeneous treatment effect estimation by baseline equity in the collateral. It also helps make sense of the full pattern of our results, by highlighting the importance of repossession risk — the borrower's risk of losing its business' primary productive asset — in shaping borrower responses to contract parameters.[4]

Our setting is well-suited for studying the implications of debt overhang and liquidity constraints for borrower behavior and lender modification strategies. Borrowers are largely subprime credit risks, with delinquency and default accordingly commonly realized states.[5] As such, repossession risk is substantial, particularly once a borrower enters the delinquency state considered in our experiment. Indeed, our GPS data on driving behavior comes from devices installed by the lender, and required to be operational per loan covenants, to facilitate repossession of the collateral. Observational data indicates that driving activity is indeed strongly negatively correlated with leverage.

[3] Other studies have found substantial measurement error in business self-reports of input utilization or effort and instead rely on enumerator observation (e.g., Bassi, Muoio, Porzio, Sen and Tugume (2022); Walker, Shah, Miguel, Egger, Soliman and Graff (2024)).

[4] O'Malley (2021) finds that removing repossession risk increases mortgage default substantially, in relative terms, even when baseline risk is low.

[5] For example, of the 13,300 loans originated by the lender in 2016 and 2017 and scheduled to mature before the start of our experiment in November 2023, 57% became 90+ days delinquent at some point and 47% had their vehicle repossessed. Bidder, Crouzet, Jacobson and Siemer (2024) find that restructuring is common even among more established borrowers, with 41% of C&I loans made by U.S. large banks modified at least once.

Minibus taxis do not follow set schedules, and firms thus have great discretion over when, how, and how much they operate. This, together with substantial "slack" in input utilization as in common in many and perhaps most business settings (Taubman and Gottschalk 1971; Walker, Shah, Miguel, Egger, Soliman and Graff 2024), implies a potentially large elasticity of entrepreneurial effort with respect to debt contract incentives.

Another attractive feature of our setting, relative to prior work on mortgage modifications, is that it includes borrowers who are *a priori* most likely to default strategically due to having very negative equity positions.[6] We show that most borrowers financing new vehicle purchases are meaningfully "underwater" (i.e., have strictly negative equity in the financed asset used as collateral) for much of their loan maturity, due to low downpayment requirements (1% at the median in our setting) coupled with the standard "drive off the lot effect" whereby new vehicles depreciate discretely upon being purchased. The post-purchase depreciation curve is also steep in our setting due to the intense, productive use of the collateralized asset, as is often the case with business equipment and its financing (Benmelech and Bergman 2008; Luck and Santos 2024).

Moreover, our setting has some instructive parallels to the mortgage markets that have received far more scrutiny than small business financing from researchers and policymakers interested in loan modifications. Our borrowers' minibus loan is almost always their primary debt obligation, as is the case for most home mortgage borrowers. Default costs are plausibly quite high— here due to lost income generation in addition to the usual costs incurred in a well-functioning credit market; in the mortgage case due to various factors (see Ganong and Noel (2023, p.1057) and references therein). Spillovers from the product market to the macroeconomy are also plausibly quite substantial, as studied extensively in mortgage and housing markets, and documented in various minibus taxis markets across the world when driver strikes impede economic activity (Eaglin 2025).

Our setting is also well-suited for shedding light on how financial frictions shape entrepreneurs' decision making (Kerr and Nanda 2011). Our borrowers are privately-owned small businesses that finance the acquisition of their main business asset (i.e., the minibus) and often hire drivers. Owners face many difficult decisions regarding input utilization and contracting, but the production function is relatively simple. Moreover, business owners have virtually no control over pricing and entry on the margin, facilitating the identification of mechanisms. Our linked data on financing and output is unusual for closely-held businesses.[7]

Motivated by our conceptual framework and following some of the previous work on consumer credit, we worked with the lender to implement the RCT in November 2023, randomizing 3,186 borrowers with equal probability across the three arms — lender's standard mod, payment reduction, and debt reduction. Our payment reduction treatment targets a 20% lower monthly payment relative to lender's standard mod by extending maturity, holding amount owed constant. Our debt

[6] Per Ganong and Noel (2023, p.1060): "... by construction, the prior literature does not study borrowers excluded from mortgage modifications —which often have stringent eligibility criteria designed to exclude strategic defaulters — and borrowers who are deeply underwater."

[7] Previous work on credit markets has examined how aggregate credit conditions affect small business creation and growth. Yet, this literature has not directly explored how specific contractual obligations influence entrepreneurs' effort choices.

reduction treatment targets a 20% reduction in the total amount owed relative to lender's standard mod, holding monthly payment constant and shortening maturity accordingly. We stratified on constraints imposed by the lender's financing covenants and accounting rules.[8] The lender communicated the modifications through its standard outreach channels, offering them on an opt-out basis because each represents a free and weakly valuable option to a borrower; e.g., someone getting a maturity extension can choose to pay more than the minimum required installment, without a prepayment penalty. As expected, the opt-out rate was less than 1%.

RCT-engineered variation in contract terms helps us shed light on key predictions from our conceptual framework. By randomizing reductions in either monthly payments or total long-term debt obligations, we isolate the effects of liquidity versus strategic factors in explaining default. Importantly, this setting can be used to test several key predictions of the interaction between liquidity and strategic incentives in shaping borrowers' behavior. If default is driven primarily by liquidity issues, relaxing this constraint is a necessary condition for inducing changes in distressed borrowers' incentives and behavior. Conversely, reducing total debt alone will not change behavior if liquidity constraints remain binding. The mechanism operates through repossession risk: debt forgiveness only benefits the borrower if they can afford to make current payments. A modification that forgives debt while leaving monthly obligations untouched (as in our debt reduction arm) may not meaningfully increase the borrower's likelihood of full repayment. In contrast, the payment reduction arm directly improves the feasibility of meeting monthly obligations, dynamically addressing debt overhang through improved repayment performance. However, for borrowers with relatively low equity at baseline, liquidity relief alone may not suffice, as strategic disincentives can remain too strong to be overcome by better payment terms.

Our results thus far are consistent with this set of predictions. Debt reduction does not improve repayment performance or induce entrepreneurial effort,[9] while payment reduction does, although its estimates of average effects on effort are noisy.[10] This pattern holds despite the fact that the effective debt reduction (i.e., 16.7%) is large in absolute terms, and (at least) comparable in size to similar interventions in the literature (Aydin 2024; Dobbie and Song 2020). The inference that payment reduction works by alleviating short-term liquidity constraints is corroborated with evidence that it reduces use of outside credit lines.[11]

[8] We targeted 20 percent reductions in both treatment arms, but constraints resulted in a mean payment reduction of 8.7 percent (relative to the mean monthly installment at origination of R 16,300 , and a mean of R 16,067 in the control group receiving the standard maturity extension), and a mean reduction of 16.7% in the total amount owed (equivalent to an loan NPV reduction of 11% per a standard debt overhang calculation). As we detail in Section 4.3, these magnitudes are comparable to those studied in prior work on effects of loan modifications.

[9] To be precise, we find that debt reduction is generally associated with economically small effects. For instance, debt reduction leads to a 1.4% standard deviation increase in the repayment index, which is an order of magnitude smaller and statistically different than the corresponding effect from payment reduction (i.e., 12.8% increase). Moreover, the effects from debt reduction are consistently statistically indistinguishable from zero at conventional significance levels.

[10] In consultation with the lender, our main and pre-registered repayment outcomes are based on measures of the loan's repayment status. We also consider amounts repaid. Our main and pre-registered effort outcomes are distance driven, days driven, and time spent on the job. We are currently working to measure risky driving behavior as well.

[11] Another finding is consistent with the model's prediction of a positive feedback loop from alleviating liquidity-constraints to lessening moral hazard: payment reduction borrowers actually pay more than their new required

The average treatment effects of payment reduction on effort are imprecisely estimated but broadly align with the model's predictions. First, repayment performance improves almost immediately, while suggestive evidence of effort increases appears only after several months of liquidity relief. Second, the noisy average effect masks significant heterogeneity driven by borrowers' initial equity positions. To explore this dimension, we pre-registered plans to estimate heterogeneous treatment effects (HTEs) of loan modifications by baseline equity, as is common in the mortgage modification literature. Our results show no evidence of increased effort among borrowers with low baseline equity (i.e., above-median loan-to-value). In contrast, we find that borrowers with high baseline equity experience large increases in effort, beginning around four months after treatment and persisting thereafter.[12] For the payment reduction arm, we also observe that higher-equity borrowers are characterized by better repayment performance and lower outside borrowing than lower equity borrowers. By contrast, debt reduction shows no such patterns. Additional results suggest that equity *per se* plays an important role, although we also want to highlight how equity HTEs are interesting for practical (e.g., targeting) purposes even if they are driven by unobserved correlates of baseline equity positions.

We then further explore how liquidity constraints dampen the standard debt overhang effect by testing its mirror image prediction: borrowers with less binding liquidity constraints *will* respond to debt reduction. To test this, we first identify less-constrained borrowers as those with greater ex-ante likelihood of returning to current-paying status (as predicted using a machine-learning approach to assess treatment heterogeneity), independent of any loan modification.[13] We then interact this predicted value with our treatment assignments, and find that debt reduction does indeed increase both repayment and entrepreneurial effort among less-constrained borrowers.

Altogether, our theoretical and empirical evidence evokes the "double-trigger" framework in household finance (O'Malley 2021; Ganong and Noel 2023), where default arises from the interaction of liquidity constraints and strategic considerations. Alleviating liquidity constraints alone may not induce behavioral change if the borrower is significantly underwater on their productive asset. Conversely, reducing the debt burden is ineffective if the borrower remains liquidity constrained. Our results suggest that collateralized lenders (and policymakers) should account for repossession risk when formulating modification strategy. The presence of material repossession risk tends to generally favor payment reduction over debt reduction, and to specifically favor targeting payment reduction to borrowers with sufficient equity in their in pledged collateral.

In sum, our study is novel in several respects. We consider voluntary debt modification by a lender, not the policy-driven modifications that have been the focus of related literatures thus

amount on average. Consequently, short-term liquidity relief works not only by reducing repossession likelihood, but also by accelerating equity accumulation at a faster rate over time—which dampens strategic default incentives by increasing the value of the collateral that would be lost conditional on repossession.

[12]The increase in monthly entrepreneurial effort for the high-equity borrowers is about 13.7% standard deviations, compared to an estimated 3.9% reduction for the low-equity borrowers.

[13]Another way to test this hypothesis would have been to add another arm to our experiment that combines payment and debt reduction. Aside from the obvious cost in statistical power terms, such modifications are rare in practice and were deemed infeasible by our partner lender.

far. We focus on small businesses, including borrowers with the strongest incentives for strategic default, unlike most papers on mortgage modifications. We have and use rich measures of borrower effort, which is typically observed relatively coarsely if at all, especially in work on SME lending thus far. We have a field experiment on collateralized debt. As such we contribute to several abovementioned literatures that often work in relative isolation from each other, including work on the effects of loan modifications, determinants of default, collateralized debt contracting, debt overhang, input utilization and slack, and entrepreneurial finance.[14]

2 Setting and data overview

This section provides background information about our setting, including the product market (minibus taxi mass transit), our partner lender and the financing market (loans collateralized by the vehicles), and an overview of borrower characteristics (we defer details on our experiment sample until Section 4.2). We then provide an overview of our various key data sources.

2.1 Market overview

As in many developing countries, a private minibus transport market sprung up decades ago to meet excess demand for mass transit and has grown to become the modal mode of mass vehicle transport in South Africa (Statistics South Africa 2020). A typical minibus in this market is a 16-seater manufactured by Toyota (Figure A.1). Approximately forty percent of the nation's population (15 million individuals) reports taking a minibus on a daily basis, with eighty percent riding at least once per year (Kerr 2017). There are an estimated 250,000 minibus taxis spanning all of the populated areas in South Africa (Figure A.2) , generating about R 100 billion in revenue annually in 2021 and thereby accounting for approximately three percent of the annual GDP (Competition Commission of South Africa 2021).[15]

Minibus taxi service is indeed a hybrid between bus and taxi services. Like a bus, it runs along a defined route. Routes are defined as a path between two points in space. The start and end points on the route are either taxi ranks, which is a formal bus station, or a bus stand where traffic density does not allow feasibility of a taxi rank (e.g., Figure A.3 depicts a route running back-and-forth between Wynberg Taxi Rank and Downtown Cape Town in the city of Cape Town). Like a taxi, route service is unscheduled and there are no formal stops: passengers hail a minibus using hand signals, and the driver picks up and drops off passengers anywhere along the route, at his discretion.

[14] Our main caveat is that we only have findings over a 12-month horizon (per our pre-registration). In principle, longer-run results could differ in various ways, depending on whether and how longer-run treatment effects on full-repayment probability and default cost differ from 12-month effects. In practice, our observational data suggests that 12-month outcomes are good proxies for longer-run outcomes (Athey, Chetty, Imbens and Kang 2024). The contracting parties' high discount rates further motivate our focus on 12-month outcomes.

[15] R denotes South African Rand, with 1 US Dollar (USD) worth about 18.7 South African Rand (R) in December 2024, at the end of our experiment.

Services on a given route are controlled in part by one of about 1,200 informal taxi associations. The taxi associations are member-based organizations run by and for the operators. These associations control who operates on a given route, limit drivers to a single route, control competition by regulating issuance of permits to operate, and set pricing for the entire length of the route. Operators nevertheless typically face stiff competition for customers. For example, in the City of Cape Town, one of the most populous metropolitan areas in South Africa with approximately 1,000 minibus routes, 200 routes have a operator financed by our partner lender alone (e.g., Figure 1 shows all official minibus routes (Panel a) and GPS coordinates for minibuses for the official in our experiment operating in the City of Cape Town (Panel b)). Of those, median route has 4 operators with a standard deviation of 8 operators. Taxi operators compensate associations through a fee structure comprised of an upfront joining fees and an recurring membership fees. The one-time upfront joining fee is due at the time of joining the association and starts from R 10,000 for routes with less customer demand or for which the association has less negotiating power over its operators. The fees can reach up to R 200,000 for routes in busiest areas (Competition Commission of South Africa 2020). Recurring membership fees pay for the right to operate the route and support costs that associations incur for operating and maintaining taxi ranks. This fee varies between a daily fee of R 25 and R 2,500 depending on profitability of the route, and is paid either daily or weekly.

The minibus operators resemble the typical small, entrepreneurial businesses found in the literature. First, despite the role of the taxi association, operators do have control over several key aspects of their business: among the other things, the operator decides when and how to drive, select the type of vehicle improvements and maintenance, and determine how how they collect passengers. These discretionary aspects are important from the perspective of a lender concerned with moral hazard in entrepreneurial effort, and we detail how we use GPS data to measure them in Section 2.3. Second, the typical business is largely owner-operated or has one employee when the owner hires a driver as operator.[16] Third, personal loans are the main form of debt outside the collateralized loan used to acquire the vehicle. This feature is consistent with the cross-country evidence about small business lending in Beck, Demirgüç-Kunt and Maksimovic (2008).

The minibuses are the primary assets of these firms, costing about R 500,000 at time of purchase, and are posted as collateral for the debt financing used to purchase them (cash purchases are rare, and our sample is comprised entirely of financed vehicles and their borrowers). They are also the primary source of liabilities for minibus-operating firms; the loan from our lender represents a mean of 82 percent of total loan balance outstanding (measuring the latter using credit bureau data), in October 2023. Financing is widely available for both new and used purchases, with new comprising 67.4 percent of the loans and 68.4 percent of the dollar value originated in our lender's portfolio. The median used minibus financed by our lender is new (with 2.6 years being the standard deviation of the age of vehicle) at time of purchase.

[16]This is similar to the US, where the typical small business is entirely owner operated (https://www.fedsmallbusiness.org/reports/survey/2023/2023-report-on-nonemployer-firms)

Given the organization of minibus-operating firms, loans are made to owners as individuals, as is often the case for SMEs worldwide. Most borrowers are in the bottom 50 percent of the credit score distribution, with mean score of 622 at origination in our lender's portfolio and standard deviation of 25 (credit scores in South Africa ranges from 300 to 850). As in the subprime auto lending market in the U.S., lenders screen and underwrite applications with risk-based pricing models that consider credit history, vehicle condition, driving records, detailed business plans for the use of the taxi, the proposed route, and the affiliated taxi association.[17] Our lender rejects approximately 65% percent of loan applications. Low down-payment, steep depreciation of the minibus and amortization schedule of loans implies that negative equity in the early life of loan common even among borrowers in good standing (Figure 2).

2.2 Our Lender

Our cooperating Lender is one of the five largest minibus financiers in the country, with about 32,000 loans and R 11.6 billion in principal outstanding in its portfolio as of October 2023. The lender has been in operation for over 18 years, is publicly-traded, and has a market share of about 15 percent. Along with providing credit for purchases of new and used minibuses, the lender also provides auxiliary services, including comprehensive coverage insurance, credit life insurance, maintenance, and spare parts. Loan proceeds are disbursed only after verified installation of a global positioning satellite (GPS) telemetric device in the vehicle in the minibus.[18] Thus far, the lender has primarily used GPS to locate vehicles in the event that a repossession vehicle is warranted. We use this data to measure borrower's entrepreneurial effort (as detailed in the next sub-section).

Figure 3 shows the distribution of loan terms in the Lender's portfolio at baseline. Panel (a) shows that most loan amounts fall in the R 350,000 to R 650,000 range, with a median loan size of approximately R 485,000 (average loan size of R 487,000). Panel (b) shows that about two-thirds of loans have a contracted maturity of 72 months, with 60, 66 and 84 months making up most of the remaining sample. There are no prepayment penalties, yet prepayment is uncommon; e.g., only 3.5 percent of about 13,300 loans originated in 2016 and 2017 reaching maturity before our baseline were prepaid in full. Borrowers are typically required to pay five to ten percent of the amount upfront.

Panel (a) of Figure 4 shows the distribution of loan-to-value (LTV) at origination.[19] The debt service on these loans is substantial relative to income, as illustrated in Panel (b) of Figure 4, which shows the distribution of debt-to-income (DTIs), measured per standard practice as the ratio of the required monthly payment (including mandatory insurance, as described below) to monthly

[17] Work on risk-based vehicle finance pricing in the U.S. subprime market has focused on the consumer side; see e.g., Einav, Jenkins and Levin (2012) and Jansen, Pierce, Snyder and Nguyen (2024).

[18] The lender requires a monthly fees (median = R 294, s.d.= R10) that covers the costs of maintaining the GPS device, and adds that to the monthly loan payment.

[19] The high LTV at origination does not imply that borrowers did not make any down-payment on average. Some borrowers rolled over their past outstanding debt with the Lender into the new loan in which case their loan amount exceeded the cost of the new financed vehicle. Furthermore, for many loans the loan value includes an origination fee. The average down-payment on the loan typically ranges between 5 to 10 percent.

income at baseline (median = 0.23 and s.d. of 0.13).[20]

Both interest and default rates are high, as one would expect given the high DTIs and low credit scores documented above, together with the substantial exposure to negative shocks. Panel (c) of Figure 3 shows that the contract interest rate varies between 13 percent and 28.5 percent, with the average rate being 21.6 percent. The share of loans 90+ days delinquent stood at 18 percent at the start of 2021, gradually increasing to about 22 percent by mid-2023.

These default rates are high despite mandatory property and liability insurance on the collateral[21], vigorous collection efforts by the lender, and several incentives to repay for borrowers. The latter include credit reporting (Section 2.3), eligibility for future loans from the lender, avoiding court proceedings and judgements, and avoiding repossession of the minibus. Repossession of the minibus leads to lost of primary income-generating asset for the borrower in an economy with limited outside employment option. Thus, many, perhaps most, borrowers face high default costs.

As a final point, we examine what factors drive the evolution of borrower equity in our sample. Figure 5 shows the distribution of LTV as measured in the baseline month (i.e. Oct 2023) for delinquent borrowers in our experiment. As expected, this group has a higher share of negative-equity borrowers than the full sample at origination. The observed heterogeneity in pre-experiment equity positions likely reflects variation in borrower and loan characteristics, which are important to understand. To quantify this, we apply an R-squared decomposition model (Huettner and Sunder 2012; Biasi and Ma 2022), which leverages the Shapley value framework to estimate how much of the variance in LTV is explained by different groups of covariates. The model includes a broad set of vehicle attributes ((log) price paid by borrower at loan origination and dummies for vehicle's make and model, for the vintage, and for whether the engine used diesel or petrol as the fuel), borrower characteristics (dummies for borrowers' age in years and gender), features of the loan at origination (interest rate, LTV, and dummies for loan maturity in months at origination), and indicator variables for the remaining loan maturity in months as of the month preceding the experiment.

The results from this analysis are reported in Appendix Figure A.4, which shows the share of variance in baseline LTV explained by each characteristic.[22] There are two main takeaways. First, the primary determinant of borrower equity is the remaining maturity of the loan at the time of the experiment. The outstanding loan maturity alone explains roughly half of the variance in baseline LTV — a substantial share in absolute terms, and nearly four times as much as the second

[20] We estimate the monthly income for operators by multiplying our estimate of monthly trips made by the operator by an average income of R 200 per trip. To arrive at the average income of R 200 per trip, we first use the average passenger trip fare of R 30, and multiply it by an average vehicle capacity utilization of 12 (in a 16-seater minibus which fits 14 passengers) which gives us revenue per trip of R 360. From this we subtract the marginal cost of 45% per trip which includes fuel costs, toll costs and other associated costs.

[21] The lender requires that the vehicle be insured for comprehensive coverage with its affiliated insurer, and adds the monthly premium (median = R 2,400, s.d. = R 921) to the required monthly loan installment. The lender also requires that the loan be insured against borrowers' death or permanent disability before the loan is fully paid off. For this, the lender require a credit life insurance and adds a monthly premium (median = R 870, s.d. = R 188) to the required monthly loan installment.

[22] We note how the ten characteristics considered in this analysis altogether explain about 94% of total variance in baseline LTV among our borrowers.

most important variable, the initial cost of the vehicle.[23] Second, loan characteristics at origination explain a relatively small share of the variance. In particular, interest rate, initial maturity and initial LTV together account for only about 18% of the variance in borrowers' baseline LTV, likely reflecting the higher degree of uniformity of borrowers' initial conditions.

2.3 Data overview

This section describes how we measure loan performance, other borrowing behavior, and entrepreneurial effort.

