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 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 (e.g., 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 and with remarkably high frequency.[1] Those 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 2022, p.1060), even though lenders must reckon with such borrowers. The three existing randomized control trials (RCT) on loan modifications concern unsecured consumer lending (Dobbie and Song 2020; Aydin 2024; Burlando, Kuhn, Prina, and Wilson 2025), but collateralized lending is contractually distinct (e.g., Bester (1985); Berger and Udell (1990); Gertler, Green and Wolfram (2024); Collier, Ellis and Keys (2025)) and economically important in most settings, including ours (as detailed in Section 2).[2]

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.[3] The RCT is implemented by a publicly-traded lender in South Africa on a near-universe of its over 3,000 delinquent loans with $76 million in debt outstanding as of November 2023, 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 additional maturity extension that lowers the monthly installment amount) or *debt reduction* (an interest write-down that leaves monthly payment unchanged). Per standard practice in our setting, these mods are offered on an opt-out basis and yield take-up rates close to 100%, effectively shutting down selection channels.

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 small business

[1] The most pertinent quantitative estimate we know of on frequency is Bidder, Crouzet, Jacobson and Siemer (2024)'s finding that 37% of single-lender corporate loans from large U.S. banks are modified at some point.

[2] In the U.S., 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, was secured by a physical asset in 2023 (Federal Deposit Insurance Corporation 2023).

[3] Our focus on the role of liquidity constraints is similar in spirit to He and Xiong (2012), as we discuss below.

borrowers pledge their business' primary productive asset as collateral and face substantial liquidity constraints and repossession risk (as detailed in Section 2.2). GPS data on driving activity, from devices embedded in the financed vehicles per loan covenants, provides unusually granular and accurate measures of entrepreneurial effort.[4] Together with data on repayments to our partner lender and outside lenders, our study paints an unusually complete picture of how contract terms shape borrower behavior over a 12-month horizon.

Our model examines how liquidity constraints and strategic incentives jointly influence borrower behavior under collateralized debt. Given our access to effort data, we model strategic incentives as a debt overhang problem, since that class of models focuses on when and how high debt burden prevents borrowers from fully capturing the long-run returns from exerting or investing effort (Myers 1977). Standard debt overhang models predict that a substantial reduction in the overall debt burden is sufficient to restore repayment incentives and effort, but we show this prediction no longer holds if liquidity constraints are binding. The possibility that liquidity constraints affect *repayment* behavior has long been a consideration for empirical work on collateralized borrowing (e.g., Adams, Einav and Levin (2009); Ganong and Noel (2022); Low (Forthcoming)), yet that work does not consider effort responses and liquidity constraints are absent in standard debt overhang models.

We show that for liquidity-constrained borrowers, reducing total debt may still fail to prevent repossession, leading to inefficient business termination ex post and discouraging effort and repayment ex ante. In contrast, modifications that ease short-run cash flow pressures while leaving the total debt burden unchanged—such as our payment reduction treatment—can have a more immediate effect on effort and repayment, provided the debt burden is not too high. We also show that, when facing additional default costs beyond the future loss of the collateralized asset or business itself, borrowers with high debt burden may increase repayment but not effort when their available liquidity improves sufficiently. In short, our model highlights the likely importance of liquidity constraints and repossession risk as drivers of borrower behavior, and the importance of accounting for these factors when designing and targeting loan modifications (and ex-ante contracts, as we discuss below).

The crux of our model is a simple insight: if *either* strategic incentives or liquidity constraints can distort borrower behavior, then lenders (and policymakers) interested in changing behavior must seek to insure that *both* distortions are not binding. Functionally, liquidity issues introduce a second borrower incentive compatibility constraint.

This generates four sets of qualitative, testable predictions that are distinct from those produced by a standard debt overhang model. These predictions motivate our experimental design, and our focus on effort as well as repayment responses. Our empirical results are broadly consistent with

[4]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)).

each of them.[5]

First, we find no evidence that debt reduction raises effort or repayment on average, contrary to the standard model's prediction. While our confidence intervals for average treatment effects (ATEs) do not exclude economically meaningful gains, the null results cannot be attributed to a small treatment size: the debt reduction we study is larger than in prior work and, in percentage terms, exceeds our payment reduction treatment (16.7% vs. 10.8%), which yields significant positive ATEs. Finally, some borrowers do respond to debt reduction, as reflected in heterogeneous treatment effects (HTEs) previewed in our third testable prediction below.