For both the entrepreneurial effort and loan measures, we take similar approaches to summarizing multiple measures and considering various horizons for outcome measurement. For summary purposes, we take the increasingly standard approach of using pre-registered, standardized indices of multiple correlated component measures that provide informative signals about the underlying construct of interest. This approach also reduces the number of statistical hypotheses tested. For horizons, we pre-registered monthly and 12-month versions of each outcome. 12-month versions of stock variables, like loan performance or balances, are defined as the 12th-month snapshot.

Minibus loan performance. The Lender shared loan performance data on its entire portfolio, in monthly snapshots pulled from January 2021. As such we have data for loans originated as far back as January 2016.

In principle, a summary measure of loan performance should capture risk-adjusted profits. In practice, most lenders lack such a summary statistic at the loan level because they do not track all variable costs, or allocate fixed costs, accordingly. As such, after consulting with the Lender, we pre-registered a standardized summary index based on three equally-weighted component measures: (1) a delinquency indicator, defined as having R 100 or more past due after the payment due date; (2) arrears amount; and (3) arrears amount scaled by the required monthly payment. Panel (a) of Appendix Table A.1 describes these variables and the correlations among them.

Credit Bureau Outcomes. We use data from Experian, one of the major credit bureaus in South Africa,[24] to help measure outside borrowing, total leverage, and overall credit access (including updated credit scores) for the estimating various treatment effects of loan modifications and other shocks. For example, Section 5.2 presents estimates of randomized loan modifications on repayment to other lenders. And Section 5.4 presents estimates of heterogeneous treatment effects by borrowers' likelihood of being less liquidity constrained ex-ante. Panel (b) to (d) of Appendix Table A.1 provide details on the measures we construct from credit bureau data.

[23] The vehicle's cost alone explains 13.4% of the variance. As expected, higher vehicle cost is associated with higher LTV.

[24] Given the prominence of owner-driver and single-employee firms, most of which are informal firms not registered with the national or local tax authority, the credit for minibus is lent out as consumer credit. As such the lender reports it to a consumer bureau instead of a business bureau. Consumer credit bureau reporting practices and market structure in South Africa are similar to the U.S.

Measuring entrepreneurial effort. As noted above, the Lender requires that each financed vehicle have an operating GPS device, for the purposes of tracking the location of the collateral. The GPS device captures the vehicle's location every six seconds and uploads the data to a vendor's server, allowing us to extract several signals about driving behavior and the resulting income generation.

We label the measures constructed using GPS information about driving behavior as "entrepreneurial effort." One key advantage of our setting is that the only relevant margin of adjustment for the entrepreneur is the level of asset utilization. Indeed, the only significant capital investment in our setting is the acquisition of the vehicle, which is a necessary condition for all borrowers in our sample. Once they own a vehicle, the strategic decisions of the entrepreneurs all aim to optimize the amount of asset utilization, which can be proxy using driving behavior. This focus on asset utilization as a key business decision is not unique to our context; it is a common pattern, especially in developing countries (Walker, Shah, Miguel, Egger, Soliman and Graff 2024). Figure 6 documents the close relationship between entrepreneurial effort and loan repayment. The figure shows a sharp drop in entrepreneurial effort among delinquent borrowers compared to those who remain current in the same month.[25] This suggests potentially large elasticity of entrepreneurial effort with respect to debt contract incentives. More broadly, this figure provides a validation of our measure of entrepreneurial effort as a good proxy of a key input decision for the business.

In our context, entrepreneurial effort, as captured by driving data, goes beyond the owner's labor allocation. Maintenance and vehicle upgrades also play a crucial role in ensuring the minibus operates at its full potential. One way to validate this claim is to examine the distribution of the proportion of days in which the vehicle operates, as a proxy for how well the vehicle is functioning.

Figure 7 shows the mean and standard deviation of days in operation over the life of vehicles in our lender's portfolio. The percentage of days in operation declines significantly over time, reflecting the role of wear and tear in driving heterogeneity.[26] However, the data also shows a high degree of heterogeneity in days in operation, particularly after the first year of operation. This evidence suggests that minibus owners can exert varying levels of entrepreneurial effort (e.g., investments in maintenance, safe driving, etc.) to minimize the impact of wear and tear, thereby maximizing asset utilization.

Specifically, we construct a standardized summary index of entrepreneurial effort by averaging the following equally-weighted component measures, each aggregated to the monthly level after excluding data points based on pre-registered rules for identifying likely data recording errors and

[25] The figures plots the estimates β^s from following two regressions for the set of account i that have the following status $s = \{1(\text{current}), 1(90+ \text{ days delinquent})\}$ every month from $t_0 = [\text{June 2024}, \text{January 2025}]$: $log(distance)_{i,t} = \alpha_i + \alpha^i_{t_0} + \sum_{k=0}^{-5} \beta^s_k \cdot \mathbf{1}(t = t^i_0 + k) + \epsilon_{it}$. t^i_0 is the month for which the status of the account i is measured. For delinquent account it is the month in which the account become delinquent for the first time. For current account, it is the month for which the account i remain current for the preceding six months. If an account remain current for multiple times between June 2024 to January 2025, we random allocate it to one of the eight months. We exclude accounts that were part of our experimental sample.

[26] The fact that the gap only appears over time suggests that the difference in days in operation does not simply reflect heterogeneity in preference for driving across operators.

non-work trips:[27] (1) distance driven in kms.; (2) number of hours driven; (3) number of days worked in the month (i.e., number of days with non-zero trips were made);[28] and (4) the number of hours spent on the job (the total duration between start of vehicle's first trip and the end of vehicle's last trip during the day). Panel (e) of Appendix Table A.1 describes these variables and the correlations among them.

We are also interested in risky driving, as a potential margin of induced moral hazard and source of negative externalities. We again construct a standardized summary index by averaging the following equally-weighted component measures, each aggregated to the monthly level after excluding data points based on pre-registered rules for identifying likely data recording errors and non-work trips:[29] (1) number of accidents (based on insurance claims filed with the Lender);[30] and (2) number of instances speeding over 120 km per hour.

3 Conceptual Framework

This section outlines a simple framework that guides our experimental design, empirical tests, and interpretation. The goal is to isolate, in the most tractable way, how debt obligations shape repayment incentives and entrepreneurial effort in a setting where a collateralized asset is used to generate value. While highly stylized, the framework captures the core economic forces we aim to test empirically. Appendix B discusses simple extensions that leave the qualitative insights unchanged.

Standard Debt Overhang Framework. To start, we consider a simple two-period setting in which an entrepreneur chooses the level of effort e to exert in running a business. The effort determines first-period profits through a strictly concave production function $f(e)$, with $f' > 0$ and $f'' < 0$. At the end of the second period, the business is sold at a price that depends on the first-period profits: $V(f(e))$, where $V' > 0$ and $V'' \leq 0$.[31] This simple formulation captures a setting in which the entrepreneur's current actions affect both immediate profits and the continuation value of the business. The entrepreneur discounts future payoffs with a factor $\beta < 1$ and faces a linear cost of effort. In this setting, the entrepreneur chooses e to maximize the total discounted value of

[27] The details are provided in the pre-analysis plan available at: https://www.socialscienceregistry.org/trials/13052

[28] We use the detailed GPS data to identify the most frequented taxi ranks for an operator over a one-year period. We consider a travel between the most frequented taxi rank for that operator as a work trip for that operator. Given the routes for the minibuses are pre-allocated, this algorithm allows us to to determine the total number of work trips made by the operator.

[29] We exclude trips which meet either one of these criteria: (i) distance covered is greater than 1000 km.; (ii) duration of the trips is more than eight hours; (iii) implied average speed (distance covered divided by time taken) for the trip was greater than 200 km per hour. We exclude these trips as these as likely due to either a GPS device measurement error, or non-work trips (details available in the pre-analysis plan).

[30] As noted above, a loan requirement is that the financed vehicle by insured by the Lender.

[31] This formulation captures the idea that business valuations are often based on recent cash flows or earnings. For instance V could be considered the multiple of recent earnings at which a business can be solved (i.e., V is just a linear function).

current and future returns minus the cost of effort:

$$\max_{e} \quad f(e) + \beta V(f(e)) - e \tag{1}$$

The first-order condition for the optimal effort e^{FB} in this case is:

$$f'(e^{FB})(1 + \beta V'(f(e^{FB}))) = 1 \tag{2}$$

This condition highlights that effort is chosen to equate the marginal cost to the marginal benefit, which includes both immediate profits and the effect on future valuation.

We now introduce a debt obligation $D = D_1 + \beta D_2$, consisting of payments D_1 and D_2 due in periods 1 and 2 respectively.[32] The entrepreneur retains the option to default in either period. For simplicity, we assume that the entrepreneur loses all equity in the business in case of default, but faces no additional penalty. As we discuss in Appendix B, our results do not depend on the presence of any default costs, and hold under more general formulations. In this setting, the entrepreneur endogenously chooses whether to repay and how much effort to exert, trading off the value of repayment against the value of walking away from the debt obligation.

This simple framework delivers the classical debt overhang effect, as in Myers (1977): a high debt burden leads to under-provision of effort. Under these assumptions, repayment occurs only if the expected continuation value exceeds the debt burden. In particular, the entrepreneur will choose to repay in full and exert first-best effort if the following condition holds:

$$\beta V(f(e^{FB}) - D \geq 0 \tag{3}$$

When this condition fails, effort will fall below the first-best level to e^{SB}, since the entrepreneur no longer fully internalizes the continuation value.[33]

This simple setup is motivated by the concern that debt overhang may significantly reduce minibus operators' incentives to exert effort in their business. Several stylized facts from our lender's data are consistent with this hypothesis. Across the lender's full portfolio in October 2023, we find that borrower equity—proxied by the loan-to-value ratio on the vehicle loan—is positively associated with the effort exerted by the entrepreneur during the same period, as measured using GPS data (Figure 8). While purely correlational, this evidence aligns with the core prediction of the debt overhang model: high debt obligations lead to lower effort.

A second aspect of our setting further amplifies these concerns. Our experiment focuses on borrowers who were already in financial distress before the intervention. For these borrowers, strategic incentives become especially relevant due to the collateralized nature of their debt. Once

[32] To be clear, this is not a model of optimal lending, and we place no structural restrictions on D_1 and D_2. One interpretation is that the loan was originated under different conditions (e.g., different expectations about future cash flows) which no longer hold due to subsequent shocks. These could include changes to the borrower's income-generating capacity, vehicle quality, or route-level traffic. As a result, the original repayment schedule may be suboptimal from both the borrower's and the lender's perspective.

[33] In our simple framework, second best effort is implicitly defined by $f'(e^{SB}) = 1$

delinquency persists, the lender initiates repossession proceedings and imposes additional legal fees, further increasing the borrower's financial burden. Since repossession results in loss of access to the income-generating asset, the borrower's incentives to invest effort in the business decline even further. Figure 6 illustrates this dynamic, showing a sharp drop in entrepreneurial effort among delinquent borrowers compared to those who remain current while operating under similar conditions. Although this evidence is correlational, it highlights why our lender may be particularly concerned about the reinforcing cycle between financial and economic distress in this setting.[34]

In the standard debt overhang framework, a reduction in debt obligations D can improve both repayment and effort. Importantly, what matters is the overall size of the reduction, not how it is distributed between short- and long-term obligations. For instance, a lender could modify the loan by reducing the long-term obligations (i.e., D_2) while keeping the short-run payment unchanged (i.e., D_1), and this could still relax the debt overhang constraint.

Combining liquidity constraints and strategic incentives. A potential limitation of the baseline framework is its assumption that entrepreneurs do not face financial constraints. While this assumption is standard in the traditional debt overhang literature, it is unlikely to hold in our setting. To assess its implications, we extend the previous model to incorporate liquidity constraints. Specifically, we assume that the entrepreneur must cover operating costs C before making any repayment in the first period, and that outside financing is unavailable.[35] This liquidity constraint introduces an additional reason for default, and effort decisions are shaped by the combined effects of strategic concerns and short-term cash flow limitations.

In this setting, the entrepreneur will exert low effort e^{SB} if *either* the overall debt burden is too large or the liquidity constraint is binding:

$$\beta V(f(e^{FB})) - D < 0 \quad \vee \quad f(e^{FB}) - C - D_1 < 0 \tag{4}$$

The intuition is that liquidity constraints effectively reduce the returns to investment, as they can lead to inefficient liquidation of the business. In this model, the incentive problem associated with debt overhang is jointly determined by liquidity issues and strategic considerations.[36]

In this context, the policy implications discussed above may no longer hold. Before we argued that, if the only constraint is high debt, reducing D_2 may be sufficient to restore incentives. However, if entrepreneurs are also liquidity constrained, reducing D_2 alone will not suffice. In such

[34] Policymakers may also share the same concern, motivated by extensive research that has shown that debt overhang in the private sector can significantly constrain business investment (Kalemli-Özcan, Laeven and Moreno 2022; Jordà, Kornejew, Schularick and Taylor 2022).

[35] In other words, our framework assumes that entrepreneurs do not have access to external financing and are therefore constrained to use only the cash generated by their business (net of C). While this assumption may be overly restrictive in general, borrowers in our data—especially after becoming delinquent—are likely to have limited access to funding. Moreover, our qualitative argument should hold even if some financing is available, as long as it is sufficiently expensive.

[36] This idea is similar to He and Xiong (2012), which studies the debt market for large corporations. As in our model, He and Xiong (2012) highlights how liquidity risk can generate credit risk and exacerbate strategic incentives in a classical debt overhang setting.

cases, policies that alleviate short-term cash flow pressures—such as reducing D_1—may be necessary to restore effort. We note that a reduction in D_1 can help a liquidity constrained borrower even if D remains unchanged.

Discussion. This framework guides our research design and empirical tests. In a setting where borrowers are likely to face both liquidity constraints and strategic incentives, it is unclear which type of loan modification is most effective in inducing repayment and mitigating the adverse effects of debt overhang on effort. This observation motivates our RCT design that compares the impact of reducing short-term payments while holding the overall debt obligation constant to the impact of reducing long-term obligations while keeping the short-term payment fixed. Studying the direct effects of these loan modifications on entrepreneurs' behavior allows us to assess which factor—liquidity or strategic behavior—is the primary driver of delinquency in our market.

In terms of analyses, this conceptual framework also highlights the importance of accounting for how liquidity and strategic incentives interact in shaping effort. For example, consider a borrower with a high debt burden who is also liquidity constrained. If the loan is modified without addressing the liquidity constraint, the borrower will remain unable to meet her obligations and is thus expected to default and face repossession. In this case, even a generous reduction in the overall debt burden D will not improve incentives to exert effort. Importantly, the opposite also holds: relaxing the liquidity constraint of a delinquent borrower may still be insufficient to induce higher effort if the debt burden remains binding (i.e., $\beta V(f(e^{FB})) - D < 0$). This interaction parallels the "double-trigger" concept in household finance (Ganong and Noel 2023), where default arises from a combination of liquidity concerns and negative equity. In our framework as well, meaningful increases in borrower effort may require addressing both constraints simultaneously. This observation motivates our pre-registered HTE analysis by baseline equity.

Before concluding, it is important to clarify why directly observing entrepreneurial effort is essential, rather than inferring behavior solely from repayment outcomes. Improved repayment does not necessarily indicate that debt overhang is no longer a binding constraint. In some cases, resolving a liquidity constraint may lead to improved repayment, but without any corresponding change in effort. For example, a borrower may find it optimal to remain current on payments in the short run—even if the overall debt burden remains too high in the long run—because timely repayment delays costly default. While this dynamic is not captured in the two-period model discussed above, it arises naturally in a slightly more general version of the framework, as we describe in Appendix B.

Overall, the framework underscores that strategic incentives and liquidity constraints cannot be considered in isolation. Appendix B discusses the simple model more extensively.

4 Experimental design and implementation

4.1 Experimental Design

We worked with our partner lender to design an experiment that helps identify the importance of borrower liquidity constraints and moral hazard for debt modification contracting, subject to the lender's operational constraints and its priors about what was worth testing. To help identify the importance of liquidity constraints, we engineer relatively generous reductions in the required monthly installment payment, leaving debt burden and other terms unchanged from baseline except for lengthening maturity accordingly.[37] To help identify the importance of moral hazard, we engineer relatively generous reductions in debt burden, leaving monthly payment and other terms unchanged except for shortening maturity accordingly.

We test our treatments relative to the lender's standard practice for modifying poorly performing loans. This "baseline modification" takes a loan that is defined as loan that had accumulated arrears of at least 1x and at most 9x of its contracted monthly payment, capitalizes its arrears into principal, and extends the maturity to keep the monthly payment and other contract terms unchanged.[38] Table 1 illustrates the mechanics. As we detail below, the resulting maturity extension is about 12 months at the median (s.d. = 8.5 months), on a baseline median of 49 remaining months. Between September 2021 and our baseline, the lender did offer baseline modification to a subsample of borrowers who were behind on their monthly payments. This modification was done in batches and our experiment sample excluded any borrowers who had received baseline modification.[39] Anecdotally, other minibus taxi lenders typically take a similar approach to modifications and other forms of debt restructuring were less common.

Despite occasional use of this approach to loan modification at baseline, it does not seem particularly attractive from either a theoretical or empirical perspective. Theoretically, it neither alleviates liquidity constraints nor reduces debt burden.[40] Empirically, the lender was motivated to experiment by prior observational data showing that repayment performance tends to improve only modestly following a baseline modification.

We sought to engineer loan-level treatments that would reduce either the total debt burden or the monthly payment by 20% relative to control loans getting the baseline modification, subject to two constraints arising from the lender's external funding covenants and the cost of capital. First, the maturity of any loan on the lender's book could not exceed 10 years. Second, the interest rate on

[37] We define debt burden as the sum of outstanding loan principal, any accumulated arrears, and total interest owed over the remaining loan maturity assuming the loan is not prepaid before the contract maturity.

[38] As with loans in good repayment status, there is no penalty for prepaying a modified loan.

[39] The affected borrowers from these programs were quite limited as the lender only targeted borrowers who were between 30 and 90 days delinquent at the time of the offer rollout.

[40] Modifications do potentially change repayment incentives through reporting to credit bureaus, although any effect is likely modest for most borrowers. The modification itself, reported as such as the lender does, has an ambiguous direct effect on a credit score. But it does reset arrears to zero, giving the borrower a fresh opportunity to improve their score by making timely repayments without first needing to pay back its arrears and delaying repossession at least in the short-run. This potentially improves repayment incentives by reducing the marginal cost of making timely repayments.

the new loan that resulted from any desired debt reduction on any loan contract had to be at least 14%.[41] The mechanics are as follows: In November 2023, we worked with the lender to first to create an experimental sample that would include nearly all of its poorly performing loans , as detailed in Section 4.2. We next performed the baseline modification on each loan in the sample before randomly assigning each loan, with equal probability, to one of the three arms: baseline modification only (control group); baseline modification + interest-write down (debt burden reduction); baseline modification + maturity extension (monthly payment reduction).[42] The randomization conditions on eight strata pertinent for the constrained randomization and heterogeneous treatment effect estimation.[43]

The constrained randomization produced an actual treatment reduction lower than the intended one of 20% in 93 percent of cases in the debt reduction arm and 72 percent cases in the payment reduction arm. Table 2 illustrates how loan characteristics change across various arms of the experiment. The first row corresponds to the baseline modification arm, which is the same as the last row of Table 1. The second row corresponds to the interest write-down modification arm. The last row corresponds to the payment reduction modification arm. Figure 9 shows the distribution of actual reductions in each treatment arm at the time of random assignment. Our primary treatment effect estimates are intent-to-treat and condition on the strata capturing this endogenous variation in treatment intensity, as we detail in Section 4.3.

After modifying the contract, the lender contacted each borrower in our experiment sample through SMS and phone calls, per its standard practices. Each message linked to borrower-specific information on the modified terms. Appendix Figure A.5 shows a letter received by a borrower in the payment reduction treatment. Borrowers had five business days to opt-out of the modification by repaying their outstanding arrears with the lender, and did so at a rate of 0.9 percent in the control arm, 1.3 percent in the payment reduction arm, and 1.2 percent in the debt burden reduction arm. The lender subsequently called each borrower in the sample who did not opt-out to further highlight the modified contract terms.

4.2 Experimental Sample Characteristics and Balance Tests

We worked with the lender to create an experiment sample frame of all 3,848 borrowers eligible for baseline loan modification by virtue of being at 30 to 270 days delinquent (defined in our setting as borrowers that accumulated arrears amounting with 1x to 9x of their monthly payment) and meeting several other criteria.[44] For each of these loans we then estimated the what the actual modification

[41] The floor on the interest rate was imposed attributing to the lender's the cost of capital that stood around 13%.

[42] Performing the baseline modification first, on all loans in the experiment sample, creates a control group that is identical to the treatment group in all respect except for the contract variation of interest.

[43] Specifically, we stratify on all combinations of indicators for: whether the loan would receive an above-median interest write-down amount if assigned to that arm x whether the loan would receive an above-median reduction in monthly payment if assigned to that arm x above-median baseline debt-to-income ratio.

[44] Standard eligibility requirements excluded borrowers that (i) had arrears amounting exceeding 9x the required monthly payment; (ii) had received an maturity extension offer in the past; (iii) had outstanding maturity of 118 months or more; (iv) were currently undergoing repossession proceedings; (v) were severely delinquent; or (vi) had a vehicle with GPS device that stopped reporting telematics data.

would be under each arm, per the constrained randomization, and limited the experiment sample to the 3,186 loans that would be eligible to receive all three modification regardless of their random assignment.

Table 3 presents summary statistics and balance tests for our key variables at baseline. Column 1 reports the means in the baseline group. The average borrower in the group has a baseline credit score of 592. 76 percent of borrowers in the baseline group are men, are 51 years old and have about 1.48 loans with the lender. 69 percent of the borrowers took out loan with the lender to finance a vehicle. The average vehicle is 3.4 years old. The average loan principal amount outstanding at baseline for this group is R 388,570 and the average arrears at baseline is R 54,020. The maturity of loan at origination for the baseline group is 73.9 months, the loan to value at origination (LTV) is 99%, and the LTV at experiment baseline is 88%. The average interest rate for the baseline group is 24 percent, the annual monthly payment is R 16,248 and average remaining maturity on the loan is 47.5 months.

Columns 2 and 3 of the table report the results from an OLS regression of assignment to interest write-down and payment reduction treatments, respectively, on the baseline characteristics, conditional on randomization strata fixed effects. The prevalence of significant correlation between whether the borrowed vehicle was new and assignment to the interest write-down (1 out of 54 cases) is what one would expect to occur by chance. The means of all of the baseline variables are similar across the baseline and the two treatment groups: the p-value from an F-test of the joint significance of all of the variables listed in Panels A-C is 0.691 for the interest write-downs (column 2) and 0.749 for the payment reductions (column 3), suggesting that the randomization was successful.

4.3 Empirical strategy and first-stage

Our main treatment effect estimation specification estimates intent-to-treat (ITT) effects of interest write-downs and monthly payment reductions as follows:

$$y_{it} = \alpha + \beta^{IW}\ 1(\text{Interest write-down})_i + \beta^{PR}\ 1(\text{Payment Reduction})_i + \Gamma_t'\ \alpha_{s(i)} + \epsilon_{it} \qquad (5)$$

where y_{it} is the outcome or first-stage measure of interest for borrower i in time t, ϵ_{it} is the error term, and $\alpha_{s(i)}$ represents the fixed effects for eight randomized strata. The omitted category is control group, which is assigned to get the baseline modification only. We cluster standard errors at the borrower level when using multiple observations per borrower.

We begin our estimation by quantifying the first-stage effects on contract terms suggested by Figure 9. Table 4 does this by estimating equation 5 at baseline i.e. at randomization time. These estimates capture the net effects of the randomization constraints (described in Section 4.1), the few opt-outs (less than 1%) on the initial loan modification terms, and any initial non-compliance by the lender (we have not detected any). Column 1 shows that the interest rate is 6.6 percent point lower in the interest write-down group compared to the baseline modification control group.

It is unchanged in the payment reduction group, as intended. Column 2 shows that the monthly installment is lower by R 1,416 in the payment reduction group. It is unchanged in the interest write-down group, as intended. Column 3 shows how maturity adjusts to engineer the results in the previous columns– specifically, the debt burden reduction holding monthly payment constant in row 1, and the monthly repayment reduction holding debt burden constant in row 2. Maturity decreases by 11.21 months in the debt burden reduction arm (row 1), and increases by 19.25 in the payment reduction group (row 2).

The lender committed to leave the randomly assigned modifications in place for at least 12 months, and month-by-month first-stage estimates thus far confirm that effects on the key contract terms are largely unchanged since the initial random assignment (Figure 10, and n.b. the Table 4 estimates are presented here at time zero).

Before concluding, it is important to highlight that our loan modifications are economically significant (Figure 10). On average, borrowers receiving a payment reduction see their monthly payments shrink by about 8.7%. Over a year, this corresponds to almost R20,000 in lower payments, equivalent to 6% of the average annual salary in the country in 2022.[45] By construction, this intervention is NPV-neutral for the borrower, which is assumed to have a cost of capital of 23.9%.

The interest rate reduction is instead designed to keep the immediate payment constant, but reduce the NPV of the debt. From the firm's perspective, we estimate that the intervention reduces the NPV of the loan by around R50 thousand, which corresponds to an 11% reduction relative to the pre-existing amount of principal outstanding plus arrears. This reduction is large in absolute terms, but also sizable compared to the literature. For instance, Dobbie and Song (2020) studies a similar reduction in interest for card borrowers, finding strong evidence of strategic response. In this case, the authors report that the maximum cost for the lender in NPV was around 11.8% of the initial loan size. Similarly, Ganong and Noel (2020) similarly studies an intervention that generates a reduction in loan balances (without any present value adjustment) of about 20%.[46]

5 Results

In this section, we examine the effects of debt restructuring using the intent-to-treat design described above.

5.1 Minibus Loan Performance

We begin by analyzing the effects of debt restructuring on minibus loan repayment. Table 5 presents the estimates of receiving an interest write-down and payment reduction on measures of repayment for the minibus loans at the end of twelve months after the experiment. Following the pre-analysis

[45] https://www.wearedevelopers.com/en/magazine/311/south-africa-average-salary

[46] Another example is Aydin (2024): in this paper, the author studies an interest rate reduction, where the interest goes down by about 29% relative to the ex-ante APR. In our case, the interest charge declines on average by 28.7% relative to the control group interest rate. As we discussed earlier, a key difference in these studies is that they focus on household borrowing, rather than small businesses.

plan, we first normalize all three outcomes of loan performance — whether the borrower was current on their loan, the outstanding amount in arrears, and scaled arrears — by subtracting the average and dividing by the standard deviation of that variable for each month. For each month, we then create a repayment index, which is an equally weighted average of the three normalized measures. The final outcomes of interest in Table 5 are measured as the 12th-month snapshot.

These estimates show that receiving an interest write-down offer has no effect on debt repayment. In fact, the results reported in column 1 highlight that the impact of an interest reduction is very small in magnitude, and this effect is statistically indistinguishable from the behavior of the control group. In columns 2, 3, and 4, we report the results for all the sub-components of the index, confirming the lack of response. Specifically, we detect no significant effects on the average probability of being current, the amount of payments in arrears, or the amount of arrears scaled.

In contrast with this finding, the payment reduction leads to an improvement in the repayment index. On average, borrowers receiving a reduction in the monthly payment are characterized by a 12.8% standard deviation increase in repayment index, which is significantly different from the control group (column 1, Table 5). The same effect is documented in all three components of our index: entrepreneurs in this condition are more likely to be current and accumulate significantly less arrears.

Figure 11 plots the month-by-month estimates of the two conditions relative to the control group. Consistent with the null effect discussed above, we find that the interest write-down is never tied to an increase in repayment. Instead, the positive impact of the payment reduction can be detected in every month, although this effect is not statistically significant during the first month of the intervention (i.e., December 2023). Altogether, this evidence confirms that relaxing the monthly payment is successful in inducing improvements in repayment behavior, but lowering the size of the debt burden is not.

Before discussing the interpretation of these findings, we provide a few additional tests to better characterize our results.[47] In column (1) of Appendix Table A.2, we estimate the impact of our loan modifications on the absolute level of payments made by borrowers, measured by the rolling total payments made by the borrower. This outcome is particularly interesting because borrowers in the payment reduction arm are more likely to be in good standing, but are also required to make smaller payments. Consistent with previous findings, the interest write-down does not affect this outcome in a statistically significant way. However, borrowers receiving a reduction in the monthly installment end up paying less overall. Combining this result with our evidence on the repayment index suggests that the payment reduction allows borrowers to remain in good standing while paying less.

We further examine this issue in the following three columns of Appendix Table A.2. In these analyses, we estimate the impact of our loan modifications on the probability that the borrower has systematically underpaid, overpaid, or paid exactly the amount due.[48] As expected, borrowers in

[47] We consider the results in Appendix Table A.2 — which has not part of our pre-analysis plan — as a way to better characterize our main result on the repayment index.

[48] We define a borrower to have systematically paid the "exact" amount if its total payments made up to a month

the payment reduction condition are less likely to underpay their loan and more likely to overpay relative to the due installment. The probability of making the exact payment remains unchanged. Consistent with earlier findings, the interest write-down does not have any effect. Thus, despite the reduction in absolute payment, the payment reduction enables borrowers to prepay part of the loan.

The differential impact between the interest write-down and payment reduction supports the notion that defaults in this market were largely driven by liquidity issues rather than strategic incentives. Specifically, we find that reducing the size of the monthly payment has a large positive effect on repayment, while a significant reduction in debt balance does not appear to change repayment relative to the control group. More broadly, this underscores the critical role of liquidity for the business owners in our sample.

5.2 Loan Performance and the Financial Conditions

Before examining the impact of our intervention on entrepreneurial effort, we consider how the payment response benefits borrowers and influences their overall financial condition. Entrepreneurs in the payment reduction arm benefited from the intervention in several ways. First, borrowers in this group were more likely to remain current on their debt obligations, facing a significantly lower probability of default compared to the other two groups. Given that the cost of default is likely substantial in this setting (Section 2), this outcome should be highly beneficial for borrowers, effectively reducing the present value of their debt burden. In contrast, borrowers in the interest reduction group did not experience similar benefits; their likelihood of remaining current and the amount of arrears accumulated were not significantly different from those in the control group.

Second, once current, borrowers in the payment reduction group benefit from loan amortization and gradually increase their equity over time. Notably, borrowers in this group do not merely make the minimum payments; on average, they tend to overpay by some margin, implying that they build equity at a faster rate than the standard repayment schedule. This factor underscores the importance of considering the dynamic effects of our modification, as our intervention will affect both the initial level of equity and its growth.

A last benefit of the payment reduction is that it allows borrowers to free up liquidity that can be used for other business purposes (e.g., maintenance). As discussed above, borrowers in the payment reduction arm improve their repayment condition but—given the substantial reduction in installment—they achieve this despite paying less. This implies that these businesses now face a lower demand for cash and, more broadly, an improved financial position.

To further explore this idea, Table 6 explores the impact of our interventions on other borrowing activity by the entrepreneur using the data from Credit Bureau discussed earlier. As specified in the pre-analysis plan, this analysis examines the impact on indexes that capture the level of credit market access, the level of borrowing of the entrepreneur outside our Lender, and the entrepreneur's

are within a 1% bandwidth around the aggregate payment due up to that point. Naturally, overpayments and underpayments are defined relative to this benchmark.

overall debt repayment on liabilities outside our Lender.

We find that neither interest write-down or payment reduction affect the level of credit access: both estimates are small and not statistically different from zero (column 1). This evidence suggests that the intervention did not improve credit market access for the businesses in our sample. However, we find that the payment reduction lowers the borrowing index, while the interest write-down has no impact (columns 2 and 3). The combined evidence in terms of lack of change in credit access but a decline in borrowing is consistent with the presence of a decline in credit demand from borrowers in the payment reduction arm. This also aligns well with our previous hypothesis that the payment reduction is relaxing some of the financing issues of the business owner.[49] Figure 12 plots the month-by-month estimates of the two conditions relative to the control group.

This discussion highlights the financial impact of the loan modification program. The payment reduction benefits borrowers by lowering their debt burden and immediately easing their overall financing needs. In contrast, the interest write-down has no significant effect on the entrepreneur's financial condition. As discussed in Section 3, the lack of response in terms of payments suggests that—despite directly reducing total debt—this intervention provides little relief.

5.3 The Impact on Entrepreneurial Effort

We now examine the impact of our interventions on entrepreneurial effort. The previous results suggest that payment reduction is more likely to influence effort by alleviating debt overhang distortions. However, as discussed in Section 3, the debt reduction achieved through payment reduction may not be sufficient to elicit a meaningful response.

Using the empirical approach outlined in Section 4.3, we examine the direct impact of loan modification in Table 7. We construct an index capturing entrepreneurial effort using GPS data, following the pre-analysis plan. Specifically, we normalize three measures of effort—distance driven, time spent on the job, and the number of operational days—by subtracting their mean and dividing by the standard deviation for each month. For each month, the index is then computed as an equally weighted average of these normalized measures. To start, we estimate the impact on the sum of the index over the year following the loan modification.

Examining the interest write-down, we find no effect on the overall entrepreneurial effort index (column 1). The estimated impact is negative but small, with the treatment linked to an average monthly decrease of 0.25% (=0.03/12) of the standard deviation of the index. More importantly, the effect is statistically insignificant. A similar pattern emerges for the sub-components of the index (columns 2, 3, and 4), with the only partial exception being total days driven; this estimate, while larger in magnitude, remains statistically insignificant. Panel (a) of Figure 13 presents the month-by-month estimates, consistently showing small, stable, and statistically non-significant effects.

This evidence suggests that the interest write-down has no impact on entrepreneurial effort no average, a result that aligns with our earlier discussion: since this intervention does not increase the

[49] Lastly, we also find no evidence that the interventions had an impact on repayments of other debts (column 4 and 5).

likelihood of borrowers staying current on their loans, it is unlikely to alter the incentives related to repossession risk.

The same table reports the effect of the payment reduction, showing consistently positive but statistically insignificant effects on effort. However, unlike the interest write-down, the estimated effects are large in magnitude. For instance, the payment reduction increases the monthly entrepreneurial effort by 5.2% (i.e., 0.624/12) of the standard deviation of the index. While we cannot reject the null, these estimates challenge the view that the policy was entirely ineffective. Consistently, Panel (b) of Figure 13 shows that, apart from the first three months, the estimated effects are generally large, with some months significantly different from zero.

In principle, the null effect of the payment reduction is not surprising relative the previous discussion. This intervention increased borrower payments, thereby reducing the risk of repossession. Additionally, entrepreneurs receiving a payment reduction were able to gradually pay down their loans, lowering their overall leverage relative to the control group. Within this framework, this reduction in leverage may not be sufficient for these borrowers, as a large share of them were already highly leveraged before the experiment began. This could explain the null effects on average, despite the relatively large estimates.

We test this hypothesis in Table 8, where we estimate the heterogeneous impact of debt restructuring across borrowers with different levels of baseline equity at the start of the experiment, measured using the loan-to-value (LTV) ratio for minibus loans, as described in Section 2. This analysis was outlined in our original pre-analysis plan. Figure 5 shows the distribution of baseline LTV for the borrowers in the experiment sample. The median LTV for the borrowers in our sample is 0.95 (s.d. = 0.22), which is similar to the median LTV of 1.02 (s.d. = 0.55) for all the borrowers with the lender at baseline. Consistent with our intuition, we find that borrowers with lower baseline LTV (i.e, higher baseline equity) significantly increased their entrepreneurial effort after the experiment (column 1). This positive effect is observed across all sub-components (columns 2, 3, and 4), with particularly strong effects on time spent on the job and total days driven.[50] Instead, borrowers with higher baseline LTV (i.e, lower baseline equity) do not significantly change their effort after the restructuring.

A potential concern with this test is that differences in equity across individual borrowers may reflect variation in other operator characteristics that could explain our findings through channels unrelated to our proposed mechanism. Our main concern centers on remaining maturity: as shown in Section 2.2, roughly half of the variation in equity is explained by differences in this variable. Borrowers with shorter remaining maturity are those who defaulted later in the life of the loan, and it is plausible that they differ systematically from borrowers who defaulted earlier. For instance, a shorter remaining maturity might proxy for better entrepreneurial quality (e.g., through higher work experience by being on the job for a longer time). These differences may confound our interpretation of the heterogeneous treatment effects.

Before presenting a few tests that directly address this concern, we want to emphasize that

[50] We also note that we find no heterogeneous effects for interest write-down.

its importance depends heavily on the objective of the analysis. The fact that shorter remaining maturity is associated with higher equity is not unique to our setting, but it is a mechanical feature of amortized loan products. Consequently, the type of selection we may worry about in our experiment is likely present in most relevant real-world contexts. Given the ubiquity of this pattern, it is not clear that this concern is particularly salient for a policymaker designing a loan modification program. In that context, identifying the mechanism behind borrower behavior may be less important than determining which borrowers are most responsive to the policy. In other words, what matters is the ability to target borrowers (such as those with higher equity) who are more likely to benefit from intervention. The precise reason why these borrowers respond more effectively is likely to be second-order from a policy perspective.

With this note in mind, we nevertheless show that the differences in effects of payment reduction between high- and low-equity borrowers remain statistically significant even when we explicitly account for differences in remaining maturity across borrowers. We present three tests. First, we replicate our main heterogeneity table while controlling for remaining maturity (normalized to have mean 0 and standard deviation 1), both directly and interacted with the payment reduction and debt reduction treatment group dummies (Table A.3, Panel A). Second, we relax the linearity assumption in the previous test by incorporating remaining maturity as a categorical variable, dividing it into quartiles (Table A.3, Panel B).[51] Third, we re-estimate our baseline model after excluding borrowers at the extremes of the remaining maturity distribution (Table A.4). This test builds on the idea that the concern discussed above is particularly salient when equity differences reflect borrowers at the tails—those close to repaying the loan in full, or those who defaulted very early. In this specification, we exclude both the top and bottom deciles of the remaining maturity distribution (Column (1)), or alternatively restrict the sample to borrowers with three to six years of remaining maturity (Column (2)).

Across all the results discussed above, we find that borrowers with high equity exhibit a relatively larger increase in entrepreneurial effort in response to a payment reduction. In fact, the estimates are generally slightly larger and more precisely estimated than in our baseline, suggesting that adjusting for remaining maturity may reduce measurement error. While these results help alleviate the concern discussed above, we view them as less informative than the baseline. Removing variation in remaining maturity also strips away conceptually meaningful variation in equity, some of which may be relevant from a policy perspective. We return to this point in the next subsection, where we present a different test that more directly speaks to the underlying mechanism.

Before concluding, we highlight two ancillary results. First, Figure 14 presents the intent-to-treat estimate of entrepreneurial effort, estimated separately for borrowers with high and low equity at baseline. Borrowers with above median equity at baseline are classified as high equity, and low

[51] As before, the quartiles are included both directly and interacted with the two treatment conditions. We note that including quartile dummies for remaining maturity interacted with the treatments requires a modification to our estimating model. In a fully saturated specification, we cannot separately identify the effects for high- and low-equity borrowers, but only their difference. Therefore, for this test, we estimate a model that includes the two treatment variables and their interactions with the high-equity dummy, and our main focus is on this interaction. To ensure comparability, Column (1) of Panel B in Table A.3 reports our baseline estimates using this same specification.

otherwise. Consistent with the evidence in Table 8, we find that the payment reduction significantly increases entrepreneurial effort among borrowers with higher ex-ante equity. Moreover, the month-by-month estimates grow larger over time, aligning with the dynamic impact of our modification on equity accumulation.

Second, Table 9 examines the same heterogeneity tests based on LTV but focuses on loan repayment. Figure 15 presents the intent-to-treat estimate of loan repayment to the lender. Here, we find little evidence that high-equity borrowers reacted more aggressively to the modifications. This null result supports our hypothesis that liquidity constraints, rather than strategic considerations, are the primary driver of default. In other words, while borrowers may respond to incentives, their underpayment behavior was largely dictated by financial constraints. Moreover, this finding suggests that the increase in entrepreneurial effort observed among high-equity borrowers does not simply reflect ex-post differences in repayment behavior.[52]

5.4 Incorporating non-experimental variation in repayments

Our results show that debt reduction is generally ineffective at increasing repayments and entrepreneurial effort. This evidence is consistent with our conceptual framework presented in Section 3 which incorporates liquidity constraints for the entrepreneur in an otherwise standard debt overhang framework. In that setting, if default is caused by liquidity, reducing the principal does not improve the borrower's ability to repay, and therefore does not significantly strengthen incentives. The flip side of our model is that we should expect a reduction in debt burden to be effective when borrowers who are not liquidity constrained.

The ideal way to test this hypothesis would have been to incorporate an additional arm in our experiment, in which borrowers received both a payment reduction and a lower debt burden. Unfortunately, this option was not feasible in our context. As an alternative, we implement a heterogeneity test that combines the randomized treatments with plausibly exogenous variation in borrowers' probability of repayment.[53]

Conceptually, the idea behind this test is as follows. The evidence about repayment presented above suggests that liquidity issues were the primary driver of default in our setting. Now assume we can measure, for each borrower i, a parameter $\mathcal{L}_i$ that captures the probability that the liquidity shock leading to default is short-lived. Borrowers with high $\mathcal{L}_i$ are those that are likely to resume full payments during the experimental period, even without a loan modification. In the language of our model, these are borrowers who may have been liquidity constrained in the recent past but are likely to become unconstrained in the near future. In our framework, we should expect that borrowers with higher $\mathcal{L}$ should be potentially responsive to a reduction in loan balance. At least

[52] In Appendix Figure A.6, we also examine whether the loan modifications had any direct effect on risk-taking behavior. We proxy for this by measuring the (normalized) number of speeding alerts received by an operator at the monthly level. While there is some month-to-month noise, we do not identify any consistent pattern in speeding alerts across either treatment group, suggesting that the modifications did not significantly alter risk-taking behavior.

[53] Because the importance of this test was not apparent at the time of the experimental design, it was not included in the pre-analysis plan.

in relative terms, borrowers with higher $\mathcal{L}$ are closer to the standard debt overhang model than borrowers with lower $\mathcal{L}$, and therefore should be sensitive to changes to the debt burden. However, we also note that the interaction between $\mathcal{L}$ and a payment reduction is less clear ex-ante.[54]

To implement this test, we developed a simple machine learning (ML) algorithm that estimates a proxy for $\mathcal{L}_i$ that is orthogonal to ex-post driving, repayment decisions, and treatment assignment. In particular, we focus on a measure $\mathcal{L}_i$ that captures the likelihood that a borrower is still current on their loan after six months following enrollment into the experiment.[55] To start, we consider a set of baseline borrower characteristic Z_i — which are pre-determined to the experiment — to train a ML method using the data from the control group and generate a predictive function $\hat{\mathcal{L}}_i \equiv \hat{\mathcal{L}}(Z_i)$.[56] Intuitively, we aim to identify borrower characteristics that predict whether they will stay current in the near future without any loan modification. This approach follows recent work on predictive approaches to assess treatment heterogeneity (PATH), which advocates using the control group to model counterfactual outcomes for treated units (Kent et al. 2020; Chernozhukov, Demirer, Duflo and Fernández-Val 2023).

To implement this approach, we first randomly distribute borrowers across treatment (payment and debt reduction combined) and control groups separately into five sub-groups.[57] We then combine each separate treatment and control sub-groups to create five "folds" from the data. This "balanced-fold" creation algorithm ensures that ratio of treatment to control observations are maintained across the five folds (Wager and Athey 2018). We iterate over each fold, using the focal fold as a test set and the remaining folds as training sets. Using *only control observations* from the training sets, we train a machine learning method to generate predictions $\hat{\mathcal{L}}_i \equiv \hat{\mathcal{L}}(Z_i)$ for *all observations* in the test set. By iterating over each fold as test set, the algorithm generates prediction over all observations in the sample. We use four ML methods (elastic net, neural net, random forest and gradient boosting) and then take the median prediction on each borrowers' likelihood of being current after six months. Appendix Section C provides more details on this procedure.

With this estimate of $\hat{\mathcal{L}}_i$ in hand, we estimate our standard heterogeneity model, examining the impact of payment reduction and debt reduction for borrowers with different levels of $\hat{\mathcal{L}}_i$. The key parameter of interest is the interaction between our high-$\hat{\mathcal{L}}_i$ dummy variable — identifying borrowers likely to be unconstrained in the near future (i.e., above median $\hat{\mathcal{L}}_i$) — and the treatment group indicators. This interaction captures the marginal effect of receiving a given loan modification for borrowers with a high ex-ante probability of remaining current on their loans. In other words, it

[54] If we assume that borrowers with high $\mathcal{L}$ are unconstrained ex-ante (or close to), we should expect that a payment reduction should be irrelevant for them.

[55] It is important to remember that every borrower in the experiment is made "current" on their minibus loan at the beginning of the experiment.

[56] We consider a set of 28 characteristics, either measured at loan origination or at experiment baseline, to construct Z_i. We provide details on these covariates in Appendix Section C.

[57] The choice of number of folds depends on the bias-variance tradeoff — higher folds decreases variance and lower folds decrease bias. Given our size of control sample (1,063 observations), we settle on our choice of five-folds following recommendation in Hastie, Tibshirani and Friedman (2009) who note that five folds already capture more than 80% of the efficiency of leave-one-out while reducing variance by roughly half.

captures the effect of the treatment for the sub-sample of borrowers for which strategic incentives are more likely to be the sole determinant of behavior. For interest write-down, we expect the intervention to have some positive effect within this sample of borrowers.

We report the results for repayment outcomes in Column (1) of Table 10. First, we note that high $\hat{\mathcal{L}}_i$ positively predicts repayment, providing a validation of our methodology: in fact, the model was designed to estimate a borrower's ex-ante probability of being current on the loan at six month post experiment roll-out, independent of experimental assignment. Consistent with our hypothesis, we also find that debt reduction increases repayment for borrowers with a higher ex-ante likelihood of staying current on the loan. This suggests that the policy improves repayment, but only for this sub-group. The interaction between the payment reduction and $\hat{\mathcal{L}}_i$ is instead statistically indistinguishable from zero, suggesting that payment reduction does not have any incremental effect for those borrowers that were likely to return to pay irrespective from the experiment.

In Columns (2)-(5) of Table 10, we estimate the same model looking at entrepreneurial effort. In line with the previous set of results, we also find in this setting that the debt reduction has a positive effect for those borrowers with ex-ante higher probability of repaying. In fact, we find that the interaction between high $\hat{\mathcal{L}}_i$ and the interest write-down is positive, consistent with the idea that this loan modification increases entrepreneurial effort within this sub-sample. The effect size is large, having a similar magnitude as the payment reduction for high-equity individuals, and it can be detected across all three sub-components of the index. Lastly, we also confirm the null interaction between payment reduction and $\hat{\mathcal{L}}_i$.

Altogether, this evidence suggests that debt reduction is not uniformly ineffective. Borrowers with a high ex-ante likelihood of repayment benefit from the intervention, exhibiting increases in both repayment and effort. This result is consistent with the interpretation that these borrowers are less likely to be liquidity constrained, and that their primary constraint is instead strategic. Importantly, this finding provides additional validation of our conceptual framework, using ex-post randomized variation in equity rather than ex-ante equity differences. It, therefore, complements the earlier results, confirming the model's predictions from a different perspective and leveraging a distinct source of variation.[58]

5.5 Discussion

Examining the experiment's results offers key insights into how debt restructuring affects small businesses. The first key takeaway from our analysis is that liquidity constraints, rather than strategic incentives, primarily drive defaults in our setting. Consistent with this idea, we find that reducing monthly payments significantly improves repayment rates, whereas lowering the debt burden does not lead to meaningful behavioral changes.

[58]The finding that debt reduction is not uniformly ineffective challenges the view that our results are driven solely by uniformly high discount rates. While liquidity constraints may imply high discounting, the heterogeneity in responses suggests this is not the full story. If all borrowers heavily discounted the future, we would expect debt reductions to have little effect and payment reductions to dominate. Our results show that this is not uniformly the case, pointing to a more nuanced mechanism.

As outlined in Section 3, evaluating repayment behavior is a critical first step in assessing whether a loan modification can meaningfully reduce debt overhang. The payment reduction helps entrepreneurs stay current on their loans and, more broadly, alleviates financial strain. These borrowers are less likely to default and face repossession, thereby directly improving their equity position relative to the control group. Additionally, the amortization structure of the loan enables them to build equity over time, further strengthening their financial position.

However, our findings also underscore the intertwined relationship between liquidity and strategic incentives. Improving payments alone may not be sufficient to fully mitigate the effects of debt overhang. For some borrowers, initial leverage is so high that the benefits of a payment reduction may not be enough to cross the tipping point (Myers 1977) at which debt overhang ceases to be a constraint. Our analysis of driving behavior supports this idea, as we find that the increase in entrepreneurial effort is concentrated among borrowers with higher ex-ante equity. The same idea is confirmed by the test looking at the impact of the debt reduction within the set of borrowers that are ex-ante more likely to stay current during the experiment period. For this group of borrowers, we find that the debt reduction leads to a meaningful increase in repayment and effort.

These results suggest a potential rationale for policies that combine payment reductions with more aggressive reductions in overall debt balances. The overall picture emerging from our analysis highlights the crucial interplay between liquidity constraints and strategic concerns in designing restructuring policies that not only improve repayments but also stimulate real economic activity.

6 Conclusion

Understanding the drivers of default and repayment behavior is crucial for designing optimal loan modification strategies. This study leverages a unique randomized experiment involving 3,186 minibus taxi operators in South Africa to examine the effects of different loan restructuring approaches on repayment behavior, entrepreneurial effort, and external borrowing. By distinguishing between liquidity constraints and strategic default incentives, we contribute to a broader understanding of debt dynamics in small business lending.

Our experiment involved three arms: a control group receiving a standard restructuring, a treatment group receiving a payment reduction via extended maturity without changing long-run debt obligations, and another treatment group receiving an interest write-down, an intervention that effectively lowers the long-term obligations for the borrowers without changing short-run liquidity. By exploiting loan repayment histories, credit bureau records, and GPS-tracked driving data, we assess how these modifications impact borrower behavior. This setting, characterized by strong competitive pressures and financially constrained entrepreneurs, provides a useful testing ground for evaluating debt restructuring policies in developing countries.

Borrowers who received a payment reduction were significantly more likely to stay current on their loans and exhibited a lower level of accumulated arrears, while those receiving an interest write-down showed no significant change in repayment behavior. We also find that borrowers in

the payment reduction group reduced their external borrowing, reinforcing the idea that improved liquidity conditions allowed them to stabilize their finances. The evidence on entrepreneurial effort is more mixed. As expected, we find that the interest write down does not have any impact on the driving. The payment reduction instead induces more entrepreneurial effort for those businesses with low leverage ex-ante.

The significant response to a payment reduction suggests that liquidity constraints are a primary driver of default in this market. However, this finding does not necessarily rule out the importance of strategic incentives. Lowering the monthly installment may help borrowers building equity and therefore reducing the cost of debt overhang. However, we find that this effect is sufficiently large only for borrowers with high baseline equity in the vehicle, suggesting that strategic incentives can still represent an important hurdle to clear to make these policies effective. Consistent with this hypothesis, we also document that the interest write-down helped borrowers that were ex-ante less likely to be liquidity constrained.

Overall, our results highlight the important interplay between liquidity and strategic concerns. Improving a borrower's repayment condition appears to be a key prerequisite for meaningfully changing debt-related incentives. However, an intervention that focuses solely on easing liquidity constraints may fall short, as strategic concerns may still influence behavior for some borrowers. Our evidence suggests that policymakers aiming to improve repayment and increase entrepreneurial effort may consider interventions that address both short-term liquidity and overall debt burden. Alternatively, if policy must focus on a single dimension, our findings offer a rationale for targeting specific subsets of borrowers who are more likely to respond to the intervention.[59]

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[59] In other words, our findings that a reduction in debt burden can be worthwhile is the policy maker is able to specifically target those borrowers that are not liquidity constrained.

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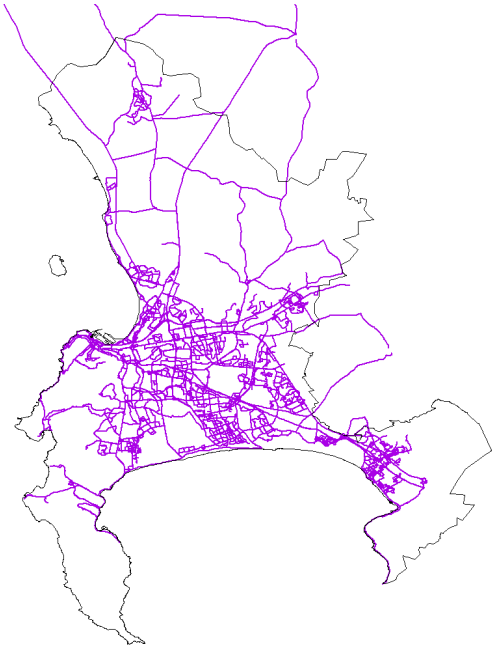
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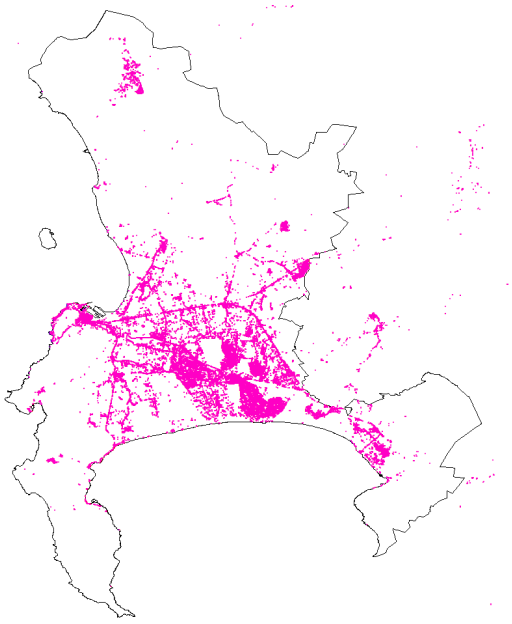
7 Figures and Tables

Figure 1: All minibus routes and GPS coordinates of minibuses from our experimental sample in the City of Cape Town

(a) Map of all minibus taxi routes

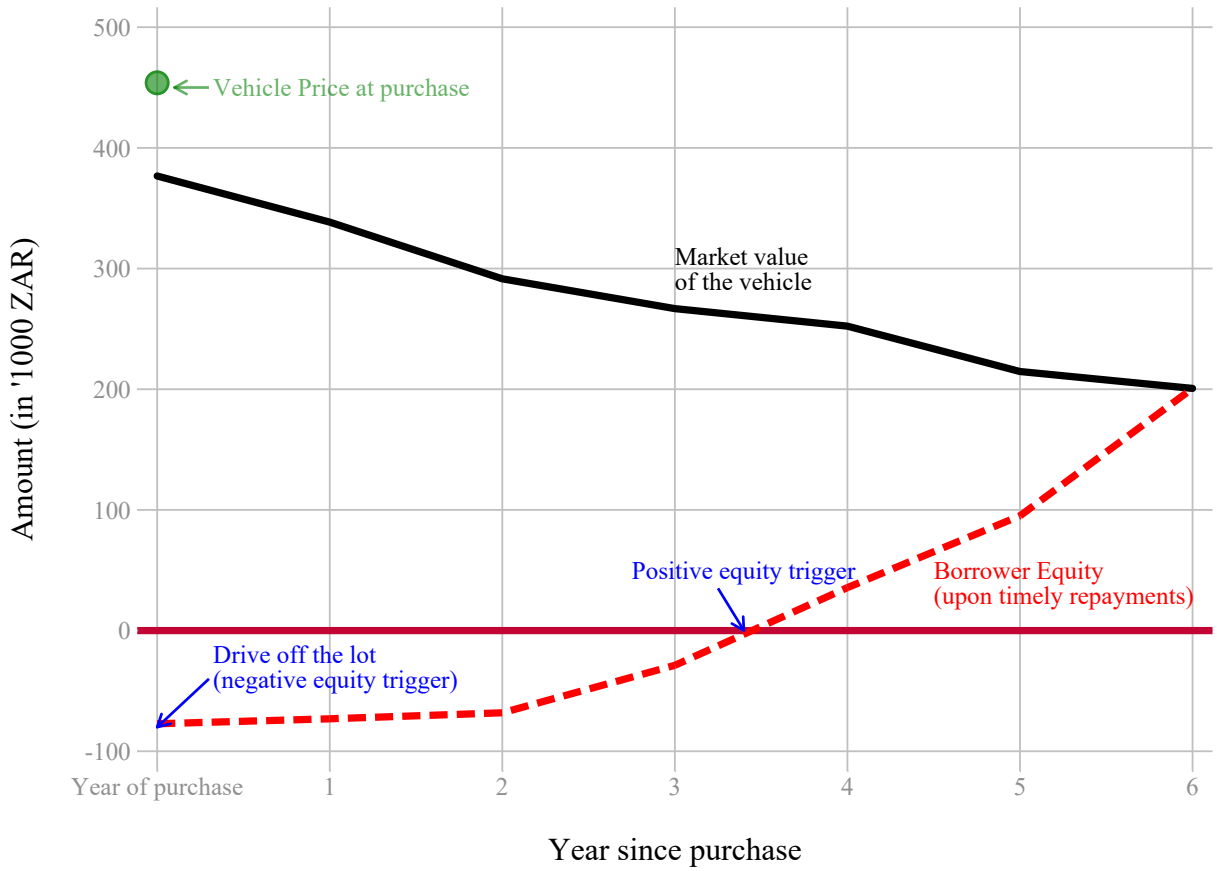


(b) Geo-coordinates of operators in experiment



Notes: Panel (a) documents all official minibus routes in the city of Cape Town. Panel (b) denotes the geo-coordinates from the GPS data for the accounts in our experiment that operate in the city of Cape Town.

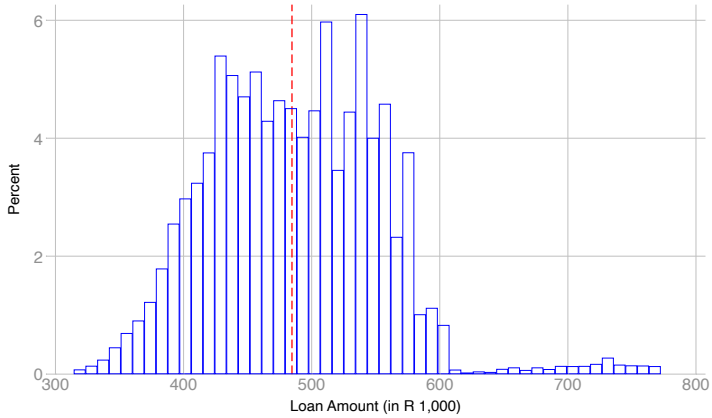
Figure 2: Evolution of equity over time for new borrowers



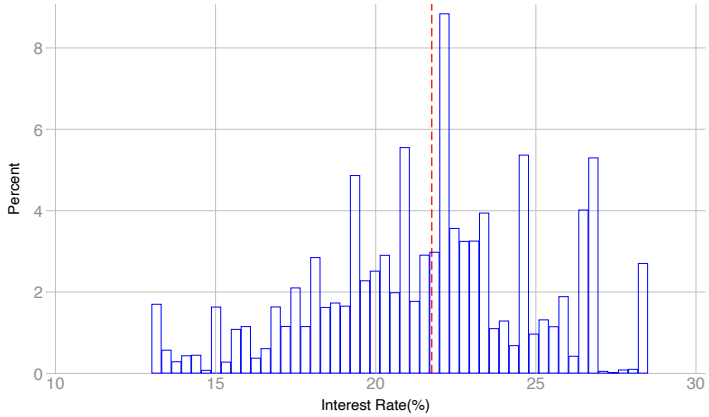
Notes: The figure provides an example of the evolution of equity (red dashed line) for borrowers that make timely repayment on loan with a newly collateralized vehicle. The black solid line represents the market value of a new minibus (Toyota Quantum 16 seater in this example). The green dot represents the market value of vehicle upon purchase. The vertical axis reports the monetary value (in R 10,000). The horizontal axis plots the time (in years) that has passed since vehicle purchase.

Figure 3: Distribution of loan terms in the Lender's portfolio

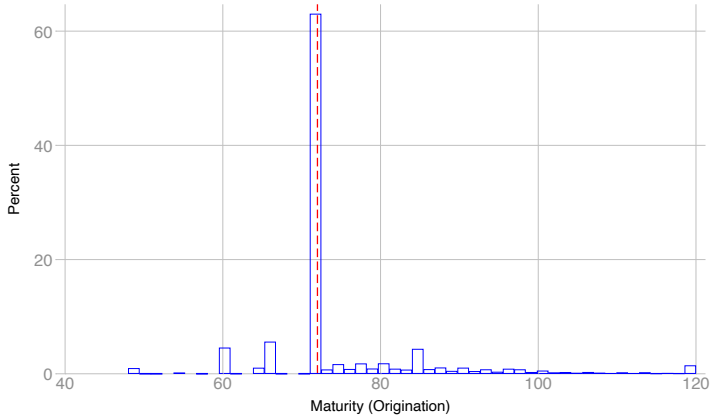
(a) Loan Amount



(b) Interest Rate



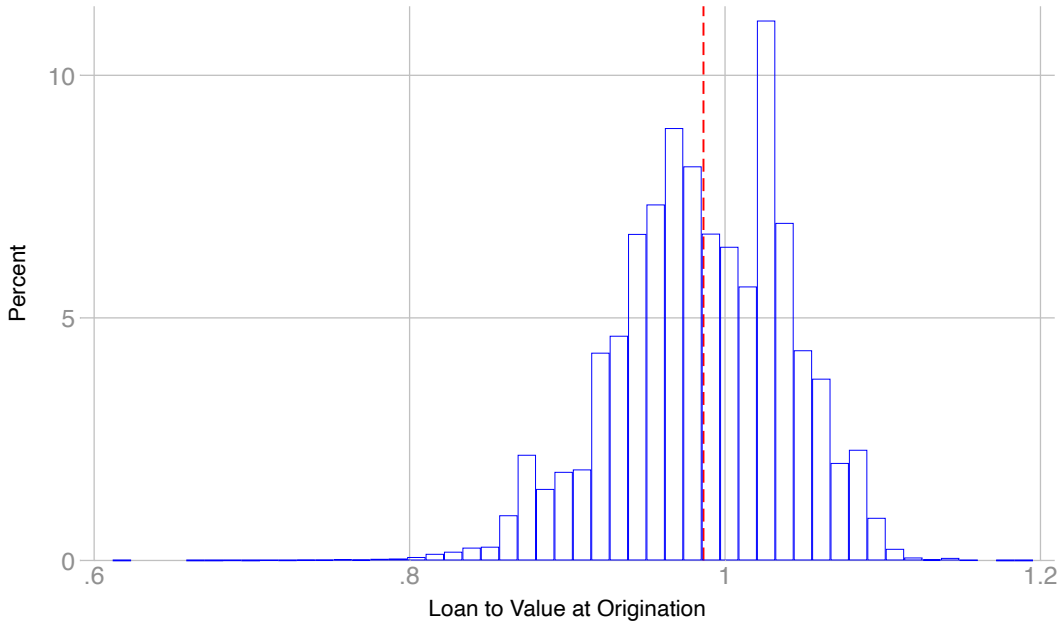
(c) Maturity (at Origination)



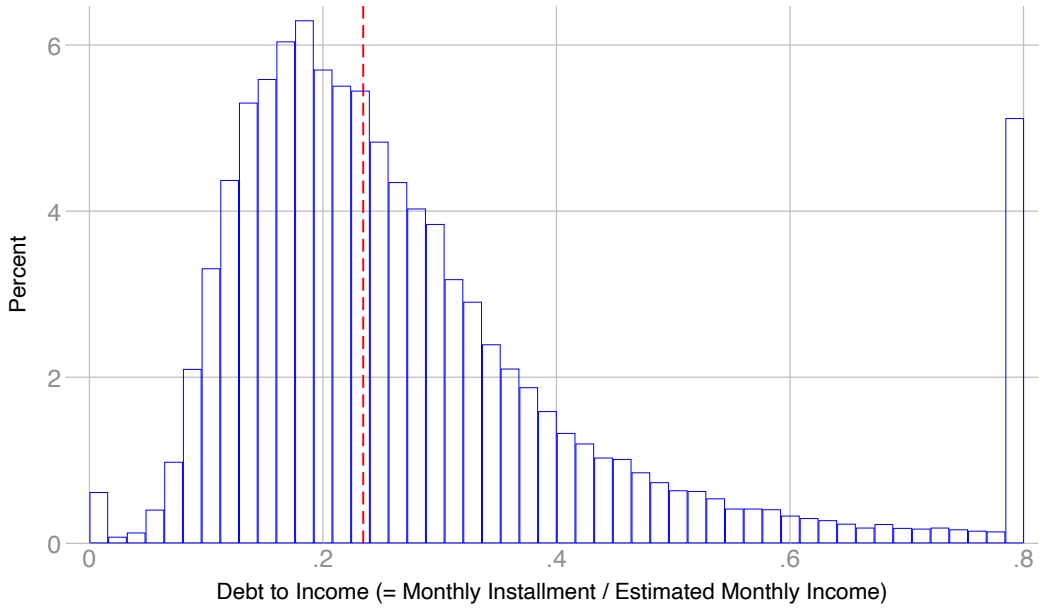
Notes: The figure plots the distribution of loan characteristics as observed at origination of the loan. The sample is all the accounts active with the lender as of October 2023 (the month before the experiment rollout). The red vertical lines on each subplot corresponds to the median value for the reported variables. Panel (a) plots the loan amount (in R 1,000); Panel (b) plots the interest rate (in percent); and Panel (c) plots the loan maturity (in months). (N = 32,079)

Figure 4: Distribution of loan-to-value (at origination) and debt-to-income

(a) Loan to Value (LTV) at origination

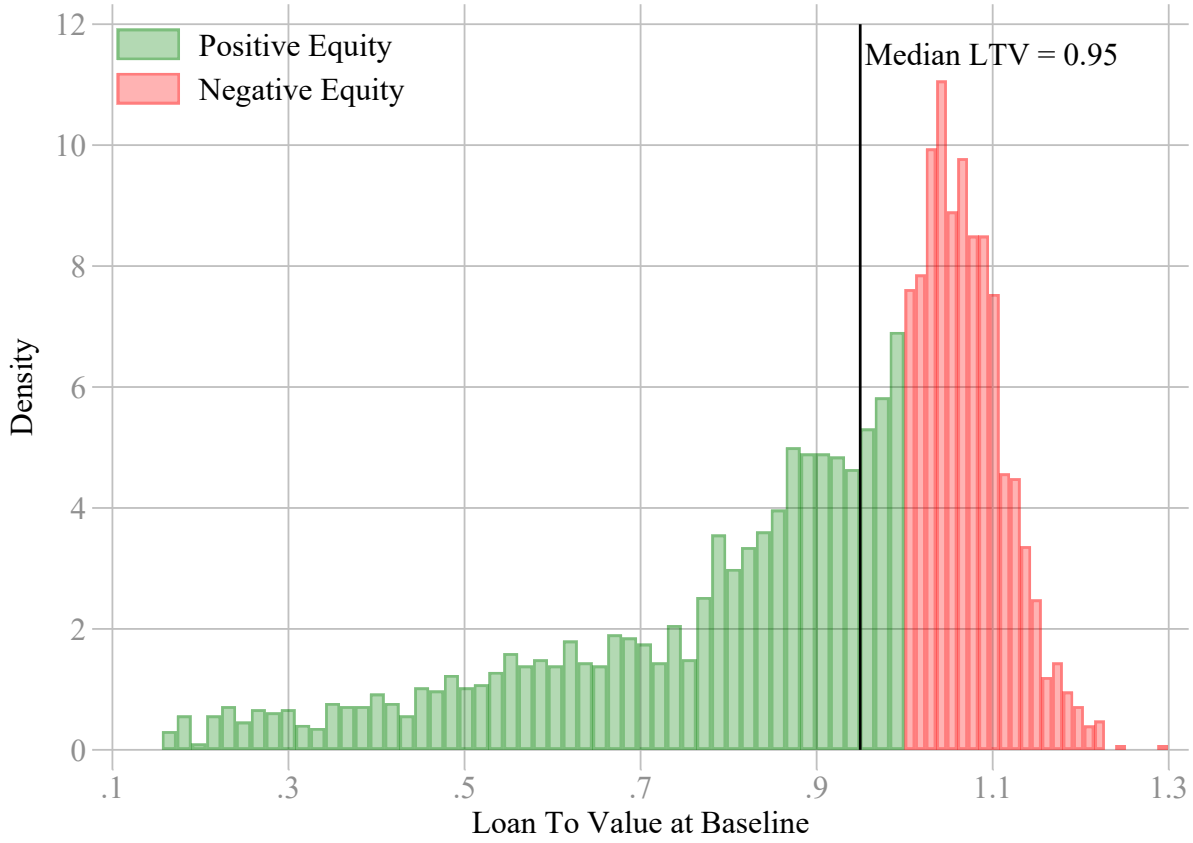


(b) Debt to Income (DTI) at baseline



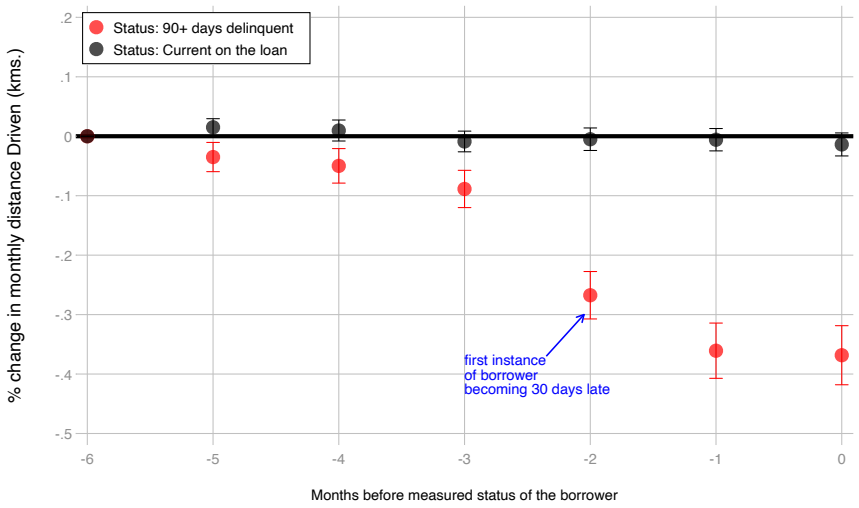
Notes: The figure plots the distribution of loan to value at loan origination (Panel a), and the debt-to-income ratio (Panel b). For Panel (b), we winsorize the observations in top 5% of the distribution. The sample is all the accounts active with the lender as of October 2023 (the month before the experiment rollout). The red vertical lines on each subplot corresponds to the median value for the reported variables. (N = 32,000)

Figure 5: Distribution of Baseline LTV in the experimental sample



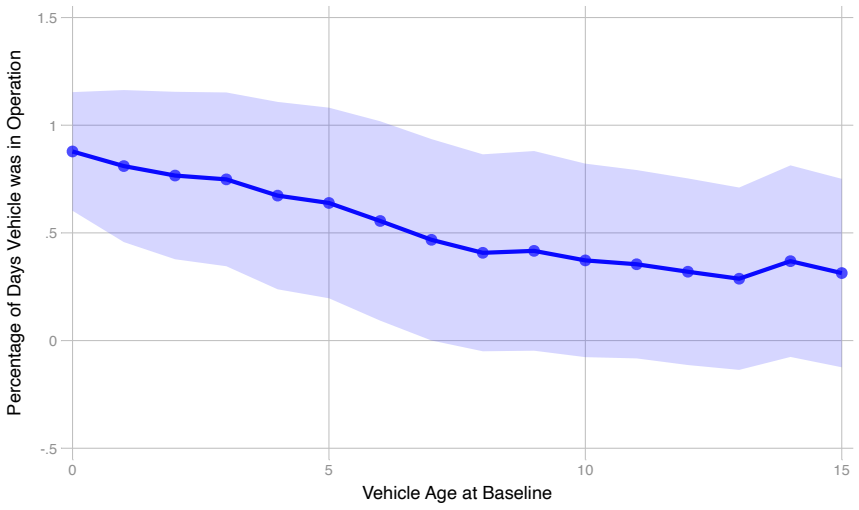
Notes: The figures plots the distribution of LTV (loan-to-value) across borrowers in our experimental sample at baseline month of October 2023. LTV is defined as the outstanding loan balance (sum of principal and any outstanding arrears) divided by the estimate of the market value of the underlying collateralized minibus. The vertical line represents the median value (LTV = 0.95) in the sample. The green bars corresponds to the accounts that have non-negative equity (LTV $\leq$ 1), while the red bars correspond to the accounts that have negative equity (LTV $>$ 1). (N = 3,186)

Figure 6: Evolution of Entrepreneurial Effort and 90+ Day Delinquency



Notes: The figures plots the estimates β^s from following two regressions for the set of account i that have the following status $s = \{1(\text{current}), 1(90+ \text{ days delinquent})\}$ every month from $t_0 = [\text{June 2024}, \text{January 2025}]$: $log(distance)_{i,t} = \alpha_i + \alpha^i_{t_0} + \sum_{k=0}^{-5} \beta^s_k \cdot \mathbf{1}(t = t^i_0 + k) + \epsilon_{it}$. t^i_0 is the month for which the status of the account i is measured. For delinquent account it is the month in which the account become delinquent for the first time. For current account, it is the month for which the account i remain current for the preceding six months. If an account remain current for multiple times between June 2024 to January 2025, we random allocate it to one of the eight months. Standard errors are clustered at the account-level. Solid dots represent the point estimates, with black dots corresponding to the accounts with current status and red dots corresponding to the accounts that enter become 90+ delinquent for the first time. We exclude accounts that were part of our experimental sample. The omitted month is month 6 before the month in which borrower status is measured. 95% confidence intervals are reported using the vertical bars.

Figure 7: Share of days driven at baseline by age of the vehicle



Notes: The figure shows the mean and standard deviations for the percentage of days a vehicle was in operation in October-2023 by the age of the vehicle (in years) as measured at baseline month.

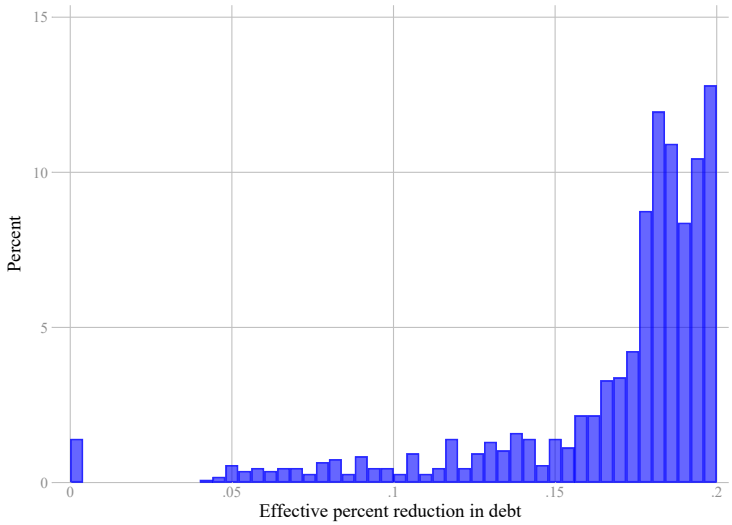
Figure 8: Borrower Equity and Entrepreneurial Effort at Baseline



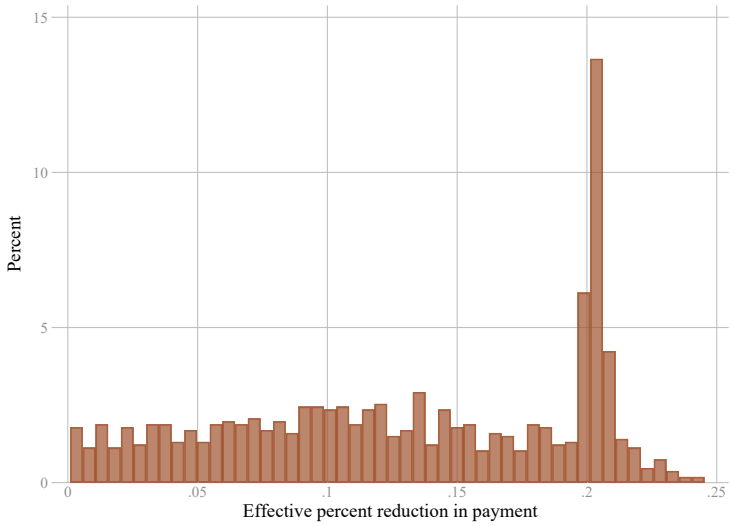
Notes: The figure plots the relationship between (log) of distance borrower — one of the component of borrower effort index — and loan to value in at baseline month (at October 2023). Controls include indictor for loan origination month and indicator variable for that takes the value of one when the vehicle is new and 0 when it is refurbished. *Sample:* All loan accounts with lender for which vehicles not repossessed in October 2023. (N = 28,519)

Figure 9: Effective treatment intensity

(a) Interest write-down

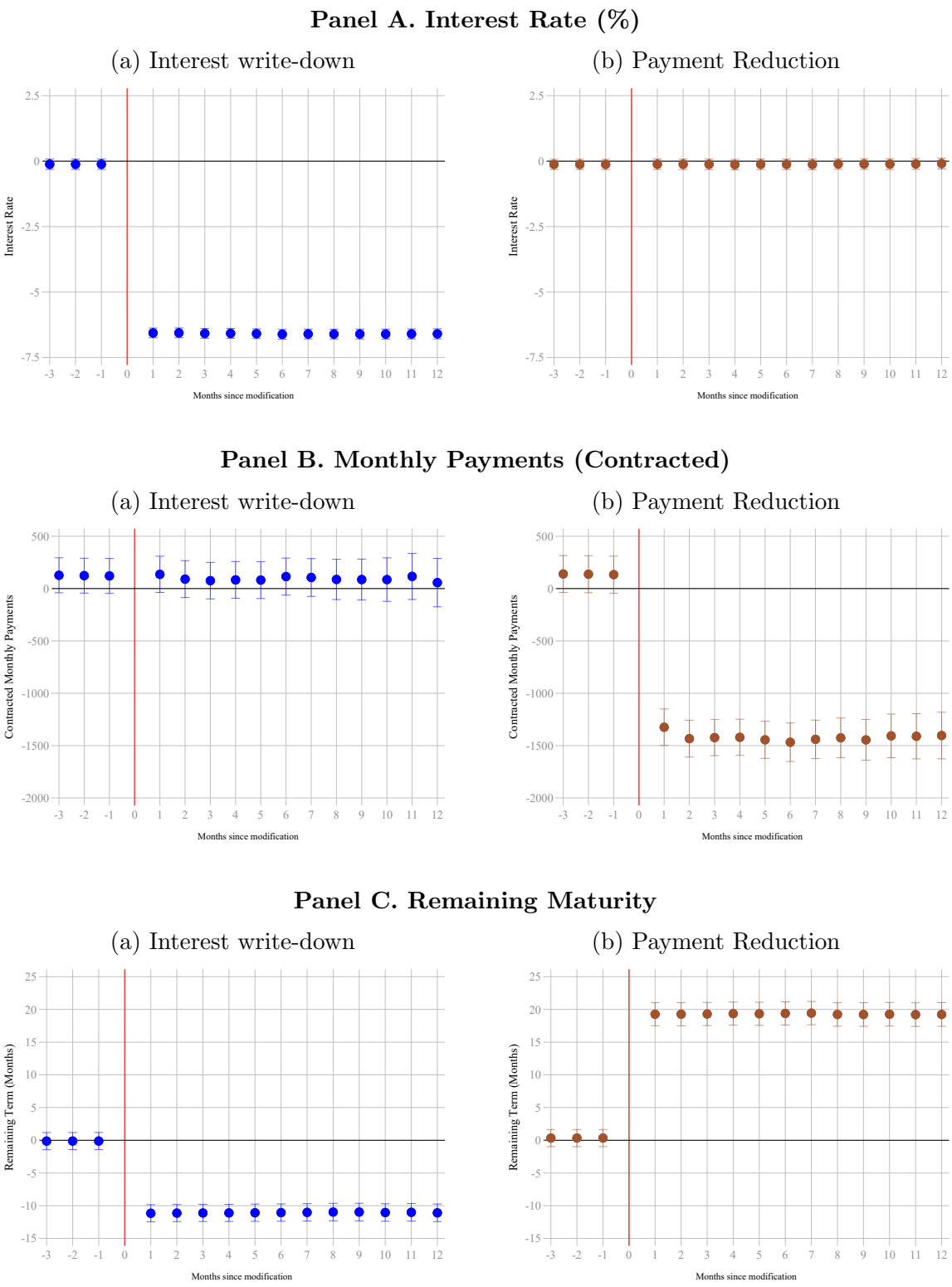


(b) Payment Reduction



Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on entrepreneurial effort index. The effort is defined as equal weighted average of (i) total distance covered by the vehicle (ii) total number of days worked in the month (iii) the number of hours on the job. The top panel reports the monthly estimates for the interest write-down modification relative to the baseline modification. The bottom panel reports the monthly estimates for the payment reduction modification relative to the baseline modification. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

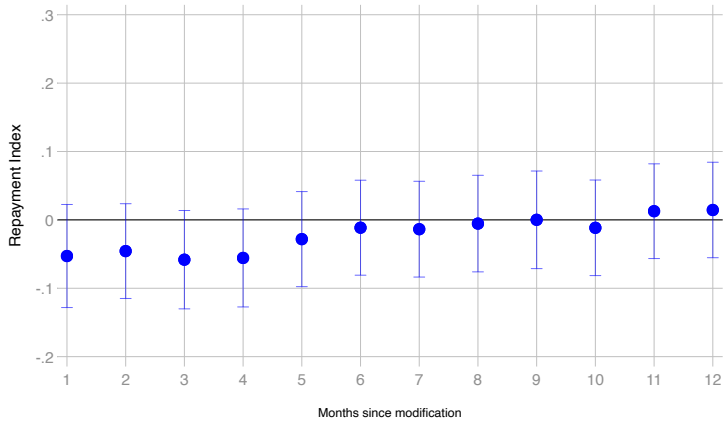
Figure 10: First-stage: Impact on contract terms across treatment arms



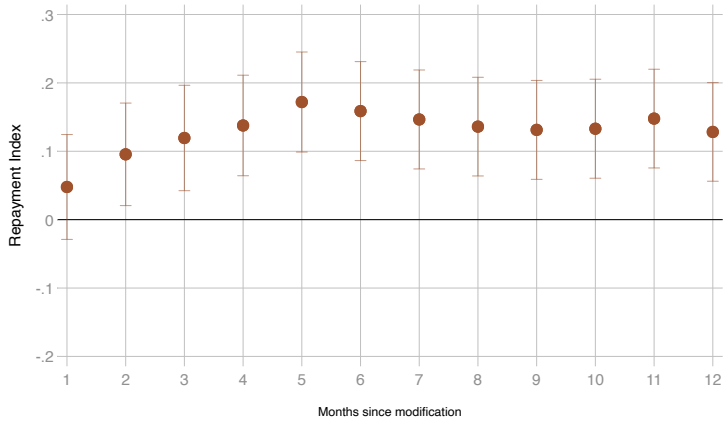
Notes: These panels report the estimates on contract terms — Interest Rate (Panel A), Contracted Monthly Payments (Panel B), and the outstanding maturity (Panel C) — in the three months before and eight months after the loan modifications (November 2023) relative to the baseline modification. For each panel, the left column reports the contract terms under the interest write-down modification relative to the baseline modification, and the right column reports the contract terms under the payment reduction modification relative to the baseline offer. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

Figure 11: Impact of loan modifications on minibus loan repayment

(a) Interest write-down



(b) Payment Reduction

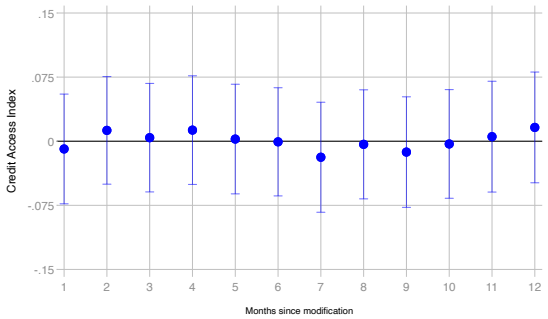


Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on minibus loan repayment. Loan repayment index is defined as equal weighted average of (i) indicator for whether a borrower is current on the loan (ii) (negative of) total amount in arrears (iii) (negative of) total amount in arrears divided by monthly owed installment. The top panel reports the monthly estimates for the interest write-down modification relative to the baseline modification. The bottom panel reports the monthly estimates for the payment reduction modification relative to the baseline modification. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

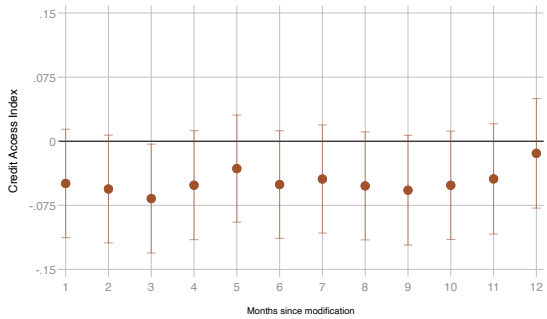
Figure 12: Impact of loan modifications on outside debt

Panel A. Credit Access Index

(a) Interest write-down

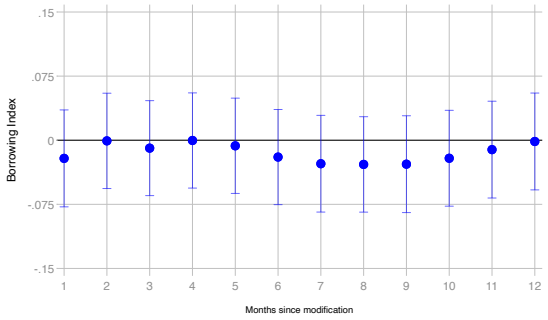


(b) Payment Reduction

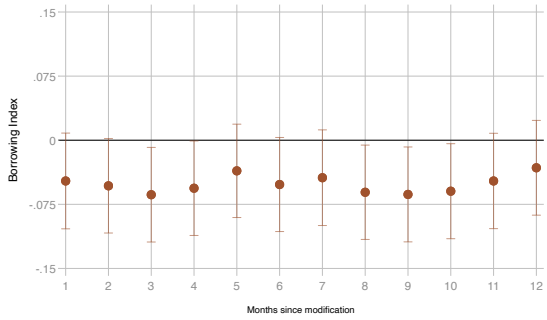


Panel B. Borrowing Index

(a) Interest write-down

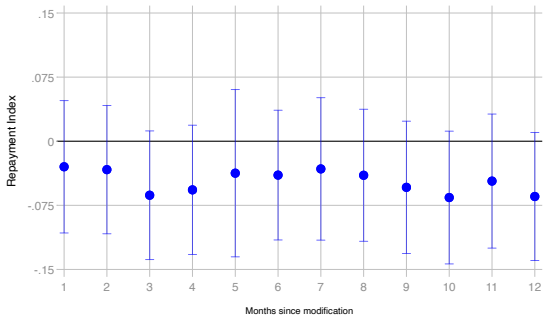


(b) Payment Reduction

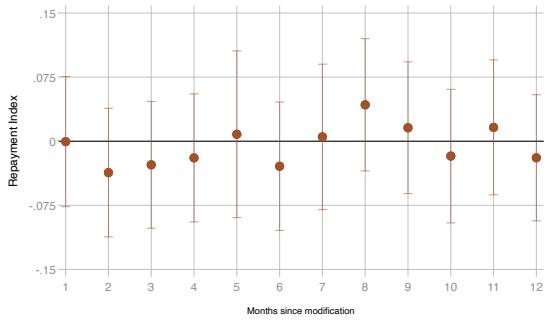


Panel C. Repayment Index

(a) Interest write-down



(b) Payment Reduction

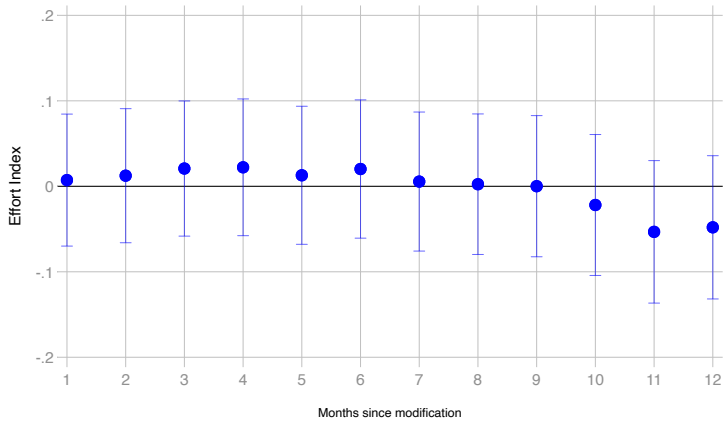


Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on three indices measuring performance on outside debt: credit access index (panel A); borrowing index (panel B); repayment index (panel C). The indices are defined as follows:
1. *Credit Access Index (month 12)* = (1(has credit card) + 1(has credit line) + Total amount on credit lines + 1(has installment loan))/ 4
2. *Borrowing index (average)*= (1(outside debt > 0) + Line Utilization + Total Amount Owed on Outside Debt)/3
3. *Repayment index (average)* = (1(any account past due)+(Num. accounts past due) + 1(any account in default)+ (Num. accounts in default) + (Balance past due) + (Balance in default))/6. Only accounts active at baseline considered.

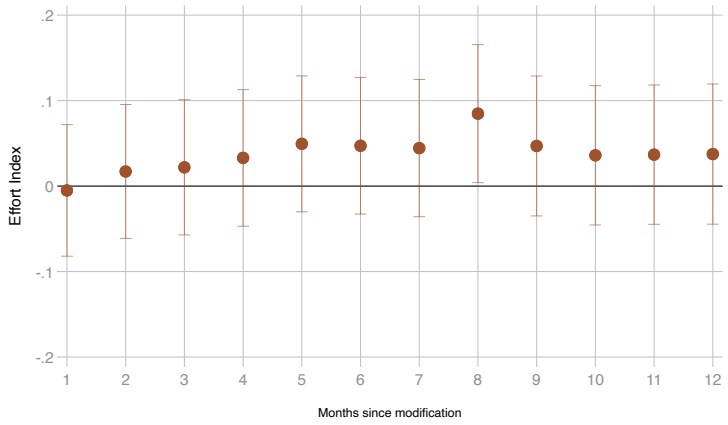
All index components are normalized to mean zero and standard deviation of one. The left sub-panels within each panel report the monthly estimates for the interest write-down modification relative to the baseline modification. The right sub-panels within each panel report the monthly estimates for the payment reduction modification relative to the baseline modification. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

Figure 13: Impact of loan modifications on entrepreneurial effort

(a) Interest write-down



(b) Payment Reduction

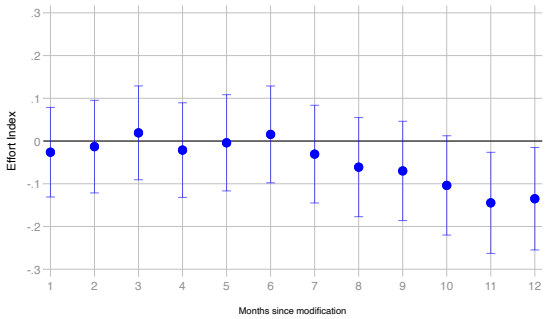


Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on borrowers' effort. The index is defined as equal weighted average of (i) total distance covered by the vehicle (ii) total number of days worked in the month (iii) the number of hours on the job. The top panel reports the monthly estimates for the interest write-down modification relative to the baseline modification. The bottom panel reports the monthly estimates for the payment reduction modification relative to the baseline modification. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

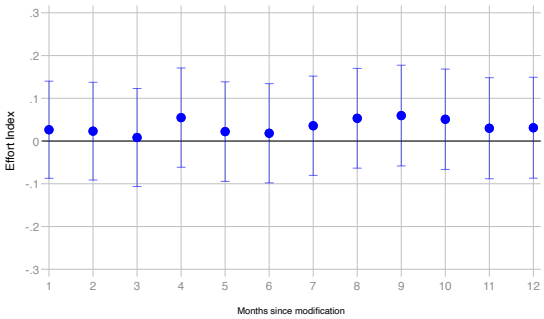
Figure 14: Dynamic effects on entrepreneurial effort

Panel A. ... following interest write-down

(a) borrowers with low baseline equity

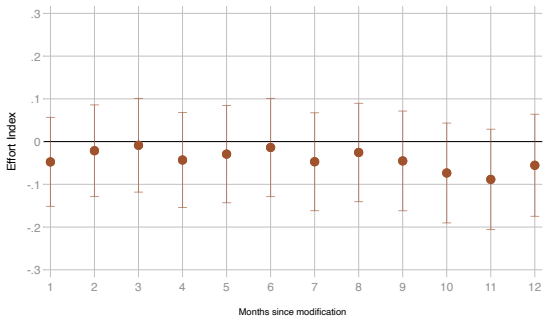


(b) borrowers with high baseline equity

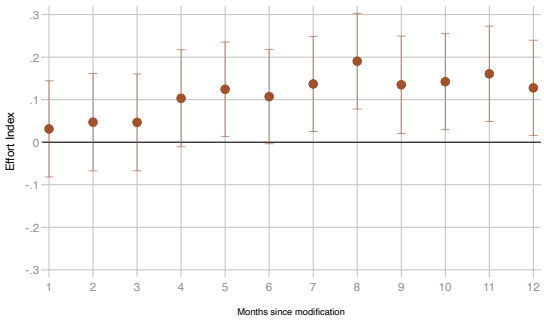


Panel B. ... following payment reduction

(a) borrowers with low baseline equity



(b) borrowers with high baseline equity

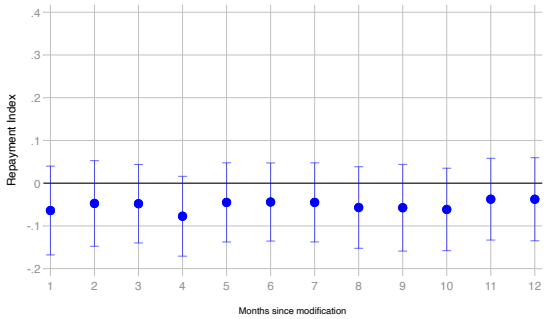


Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on borrowers' effort by above-median (high) or below-median (low) baseline borrower equity. The index is defined as equal weighted average of (i) total distance covered by the vehicle (ii) total number of days worked in the month (iii) the number of hours on the job. The top panel reports the monthly estimates for the interest write-down modification relative to the baseline modification. The bottom panel reports the monthly estimates for the payment reduction modification relative to the baseline modification. Panel (a) reports estimates for low baseline equity and Panel (b) reports estimates for high baseline equity. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

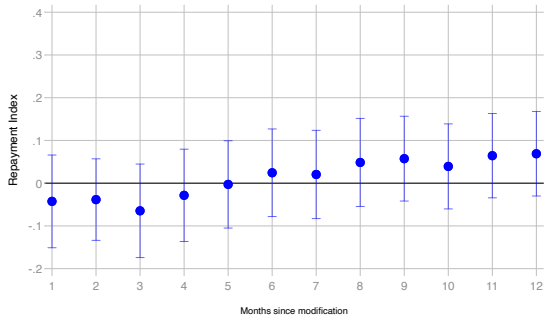
Figure 15: Dynamic effects on minibus loan repayment

Panel A. ... following interest write-down

(a) borrowers with low baseline equity

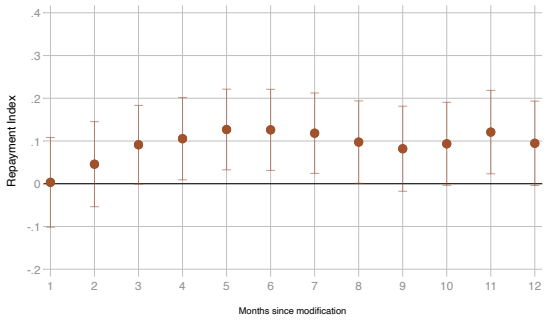


(b) borrowers with high baseline equity

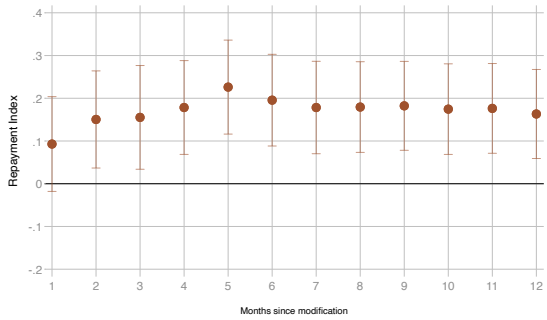


Panel B. ... following payment reduction

(a) borrowers with low baseline equity



(b) borrowers with high baseline equity



Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on minibus loan repayment index by above-median (high) or below-median (low) baseline borrower equity. The index is defined as equal weighted average of (i) indicator for whether a borrower is current on the loan (ii) (negative of) total amount in arrears (iii) (negative of) total amount in arrears divided by monthly owed installment. The top panel reports the monthly estimates for the interest write-down modification relative to the baseline modification. The bottom panel reports the monthly estimates for the payment reduction modification relative to the baseline modification. Panel (a) reports estimates for low baseline equity and Panel (b) reports estimates for high baseline equity. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

Table 1: Illustrative example of baseline modification

Status of the account ...	Loan characteristics					
	Principal Outstanding (1)	Accumulated Arrears (2)	Total Amount Outstanding (3) = (1) + (2)	Interest Rate (4)	Monthly Payments (5)	Remaining Months (6)
... *if* it was current	R 391,931	—	R 391,931	23.9%	R 12,824.7	47.6
... *actual status*: in arrears	R 391,931	R 54,829	R 446,761	23.9%	R 14,618.9	47.6
... after modification	R 446,761	—	R 446,761	23.9%	R 12,824.7	59.9

Notes: The table illustrates how enrollment into the baseline arm changes the loan contract 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 borrowers. Column (3) shows the total amount outstanding which is the sum of the original outstanding principal and accumulated arrears. Column (4) shows the annualized interest rate. Column (5) shows the effective monthly payments under each loan status. Column (6) shows the new maturity for the loan contract.

Table 2: Illustrative Example of Randomized Treatments

Treatments		Loan characteristics			
Interest write-down (1)	Payment Reduction (2)	Interest Rate (3)	Monthly Payment (4)	Remaining Maturity (5)	Total Interest (6)
—	—	23.9%	R 12,824.7	59.9	R 322,625
6.6 p.p.	—	17.3%	R 12,824.7	48.7	R 178,426
—	12.9%	23.9%	R 11,170.3	80.7	R 454,677

Notes: The table illustrates how loan characteristics change across various arms of the experiment. Row 1 corresponds to the baseline modification arm, which is the same as Row 3 of Table 1. Row 2 corresponds to the interest write-down modification arm. Row 3 corresponds to the payment reduction modification arm. Column (1) shows the average interest write-down (in percentage points). Column (2) shows the average payment reduction (in percent) over the average payment based on loan amortization. Column (3) shows the average interest rate. Column (4) shows the average monthly loan payment. Column (5) shows the outstanding loan maturity. Column (6) shows the total gross interest that will be paid upon full and timely repayment on the loan.

Table 3: Summary Statistics and Balance

Sample: *All Baseline: 3,186 firms*	**Control mean** (1)	**Interest Write-down** (2)	**Payment Reduction** (3)
Panel A. Borrower characteristics:			
Credit Score	592.194	0.001	–0.000
		(0.000)	(0.000)
1(male)	0.761	–0.005	0.009
		(0.020)	(0.020)
Borrower's Age (in years)	51.098	–0.000	0.000
		(0.001)	(0.001)
No. of deals with lender	1.479	–0.020**	0.010
		(0.009)	(0.010)
Panel B. Loan characteristics:			
1(vehicle is new)	0.690	0.002	–0.017
		(0.032)	(0.032)
Age of the Vehicle	3.412	0.000	–0.000
		(0.007)	(0.007)
Loan Principal (R 1,000)	388.570	–0.000	0.000
		(0.000)	(0.000)
Arrears (R 1,000)	54.040	0.001	–0.000
		(0.001)	(0.001)
Maturity (Origination)	73.952	–0.003	0.003
		(0.002)	(0.002)
Loan to Value (Origination)	0.999	0.314	–0.126
		(0.230)	(0.231)
Loan to Value (Baseline)	0.879	–0.092	0.087
		(0.161)	(0.162)
Panel C. Baseline contract terms:			
Interest Rate	0.240	–0.538	–0.115
		(0.548)	(0.547)
Installments (R 1,000)	16.248	0.006	–0.002
		(0.009)	(0.008)
Remaining Maturity	47.492	0.002	–0.004
		(0.003)	(0.003)
Panel D. Baseline outcomes (normalized):			
Repayment Index	0.010	0.014	–0.007
		(0.020)	(0.022)
Effort Index	–0.007	0.001	0.002
		(0.010)	(0.010)
Credit Access Index	0.013	0.020	–0.024
		(0.021)	(0.021)
Borrowing Index	0.011	–0.001	–0.002
		(0.024)	(0.024)
p-value (joint F-test)	—	[0.691]	[0.749]
Observations	1,063	1,062	1,061

Notes: The table reports the correlation of intent to treat with baseline characteristics for the loan and the borrower. All regressions control for randomization strata fixed effects. Standard errors are clustered at the loan account level.

Table 4: First-stage: Treatment Intensity

	Interest Rate (%) (1)	Monthly Installment (2)	Remaining Maturity (3)
β^{IW} : 1(interest write-down)	-6.572***	96.948	-11.122***
	[0.095]	[91.933]	[0.669]
β^{PR} : 1(payment reduction)	-0.117	-1,421.016***	19.234***
	[0.102]	[90.804]	[0.897]
Observations	3,186	3,186	3,186
R-squared	0.713	0.197	0.484
Control mean	23.92	16067.48	55.18
p-value ($\beta^{IW} = \beta^{PR}$)	0.00	0.00	0.00
Strata f.e.	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of interest write-downs and payment reduction on contract terms. Column (1) reports the changes to the annual interest rate (%); Column (2) reports the changes to the monthly installment amount (in R); Column (3) reports the changes in the remaining loan maturity. All dependent variables are measured as an average over the 12 month period following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

Table 5: Results on minibus loan repayment

	Repayment Index (1)	1(current) (2)	Arrears Amount (3)	Arrears (Scaled) (4)
β^{IW} : 1(interest write-down)	0.014	0.021	-0.004	-0.018
	[0.036]	[0.040]	[0.042]	[0.042]
β^{PR} : 1(payment reduction)	0.128***	0.150***	-0.165***	-0.070
	[0.037]	[0.043]	[0.043]	[0.043]
Observations	3,186	3,186	3,186	3,186
R-squared	0.077	0.047	0.077	0.054
Control mean	-0.05	-0.06	0.06	0.03
p-value ($\beta^{IW} = \beta^{PR}$)	0.00	0.00	0.00	0.21
Strata f.e.	✓	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of interest write-downs and payment reduction on minibus loan repayment. Column (1) reports the effects in the repayment index; Column (2) reports the effects on probability of being current on the minibus loan; Column (3) reports the effects on total amount classified as arrears; Column (4) reports the effects on scaled arrears (defined as total outstanding arrears divided by the contracted monthly installment). The variables in Column (2) to (4) are are normalized by subtracting the mean and dividing by the standard deviation for every month. Repayment index is calculated as the average of the normalized measures for 1(current), Arrears Amount and Scaled Arrears. All dependent variables are measured as of month 12 following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

Table 6: Externalities on outside debt

	Credit Access Index	Borrowing Index	Borrowing Index (Winsorized)	Repayment Index	Repayment Index (Winsorized)
	(1)	(2)	(3)	(4)	(5)
β^{IW} : 1(interest write-down)	0.016	-0.015	-0.009	-0.048	-0.059*
	[0.033]	[0.026]	[0.026]	[0.033]	[0.033]
β^{PR} : 1(payment reduction)	-0.014	-0.051**	-0.050*	-0.004	-0.014
	[0.033]	[0.025]	[0.026]	[0.032]	[0.033]
Observations	3,186	3,186	3,186	2,947	2,947
R-squared	0.027	0.070	0.073	0.025	0.025
Control mean	-0.00	0.02	0.02	0.09	0.10
p-value ($\beta^{IW} = \beta^{PR}$)	0.36	0.14	0.11	0.15	0.17
Strata f.e.	✓	✓	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of interest write-downs and payment reduction on outside debt. Column (1) reports the effects on the credit access index as measured at the end of the month 12 after the intervention; Column (2) reports the effects on borrowing index (non-winsorized); Column (3) reports the effects on borrowing index (winsorized at 5%); Column (4) reports the effects on repayment index (non-winsorized); and Column (5) reports the effects on repayment index (winsorized at 5%). The indices are defined as follows:
(1) Credit Access Index (month 12) = (1(has credit card) + 1(has credit line) + Total amount on credit lines + 1(has installment loan))/ 4
(2) Borrowing index (average)= (1(outside debt > 0) + Line Utilization + Total Amount Owed on Outside Debt)/3
(3) Repayment index (average) = (1(any account past due)+(Num. accounts past due) + 1(any account in default)+ (Num. accounts in default) + (Balance past due) + (Balance in default))/6. Only accounts active at baseline considered.
All index components are normalized by subtracting the mean and dividing by the standard deviation for every month. All dependent variables are measured as of month 12 following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

Table 7: Results on entrepreneurial effort

	Effort Index (1)	Distance driven (2)	Time Spent on job (3)	Total days driven (4)
β^{IW} : 1(interest write-down)	-0.029	-0.162	-0.041	0.115
	[0.532]	[0.580]	[0.560]	[0.555]
β^{PR} : 1(payment reduction)	0.624	0.422	0.627	0.822
	[0.528]	[0.586]	[0.552]	[0.551]
Observations	3,178	3,178	3,178	3,178
R-squared	0.026	0.009	0.035	0.035
Control mean	-0.20	-0.08	-0.19	-0.31
p-value ($\beta^{IW} = \beta^{PR}$)	0.20	0.30	0.22	0.19
Strata f.e.	✓	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of interest write-downs and payment reduction on entrepreneurial effort. Column (1) reports the effects on the effort index; Column (2) reports the effects on total distance driven by the operator; Column (3) reports the effects on the total time spent by the operator on the job (defined as the time spent between vehicles first and last ignition for the day); Column (4) reports the effects on total days that the vehicles was in operation. The variables in Column (2) to (4) are are normalized by subtracting the mean and dividing by the standard deviation for every month. Effort index is calculated as the average of the normalized measures for distance driven, time spent on the job and total operational days. All dependent variables are measured as a sum over the 12 months following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

Table 8: Heterogeneous Treatment Effects by Baseline Equity: Effects on entrepreneurial effort

	Effort Index (1)	Distance driven (2)	Time Spent on job (3)	Total days driven (4)
β^{IW+LE}: 1(interest write-down)	-0.659	-0.710	-0.916	-0.352
× 1(low baseline equity)	[0.732]	[0.814]	[0.772]	[0.762]
β^{IW+HE}: 1(interest write-down)	0.519	0.304	0.738	0.515
× high baseline equity	[0.770]	[0.822]	[0.807]	[0.808]
β^{PR+LE}: 1(payment reduction)	-0.465	-0.477	-0.753	-0.165
× 1(low baseline equity)	[0.735]	[0.832]	[0.769]	[0.762]
β^{PR+HE}: 1(payment reduction)	1.644**	1.250	1.926**	1.756**
× 1(high baseline equity)	[0.754]	[0.823]	[0.787]	[0.795]
1(high baseline equity)	-2.769***	-2.725***	-3.347***	-2.234***
	[0.813]	[0.897]	[0.849]	[0.853]
Observations	3,178	3,178	3,178	3,178
R-squared	0.031	0.013	0.041	0.038
Control mean	-0.20	-0.08	-0.19	-0.31
$p[\beta^{IW+LE} = \beta^{PR+LE}]$	0.79	0.77	0.83	0.80
$p[\beta^{IW+HE} = \beta^{PR+HE}]$	0.13	0.23	0.13	0.11
$p[\beta^{IW+HE} = \beta^{IW+LE}]$	0.27	0.38	0.14	0.44
$p[\beta^{PR+HE} = \beta^{PR+LE}]$	0.05	0.14	0.02	0.08
Strata f.e.	✓	✓	✓	✓

Notes: The table reports the heterogeneous treatment effects of interest write-downs and payment reduction on measures of entrepreneurial effort by measures of baseline equity. High baseline equity takes the value of one if the measured baseline loan-to-value for the operator is below median value in our experimental sample, and zero otherwise. Baseline loan-to-value is calculated as the total face value of loan outstanding for the borrowers (which is the sum of remainder of loan principal and any unpaid arrears) measured before the intervention divided by the estimated market value of the vehicle in September 2023. Column (1) reports the effects on the effort index; Column (2) reports the effects on total distance driven by the operator; Column (3) reports the effects on the total time spent by the operator on the job (defined as the time spent between vehicles first and last ignition for the day); Column (4) reports the effects on total days that the vehicles was in operation. The variables in Column (2) to (4) are are normalized by subtracting the mean and dividing by the standard deviation for every month. Effort index is calculated as the average of the normalized measures for distance driven, time spent on the job and total operational days. All dependent variables are measured as a sum over the 12 months following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

Table 9: Heterogeneous Treatment Effects by Baseline Equity: Effects on minibus repayment and outside debt

	Summary Index for					
	Minibus Repayment	Credit Access	Borrowing	Borrowing (Winsorized)	Repayment	Repayment (Winsorized)
	(1)	(2)	(3)	(4)	(5)	(6)
β^{IW+LE}: 1(interest write-down)	-0.033	0.038	0.009	0.010	-0.007	-0.012
× 1(low baseline equity)	[0.050]	[0.046]	[0.032]	[0.033]	[0.043]	[0.047]
β^{IW+HE}: 1(interest write-down)	0.069	-0.005	-0.036	-0.026	-0.086*	-0.102**
× 1(high baseline equity)	[0.050]	[0.048]	[0.040]	[0.040]	[0.049]	[0.046]
β^{PR+LE}: 1(payment reduction)	0.099**	-0.020	-0.027	-0.028	0.038	0.051
× 1(low baseline equity)	[0.050]	[0.046]	[0.032]	[0.034]	[0.044]	[0.047]
β^{PR+HE}: 1(payment reduction)	0.164***	-0.007	-0.075*	-0.071*	-0.044	-0.076*
× 1(high baseline equity)	[0.053]	[0.046]	[0.038]	[0.038]	[0.046]	[0.046]
1(high baseline equity)	0.187***	0.033	0.060	0.049	0.138***	0.179***
	[0.055]	[0.049]	[0.038]	[0.038]	[0.049]	[0.050]
Observations	3,186	3,186	3,186	3,186	2,947	2,947
R-squared	0.093	0.027	0.071	0.074	0.028	0.031
Control mean	-0.05	-0.00	0.02	0.02	0.09	0.10
$p[\beta^{IW+LE} = \beta^{PR+LE}]$	0.01	0.21	0.27	0.27	0.28	0.17
$p[\beta^{IW+HE} = \beta^{PR+HE}]$	0.07	0.97	0.32	0.25	0.35	0.58
$p[\beta^{IW+HE} = \beta^{IW+LE}]$	0.15	0.52	0.38	0.50	0.23	0.17
$p[\beta^{PR+HE} = \beta^{PR+LE}]$	0.38	0.83	0.34	0.40	0.20	0.05
Strata f.e.	✓	✓	✓	✓	✓	✓

Notes:The table reports the heterogeneous treatment effects of interest write-downs and payment reduction on measures of entrepreneurial effort by measures of baseline equity. High baseline equity takes the value of one if the measured baseline loan-to-value for the operator is below median value in our experimental sample, and zero otherwise. Baseline loan-to-value is calculated as the total face value of loan outstanding for the borrowers (which is the sum of remainder of loan principal and any unpaid arrears) measured before the intervention divided by the estimated market value of the vehicle in September 2023. Column (1) reports the effects on the credit access index as measured at the end of the month 12 after the intervention; Column (2) reports the effects on borrowing index (non-winsorized); Column (3) reports the effects on borrowing index (winsorized at 5%); Column (4) reports the effects on repayment index (non-winsorized); and Column (5) reports the effects on repayment index (winsorized at 5%). The indices are defined as follows:
(1) Credit Access Index (month 12) = (1(has credit card) + 1(has credit line) + Total amount on credit lines + 1(has installment loan))/ 4
(2) Borrowing index (average)= (1(outside debt > 0) + Line Utilization + Total Amount Owed on Outside Debt)/3
(3) Repayment index (average) = (1(any account past due)+(Num. accounts past due) + 1(any account in default)+ (Num. accounts in default) + (Balance past due) + (Balance in default))/6. Only accounts active at baseline considered.
All index components are normalized by subtracting the mean and dividing by the standard deviation for every month. All dependent variables are measured as of month 12 following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

Table 10: Heterogeneous Treatment Effects by Repayment Probability

	Repayment Index (1)	Effort Index (2)	Distance driven (3)	Time Spent on job (4)	Total days driven (5)
1(interest write-down)	-0.072	-1.124	-1.319	-1.224	-0.829
	[0.049]	[0.756]	[0.815]	[0.796]	[0.799]
1(interest write-down) × high $\hat{\mathcal{L}}_i$	0.171**	2.151**	2.273**	2.323**	1.857*
	[0.070]	[1.063]	[1.159]	[1.118]	[1.109]
1(payment reduction)	0.096*	0.401	0.270	0.289	0.644
	[0.050]	[0.740]	[0.826]	[0.774]	[0.771]
1(payment reduction) × high $\hat{\mathcal{L}}_i$	0.082	0.422	0.266	0.648	0.353
	[0.073]	[1.055]	[1.172]	[1.103]	[1.103]
high $\hat{\mathcal{L}}_i$	0.265***	-0.623	-0.752	-0.853	-0.265
	[0.053]	[0.794]	[0.885]	[0.830]	[0.825]
Observations	3,178	3,178	3,178	3,178	3,178
R-squared	0.112	0.027	0.010	0.037	0.036
Control mean	-0.05	-0.20	-0.08	-0.19	-0.31
Strata f.e.	✓	✓	✓	✓	✓

Notes: The table reports the heterogeneous treatment effects of interest write-downs and payment reduction on measures of entrepreneurial effort by predicted measures of being current on the loan after six month of enrollment in the experiment. High $\hat{\mathcal{L}}_i$ takes the value of one if the predicted value is below median value in our experimental sample, and zero otherwise. $\hat{\mathcal{L}}_i$ is caluclated using machine learning algorithm described in Appedix Section C. Column (1) reports the effects on minibus repayment index measured as of month 12 following the intervention. Column (2) reports the effects on the effort index; Column (3) reports the effects on total distance driven by the operator; Column (4) reports the effects on the total time spent by the operator on the job (defined as the time spent between vehicles first and last ignition for the day); Column (5) reports the effects on total days that the vehicles was in operation. The variables in Column (3) to (5) are are normalized by subtracting the mean and dividing by the standard deviation for every month. Effort index is calculated as the average of the normalized measures for distance driven, time spent on the job and total operational days. Repayment index is calculated as the average of the normalized measures for 1(current), Arrears Amount and Scaled Arrears, and is reported at the 12th-month snapshot. All dependent variables from Column (2) to (5) — measures of entrepreneurial effort — are measured as a sum over the 12 months following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

A Appendix Figures and Tables

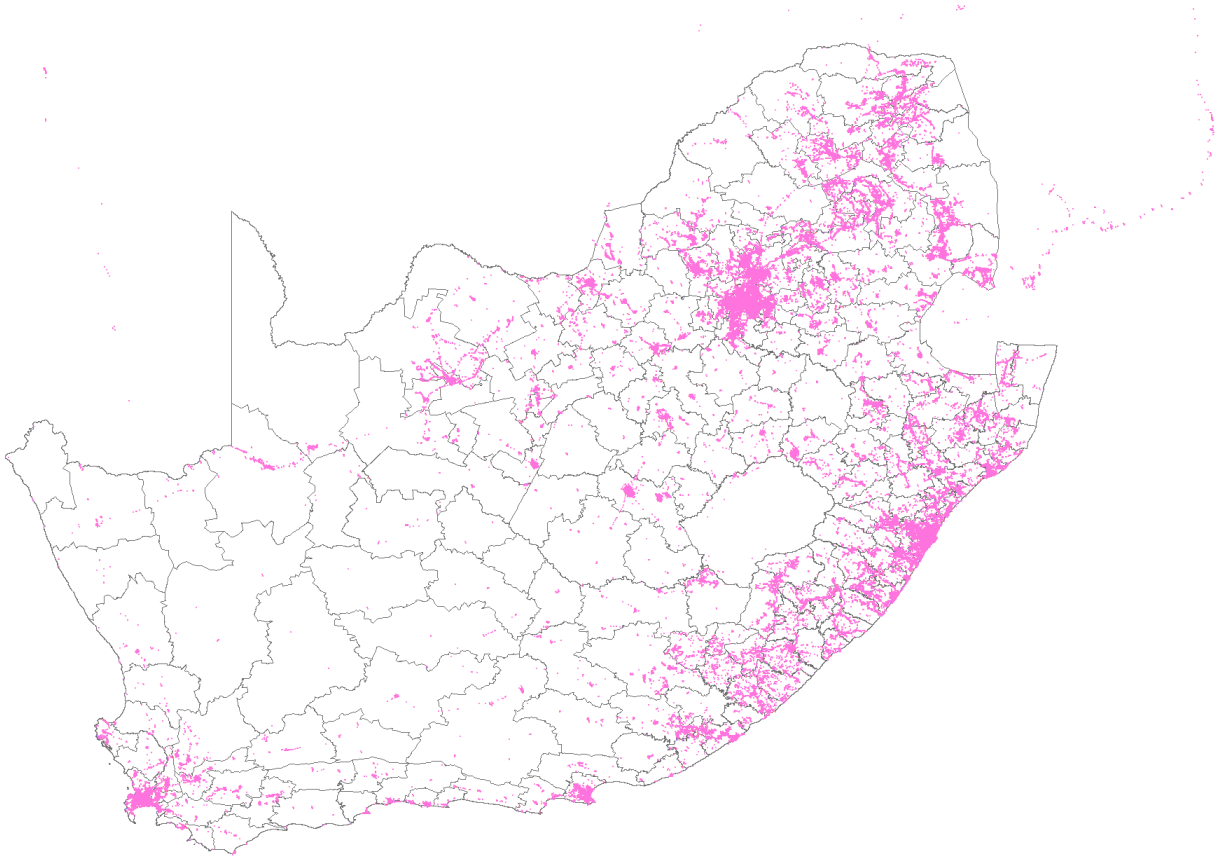
Figure A.1: A Toyota Quantum Minibux Taxi





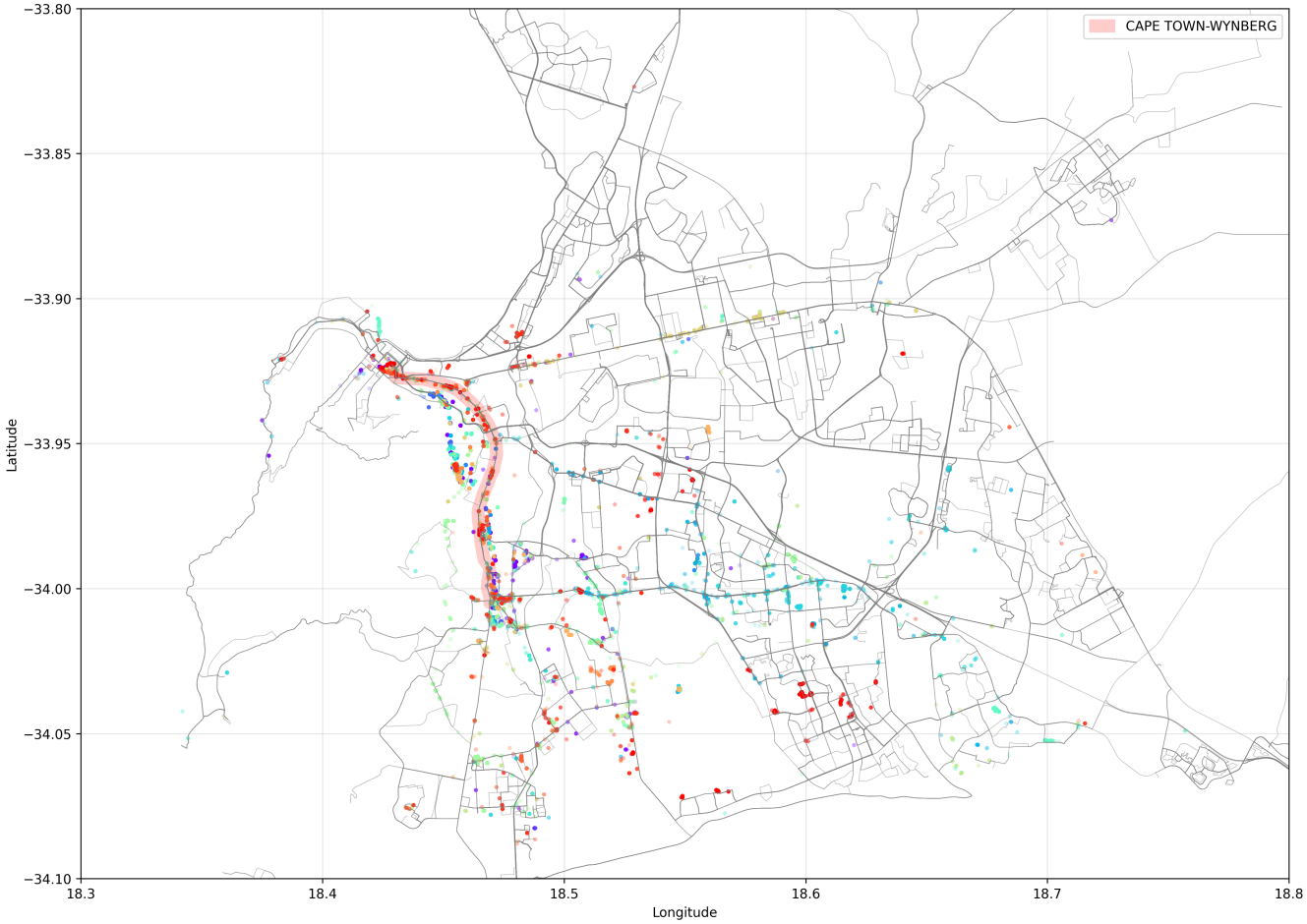
Notes: Panel (a) of the figure shows the 16-seater minibus from Toyota that constitute 80% of the collateralized vehicles in our sample. Panel (b) of the figure shows the example of a taxi ranks.

Figure A.2: GPS coordinates of all minibus taxis in experiment sample



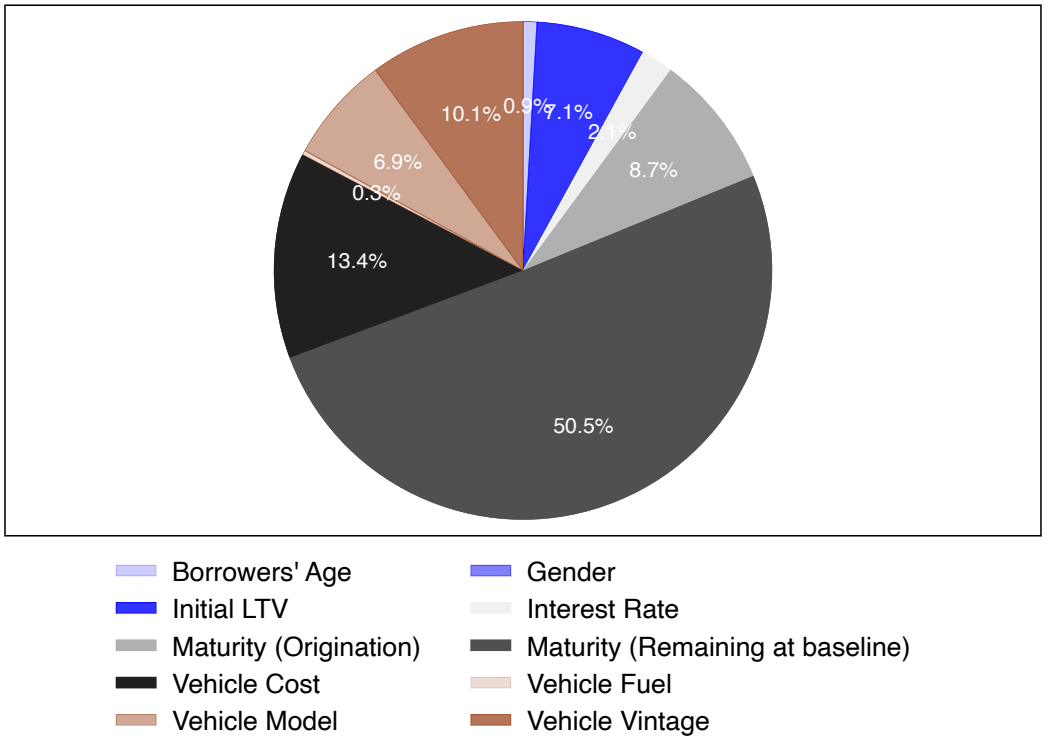
Notes: The figure shows the municipalities in South Africa. Each dot on the map denotes the geo-coordinates from the GPS data for the accounts in our experiment.

Figure A.3: Example of a minibus route in Cape Town



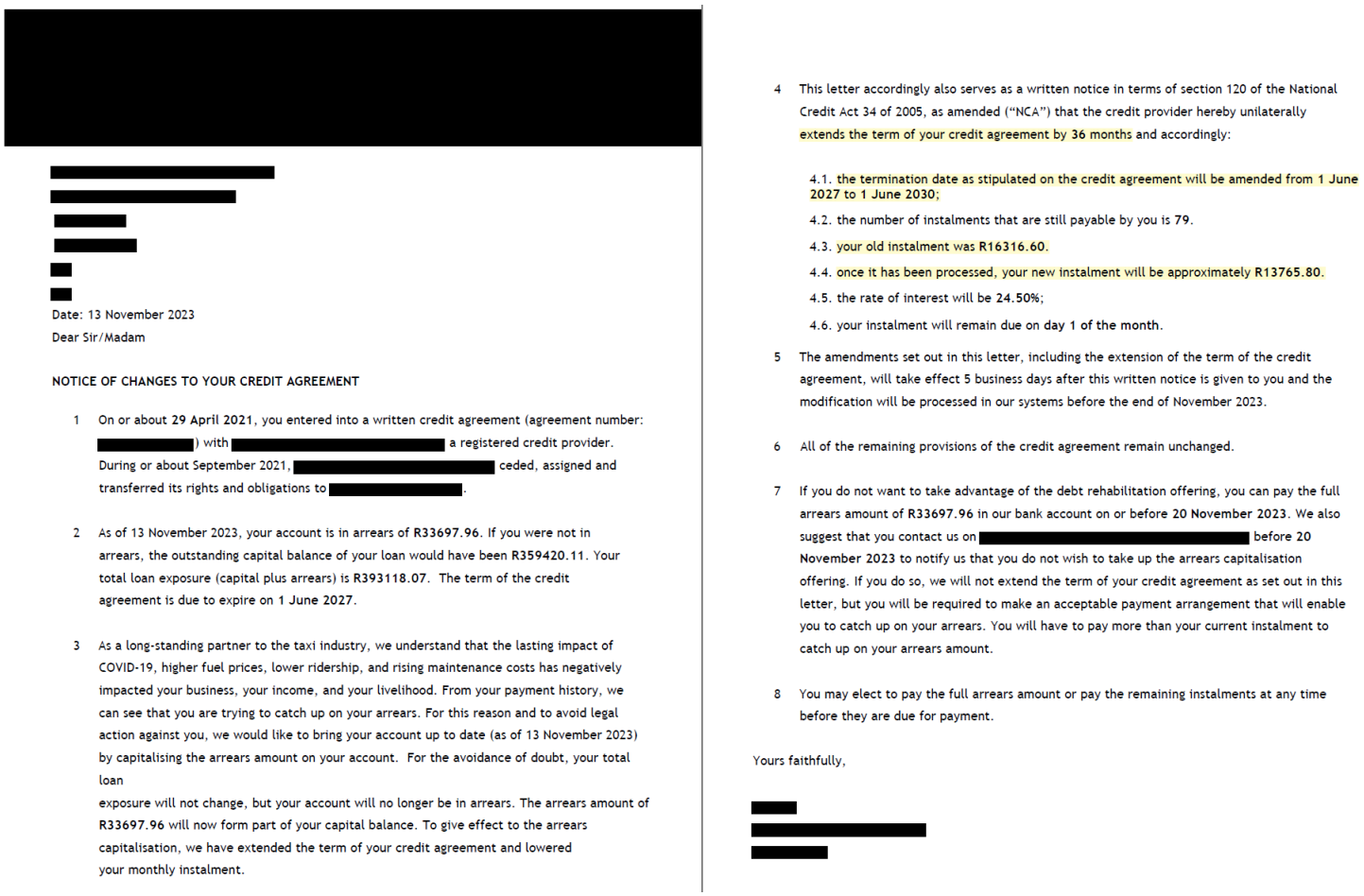
Notes: The gray lines indicates the official routes; the red shaded thick line represents the official route of Cape Town CBD to Wynberg (and back); the dots represents the coordinates of various vehicles determined to operate on the Cape Town CBD - Wynberg Route Jan'24 to Feb'25, with each color of the dot representing a different vehicle (total = 17 vehicles).

Figure A.4: Variance decomposition of baseline LTV



Notes: The figure presents results from an R-squared decomposition model (Huettner and Sunder 2012), which leverages the Shapley value framework to estimate how much of the variance in LTV is explained by different groups of covariates. The model vehicle attributes ((log) vehicle cost which is price paid by borrower at loan origination and dummies for vehicle's make and model, for the vintage, and for whether the engine used diesel or petrol as the fuel), borrower characteristics (dummies for borrowers' age in years and gender), features of the loan at origination (interest rate, LTV, and dummies for loan maturity in months at origination), and indicator variables for the remaining loan maturity in months as of the month preceding the experiment.

Figure A.5: Modification Communication Example



[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

Date: 13 November 2023

Dear Sir/Madam

NOTICE OF CHANGES TO YOUR CREDIT AGREEMENT

1 On or about **29 April 2021**, you entered into a written credit agreement (agreement number: [redacted]) with [redacted] a registered credit provider. During or about September 2021, [redacted] ceded, assigned and transferred its rights and obligations to [redacted].

2 As of 13 November 2023, your account is in arrears of **R33697.96**. If you were not in arrears, the outstanding capital balance of your loan would have been **R359420.11**. Your total loan exposure (capital plus arrears) is **R393118.07**. The term of the credit agreement is due to expire on **1 June 2027**.

3 As a long-standing partner to the taxi industry, we understand that the lasting impact of COVID-19, higher fuel prices, lower ridership, and rising maintenance costs has negatively impacted your business, your income, and your livelihood. From your payment history, we can see that you are trying to catch up on your arrears. For this reason and to avoid legal action against you, we would like to bring your account up to date (as of 13 November 2023) by capitalising the arrears amount on your account. For the avoidance of doubt, your total loan
exposure will not change, but your account will no longer be in arrears. The arrears amount of **R33697.96** will now form part of your capital balance. To give effect to the arrears capitalisation, we have extended the term of your credit agreement and lowered your monthly instalment.

4 This letter accordingly also serves as a written notice in terms of section 120 of the National Credit Act 34 of 2005, as amended ("NCA") that the credit provider hereby unilaterally extends the term of your credit agreement by **36 months** and accordingly:

4.1. the termination date as stipulated on the credit agreement will be amended from **1 June 2027** to **1 June 2030**;

4.2. the number of instalments that are still payable by you is **79**.

4.3. your old instalment was **R16316.60**.

4.4. once it has been processed, your new instalment will be approximately **R13765.80**.

4.5. the rate of interest will be **24.50%**;

4.6. your instalment will remain due on **day 1 of the month**.

5 The amendments set out in this letter, including the extension of the term of the credit agreement, will take effect 5 business days after this written notice is given to you and the modification will be processed in our systems before the end of November 2023.

6 All of the remaining provisions of the credit agreement remain unchanged.

7 If you do not want to take advantage of the debt rehabilitation offering, you can pay the full arrears amount of **R33697.96** in our bank account on or before **20 November 2023**. We also suggest that you contact us on [redacted] before **20 November 2023** to notify us that you do not wish to take up the arrears capitalisation offering. If you do so, we will not extend the term of your credit agreement as set out in this letter, but you will be required to make an acceptable payment arrangement that will enable you to catch up on your arrears. You will have to pay more than your current instalment to catch up on your arrears amount.

8 You may elect to pay the full arrears amount or pay the remaining instalments at any time before they are due for payment.

Yours faithfully,

[redacted]

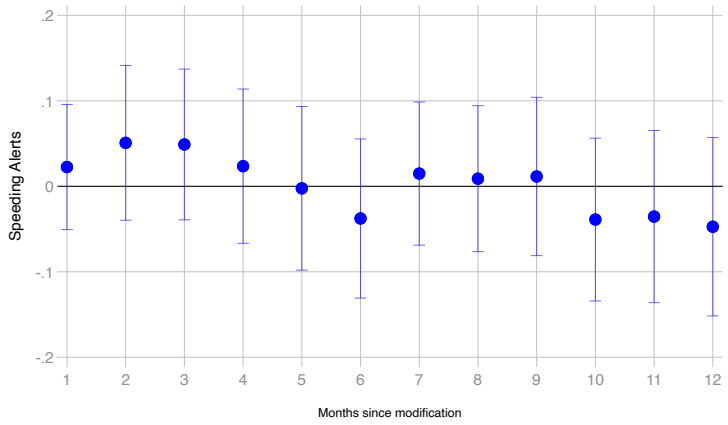
[redacted]

[redacted]

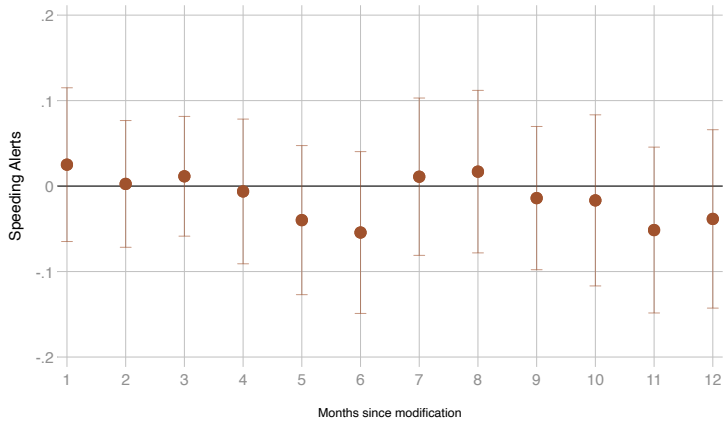
Notes: This figure shows the letter sent by the lender to the borrower in the experiment sample through messages. The example shows borrower receiving a payment reduction treatment. It provides details on modified payment terms as explained to borrowers in the modification agreement. Example terms are shown for a loan with a post-modification principal balance of R 393,118, payment reduction of R 2,500 (a 15.6 percent reduction), new loan term of 79 months (an extension of 36 months from a loan payoff date from 1 June 2027 to 1 June 2030), and unchanged interest rate of 24.50%. The main changes to the contract are highlighted in yellow by the research team for illustration. The lender name and any personally identifiable information for the borrower has been redacted.

Figure A.6: Impact of loan modifications on speeding alerts

(a) Interest write-down



(b) Payment Reduction



Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on minibus speeding alerts received above vehicle speed of 120 km per hr. The dependent variable is normalized to have mean zero and standard deviation 1. The top panel reports the monthly estimates for the interest write-down modification relative to the baseline modification. The bottom panel reports the monthly estimates for the payment reduction modification relative to the baseline modification. All regressions control for randomization strata-month fixed effects. Standard errors are clustered at the loan account level. Vertical lines indicate 95% confidence intervals.

Table A.1: Correlation across index component for main outcomes indices

Panel a. Minibus loan performance

	Repayment Index	1(current)	Arrears Amount	Arrears (Scaled)	
Repayment Index	1				
1(current)	0.756	1			
Arrears Amount	-0.920	-0.483	1		
Arrears (Scaled)	-0.918	-0.478	0.904	1	

Panel b. Credit Access Index

	Credit Access Index	1(has card)	1(has credit line)	1(has installment loan)	Number of credit lines
Credit Access Index	1				
1(has card)	0.842	1			
1(has credit line)	0.860	0.765	1		
1(has installment loan)	0.525	0.166	0.208	1	
Number of credit lines	0.825	0.640	0.651	0.227	1

Panel c. Borrowing Index

	Borrowing Index	1(non -zero debt)	Credit Utilization	Balance (Installment loans)	Borrowings (Credit Lines)
Borrowing Index	1				
1(non-zero debt)	0.763	1			
Credit Utilization	0.733	0.603	1		
Balance (Installment Loans)	0.547	0.211	0.0676	1	
Borrowings (Credit Lines)	0.640	0.233	0.296	0.188	1

Panel d. Repayment Index

	Repayment Index	1(any past due account)	Number of past due accounts	Overdue Amount	
Repayment Index	1				
1(any past due account)	-0.798	1			
Number of past due accounts	-0.880	0.644	1		
Overdue Amount	-0.725	0.272	0.469	1	

Panel e. Effort Index

	Effort Index	Distance Driven	Drive Time	Time in job (hours)	Total days driven
Effort Index	1				
Distance Driven	0.895	1			
Drive Time	0.944	0.844	1		
Time in job (hours)	0.951	0.759	0.858	1	
Total days driven	0.925	0.719	0.801	0.914	1

Notes: This table the correlations across the various components with our main outcomes indices.

Table A.2: Other Results on Repayment

	Repayment metrics ...			
	Total Payment	1(Payment in Full)	1(Under Payment)	1(Over Payment)
	(1)	(2)	(3)	(4)
β^{IW} :1(interest writedown)	-3,186.882	0.009	-0.002	-0.007
	[2,843.014]	[0.008]	[0.012]	[0.010]
β^{PR} :1(payment reduction)	-6,616.986**	0.003	-0.039***	0.036***
	[2,841.116]	[0.008]	[0.013]	[0.011]
Observations	3,186	3,186	3,186	3,186
R-squared	0.026	0.006	0.032	0.029
Control mean	123,654	0.03	0.91	0.06
p-value ($\beta^{IW} = \beta^{PR}$)	0.21	0.49	0.01	0.00
Strata f.e.	✓	✓	✓	✓

Notes: This table reports the impact on other repayment metrics. All regressions control for randomization strata fixed effects. Standard errors are clustered at the loan account level.

Table A.3: Robustness on Subsample Analysis: Effect on entrepreneurial effort

	Effort Index	
	(1)	(2)
Panel A. Z_i = Normalized baseline remaining maturity		
β^{IW+LE}: 1(interest write-down)	-0.659	-0.964
× 1(low baseline equity)	[0.732]	[0.917]
β^{IW+HE}: 1(interest write-down)	0.519	0.829
× 1(high baseline equity)	[0.770]	[0.969]
β^{PR+LE}: 1(payment reduction)	-0.465	-1.245
× 1(low baseline equity)	[0.735]	[0.927]
β^{PR+HE}: 1(payment reduction)	1.644**	2.405**
× 1(high baseline equity)	[0.754]	[0.936]
1(high baseline equity)	-2.769***	-3.033***
	[0.813]	[1.153]
Observations	3,178	3,178
R-squared	0.031	0.032
Control mean	-0.20	-0.20
$p[\beta^{IW+LE} = \beta^{PR+LE}]$	0.79	0.75
$p[\beta^{IW+HE} = \beta^{PR+HE}]$	0.13	0.09
$p[\beta^{IW+HE} = \beta^{IW+LE}]$	0.27	0.25
$p[\beta^{PR+HE} = \beta^{PR+LE}]$	0.05	0.02
Strata f.e.	✓	✓
1(interest writedown) × Z_i	✓	✓
1(payment reduction) × Z_i	✓	✓
Panel B. Z_i = Quartiles of baseline remaining maturity f.e.		
1(interest writedown)	-0.659	-0.421
	[0.732]	[1.139]
1(interest writedown)	1.178	2.583
× 1(high baseline equity)	[1.065]	[1.663]
1(payment reduction)	-0.465	0.494
	[0.735]	[1.151]
1(payment reduction)	2.109**	3.515**
× 1(high baseline equity)	[1.054]	[1.611]
1(high baseline equity)	-2.769***	-4.348***
	[0.813]	[1.211]
Observations	3,178	3,178
R-squared	0.031	0.039
Control mean	-0.20	-0.20
Strata f.e.	✓	✓
1(interest writedown) × Z_i	✓	✓
1(payment reduction) × Z_i	✓	✓

Notes: The table reports the robustness of heterogeneous treatment effects of interest write-downs and payment reduction on entrepreneurial effort by baseline equity. Panel A includes the two treatment group dummies interacted with normalized remaining maturity (mean 0 and standard deviation 1). Panel B includes the two treatment groups interacted with quartiles of remaining maturity. Column (1) presents the results from baseline specification. Column (2) presents the estimates after including the the two proxies of remaining maturity and their interactions with the two treatment group dummy variables. All variables are defined in Table 8. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

Table A.4: Robustness on subsample analysis after removing outliers: Effect on entrepreneurial effort

Outcome: Effort Index	Sample after ...	
	... removing remaining maturity in top and bottom deciles (1)	... removing remaining maturity $\leq$ 3 year or $\geq$ 6 year (2)
β^{IW+LE}: 1(interest write-down) $\times$ low baseline equity	-0.758	-0.655
	[0.814]	[0.796]
β^{IW+HE}: 1(interest write-down) $\times$ high baseline equity	0.562	0.498
	[0.871]	[1.096]
β^{PR+LE}: 1(payment reduction) $\times$ low baseline equity	-0.759	-0.648
	[0.818]	[0.809]
β^{PR+HE}: 1(payment reduction) $\times$ high baseline equity	1.818**	2.284**
	[0.829]	[1.042]
1(high baseline equity)	-2.490***	-2.519**
	[0.888]	[1.013]
Observations	2,534	2,185
R-squared	0.027	0.025
Control mean	0.46	0.38
$p[\beta^{IW+LE} = \beta^{PR+LE}]$	1.00	0.99
$p[\beta^{IW+HE} = \beta^{PR+HE}]$	0.13	0.08
$p[\beta^{IW+HE} = \beta^{IW+LE}]$	0.27	0.40
$p[\beta^{PR+HE} = \beta^{PR+LE}]$	0.03	0.03
Strata f.e.	✓	✓

Notes: The table reports the robustness of heterogeneous treatment effects of interest write-downs and payment reduction on entrepreneurial effort by baseline equity after removing the outlier values of remaining maturity. Column (1) presents the estimates after removing the remaining maturity in the top 10% and both 10% of its observed value in the experiment sample. Column (2) presents the estimates after removing remaining maturity less than or equal to three years, or greater than or equal to six years in the experiment sample. All variables are defined in Table 8. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.

B Simple Model Appendix

This appendix presents a stylized model to guide the interpretation of our empirical findings. The goal is not to fully characterize the optimal contract or the detailed dynamics of repayment, but rather to illustrate the key mechanisms that link debt obligations, effort, and default decisions in a tractable environment.

B.1 Baseline Case

We consider a simple two-period setting in which an entrepreneur chooses the level of effort e to exert in running a business. Effort generates profits in the first period according to a strictly concave function $f(e)$, with $f' > 0$ and $f'' < 0$. In the second period, the business is sold at a price that depends on first-period profits: $V(f(e))$, where $V' > 0$ and $V'' \leq 0$. The entrepreneur discounts future payoffs with a factor $\beta < 1$ and incurs a linear cost of effort. The entrepreneur chooses e to maximize total discounted value:

$$\max_e f(e) + \beta V(f(e)) - e \tag{B.1}$$

The first-best level of effort e^{FB} satisfies the first-order condition:

$$f'(e^{FB})(1 + \beta V'(f(e^{FB}))) = 1 \tag{B.2}$$

This condition captures the fact that effort is chosen to balance the marginal cost of effort with the marginal benefits, which include both current profits and the future valuation of the business.

B.2 Standard Debt Overhang Case

We now consider the case in which the entrepreneur faces a fixed debt burden consisting of a short-term payment D_1 and a long-term payment D_2. The present value of debt is $D = D_1 + \beta D_2$. The entrepreneur can default at any time. In this section, we assume that default leads to the full loss of the business: in other words, the entrepreneur loses all the equity in case of default. As we discuss in details below, this assumption does not affect our conclusion about optimal effort.

In this setting, the entrepreneur will repay only if the net value of continuing exceeds the debt burden. In particular, full repayment and first-best effort occur if:

$$\beta V(f(e^{FB})) - D \geq 0 \tag{B.3}$$

If this condition fails, the entrepreneur will default and exert lower effort e^{SB}, which is implicitly defined by $f'(e^{SB}) = 1$. This is the classical debt overhang problem, where overborrowing may lead to lower effort in equilibrium. We note that - if the condition above does not hold - the borrower also defaults in the first period and clearly continue to pay zero in the second period as well (i.e., $(P_1, P_2) = (0, 0)$).

As we discussed in the paper, a lender interested in improving repayments and solve the debt overhang problem should reduce the total size of the debt burden D. For instance, reducing D_2 while holding D_1 fixed may still be sufficient to relax the debt overhang constraint and restore first-best effort.

B.3 Debt Overhang under Alternative Assumptions

Before moving forward, we want to highlight how the specific results discussed in the model above depend on specific assumption about default cost.

(i) No Cost of Default. In the simple model above, we assume that the entrepreneur faces a high cost of financial distress, as she loses all equity in the event of default. While we believe this assumption is particularly relevant in our context, it is important to note that the debt overhang result still holds even in the absence of financial distress costs. In the model, this corresponds to assuming that the entrepreneur retains full equity in the business even after default. In this case, the qualitative result remains unchanged: the entrepreneur will still default and exert lower effort e^{SB} whenever $V(f(e^{FB})) - D_2 < 0$. [60]

(ii) General Default Cost. More generally, the result also holds if we consider a more general class of costs of financial distress. Suppose the entrepreneur faces:

- A fixed default cost ϕ, which the entrepreneur pays immediately after default happens. This parameter may capture the cost attached to having a default flag in the credit report, or the intrinsic benefits of paying on time;
- A equity loss γ, such that the entrepreneur will lose a portion γ of the equity in case of default. This assumption is consistent with a large empirical literature documenting the presence of a significant discount for assets sold during bankruptcy. Our baseline case assumes $\gamma = 1$.

Even in this richer setting, the basic mechanism remains: high debt burdens reduce the net value of continuation, leading to default and under-investment in effort. The precise cutoff for repayment depends on γ and ϕ, but the qualitative result—debt overhang induces lower effort—remains unchanged. The only qualitative change is related to repayment, and it is discussed in the next paragraph.

(iii) Repayment with immediate cost of default. Once $\phi > 0$, the entrepreneur may find it optimal to repay in the short run even if she anticipates defaulting later. In this case, short-run repayment allows her to delay the cost of default. For simplicity, we consider the baseline case (i.e., $\gamma = 1$). In this case, we still obtain the qualitatively equivalent result regarding effort: the entrepreneur will exert lower effort if and only if $V(f(e^{FB})) - D_2 < -\beta\phi$. However, the optimal

[60] This result is a direct consequence of limited liability: the entrepreneur captures upside gains only if the business remains solvent.

payment decision is different. When $V(f(e^{FB})) - D_2 < -\beta\phi$, the entrepreneur may sometimes still find optimal to pay in the short-run D_1 if default costs are high enough (i.e., $D_1 \geq (1-\beta)\phi$). The result is intuitive: if default costs are high, postponing default by one period may have significant benefits.

In general, we view $\phi > 0$ as a realistic assumption, reflecting reputational or legal costs associated with missed payments. In a more realistic multi-period model, the same effect can be generated because the entrepreneur may generate some flow value from running a business: in this case, even if the debt burden is too large in the long-run, she may find optimal to keep paying in the short-run to avoid repossession and keeping the business alive.

B.4 Debt Overhang with Liquidity Constraints

We now extend the standard model to incorporate liquidity constraints. Specifically, we assume the entrepreneur must cover operating costs C before making repayment in period one. That is, she must satisfy:

$$f(e) - C - D_1 \geq 0 \tag{B.4}$$

This constraint may prevent repayment even when the entrepreneur would find it optimal in expectation. In this setting, repayment and effort are jointly determined by both the continuation value of the business and short-run liquidity.

As discussed in the paper, the presence of the liquidity constraint implies that lower effort e^{SB} can be generated by either the traditional debt overhang constraint or liquidity issues. Formally, the entrepreneur will fail to repay and exert low effort if either the debt burden condition or the liquidity condition fails:

$$\beta V(f(e^{FB}) - D < 0 \ \vee \ f(e^{FB}) - C - D_1 < 0 \tag{B.5}$$

This expression highlights how debt overhang and liquidity interact in determining behavior.[61] Addressing only one constraint may be insufficient if the other remains binding.

The presence of liquidity constraints changes the optimal intervention. If the entrepreneur is only constrained by the overall debt burden, reducing D_2 can restore repayment and effort. But if liquidity constraints are binding, reducing D_2 alone may not suffice. In such cases, easing short-run cash flow pressures—e.g., by lowering D_1—is necessary to support both repayment and effort. However, also this type of intervention may not work: if both constraints are binding (i.e., liquidity constrained borrower with low equity), an intervention may be successful at inducing more effort and higher payments only if it lowers D_1 as well as the overall debt burden D.

[61] Also in this case, it is easy to incorporate $\phi > 0$, and therefore show that in some cases the entrepreneur may find optimal to pay even if she plans to default in the long-run because of strategic incentives.

C Machine Learning Approach to Heterogeneous Treatment Effects (Online Appendix)

In this section, we describe the machine learning (ML) methodology designed to estimate heterogeneous treatment effects in Section 5.4. The algorithm addresses a fundamental challenge in causal inference: predicting individual-level treatment effects when we observe each unit in only one treatment state. We motivate the methodology using recent application of machine learning approaches in the fields on medicine (Kent et al. 2020) and economics (Chernozhukov, Demirer, Duflo and Fernández-Val 2023). Our approach combines multiple machine learning methods through cross-validation to generate robust predictions of counterfactual outcomes. We describe our approach below.

The Fundamental Problem and Our Proposed Approach. In causal inference, fundamental problem is that the econometrician cannot observe both potential outcomes $Y_i(1)$ and $Y_i(0)$ for any individual i. To estimate individual treatment effects $\tau_i = Y_i(1) - Y_i(0)$, they must predict the unobserved counterfactual outcome. The machine learning methodology addresses aims to address this by training machine learning models exclusively on control group observations to predict $\hat{Y}_i(0)$, and the using cross-validation to prevent overfitting and ensure out-of-sample validity. In order to improve prediction accuracy, we consider four ML methods and then consider the median prediction across the four methods for each subject.

Data. Our analysis uses the following key variables. For the main outcome variable, we consider whether the borrower was current on their loan with the lender after month 6 of the experiment rollout (we refer to this as $\mathcal{L}_i$ in Section 5.4). We then consider a set of 28 borrower characteristic at baseline (Z_i) — either in the month before the experiment or the loan origination — as independent variables to the ML methods. These characteristics include loan characteristics (interest rate, maturity at origination, remaining maturity, LTV at origination, LTV at baseline, scaled arrears, share of loan principal outstanding, log of total loan amount outstanding with the lender, share of owed installment made in the past three months), borrower characteristics and demographics (age, gender, high or low debt-to-income, number of loans borrowers has with the lender), and normalized borrower credit bureau information (credit score, credit utilization, credit access index, borrowing index, access to a credit card, access to a credit line, whether the borrower has an installment loan, number of credit lines, whether the borrower has non-zero debt outside minibus debt, total balance on installment loans, total borrowings on credit lines). We consider two groups within our sample: control group (which is borrowers in our baseline modification arm), and treatment group (which combines borrowers in our payment reduction and debt reduction arm).

Machine Learning Methods We consider four distinct machine learning algorithms, each capturing different aspects of the relationship between covariates (X) and outcomes (y).

1. Elastic Net Regression

Elastic Net combines LASSO and Ridge regression penalties, providing both variable selection and coefficient shrinkage:

$$\min_{\beta} \frac{1}{2n}||y - X\beta||_2^2 + \lambda \left[\alpha||\beta||_1 + (1-\alpha)||\beta||_2^2\right]$$

This method is particularly effective when dealing with correlated predictors and performs automatic feature selection.

2. Gradient Boosting Machines (GBM)

GBM builds models sequentially, where each new model corrects errors from previous models:

$$F_m(X) = F_{m-1}(X) + \gamma_m h_m(X)$$

This ensemble method excels at capturing non-linear relationships and interactions between variables.

3. Principal Component Neural Networks (pcaNNet)

This approach combines dimensionality reduction through Principal Component Analysis with neural network prediction, making it effective for high-dimensional data while maintaining interpretability.

4. Random Forest

Random Forest creates multiple decision trees using bootstrap samples and random feature selection:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b(X)$$

This method provides natural handling of non-linearities and variable interactions while being robust to outliers.

Cross-Validation with Balanced Folds. Following Wager and Athey (2018), we create balanced folds that maintain the treatment/control ratio within each validation fold. This ensures that each fold contains representative samples from both treatment and control groups. Following recommendation form Hastie, Tibshirani and Friedman (2009), we use five folds to ensure that training sets maintain sufficient control observations for model fitting. This approach maintains the original study's treatment assignment structure.

Balanced fold creation and cross-validation algorithm. We now formally describe the algorithm. We begin by separating data into treatment (T) and control (C) groups. We then create

$K = 5$ folds for treatment group: $T_1, T_2, \ldots, T_K$, and for control group: $C_1, C_2, \ldots, C_K$. Finally, to create Fold_k, we combine the data from the *k-th* treatment and control fold ($\text{Fold}_k = T_k \cup C_k$).

For each fold $k \in \{1, 2, 3, 4, 5\}$, Fold_k serves as the test set while the remaining folds $\{1, \ldots, K\} \setminus \{k\}$, in combination, serve as the training set. We then train each of the four ML method using *only control observations* from the training set, and generate predictions for *all observations* — both control and treatment — in the test set. This procedure prevents overfitting by ensuring that the ML models never observe test data during training. Thus, by training only on the control observations maintains the validity of causal inference. Importantly, the cross-validation methodology ensures that all observations, including the control group, receive out-of-sample predictions.

Combining outcomes to arrive at final prediction. Finally, we use output from these four ML methods and then take the median prediction on each borrowers' likelihood of being current after six months, providing us with our prediction $\hat{\mathcal{L}} \equiv \hat{\mathcal{L}}(Z_i)$. Taking the median value across prediction has the advantage of being less sensitive to outlier predictions from individuals methods while being a simple non-parametric transparent combination rule. Timmermann (2005) shows that combining predictions using median statistic frequently dominates the single best learner in out-of-sample tests.