Second, we do find evidence that payment reduction increases effort and repayment, although ATE estimates for the former are noisy. Payment reduction also reduces use of outside credit lines, further confirming the importance of liquidity *per se*.

Third, we find evidence that liquidity constraints and debt overhang interact in two ways predicted by the model. One way is that payment reduction is relatively effective at changing behavior for borrowers with relatively high equity in their vehicle at baseline. The second way is that debt reduction actually is effective for borrowers with less binding liquidity constraints at baseline.[6] These two HTEs further validate our model, and the second one also pushes against interpreting our lack of ATEs on debt reduction as stemming from a low-powered treatment.

Fourth, month-by-month treatment effects provide suggestive but noisy evidence that payment relief does dynamically induce repayment increases before effort increases, which is consistent with our model's prediction that repayment and effort responses can diverge when liquidity constraints and reposession risk interact in the presence of additional default costs.

Our results also have implications for lender modification strategies. At a coarse level, they validate lenders' apparent strong revealed preference maturity extensions (payment relief), which are not only more effective than debt writedowns but also much cheaper in NPV-terms.[7] More finely, they suggest a targeting pecking order of sorts: first target payment relief to borrowers with sufficient equity, then consider giving some debt relief to any remaining borrowers with sufficient liquidity, then consider giving both payment and debt relief to the residual group (i.e., to those with both low equity and low liquidity).[8]

Our work contributes to several literatures cited above, some of which focus on collateralized debt due to its economic importance and distinct features, and others that consider debt contracting and small business financing more broadly.

[5]We pre-registered most of the empirical tests motivated by our testable predictions. Section 5 details which tests are and are not pre-registered and why.

[6]Measuring baseline equity and liquidity constraints is non-trivial, and we devote considerable attention to measurement, and related inference issues, in Sections 5.2 and 5.3.

[7]For example, Bidder, Crouzet, Jacobson and Siemer (2024) find that 75% of single-lender commercial loan modifications change maturity while only 33% change debt owed (through changes to interest rate). For mortgages in the U.S., around 66% of loan modifications are maturity extensions (as reported by the Federal Housing Finance Agency (FHFA) in their most recent (2025, quarter 1) Foreclosure Prevention and Refinance Report).

[8]Modifying both maturity and total debt seems to be exceedingly rare in pratice, both in Bidder et al.'s data (only 3% of mods) and anecdotally. Indeed our partner lender deemed it infeasible due to various operational, funding, and accounting constraints.

One set of contributions is to work on the effects of collateralized debt modifications. Our novel sample, data, identification, and model are each key here. We consider voluntary debt modification by a lender, not the policy-driven modifications that have been the focus of related literatures thus far. Our sample includes borrowers who are *a priori* most likely to default strategically due to having very negative equity positions, in contrast to most prior work on mortgage modifications.[9] Our data on entrepreneurial effort, and accounting for potentially key externalities, permit inferences about efficiency along new margins. Our field experiment is, to our knowledge, the first one on modifications in a collateralized debt market, and the first one on modifications in a SME lending market.[10] Together with testable predictions generated by our theoretical model, our experiment generates the suggestive guidance on modification design and targeting that we previewed above, including the new insight that modifications should take both strategic incentives and liquidity constraints into account even if *default* has only a single trigger (e.g., even if liquidity is the primary driver of default as found in Ganong and Noel (2020, 2022), and Low (Forthcoming)). We also generate empirical evidence on potential externalities for policy consideration, finding no evidence of credit risk spillovers to other lenders or of changes in risky driving behavior that could affect other road users and insurers.

We also contribute to empirical work on the drivers of collateralized loan default, by identifying effects of changes in contract terms. We connect to prior work in several ways, starting with a setup that makes our model applicable to any stage of loan contracting. Empirically, most loans originated by our lender default at some point, and everyone in our experiment is brought current at the time of randomization. As such our empirical results identify effects on default, or at least re-default, in a sample of borrowers close to the margin of default. This complements prior work using randomized variation in collateral requirements on agricultural loans in Kenya (Jack, Kremer, de Laat and Suri 2023) and school fee loans in Uganda (Gertler, Green and Wolfram 2024), by randomizing debt amount and maturity given to SMEs. We also complement work on consumer vehicle and mortgage markets, which has used non-randomized sources of variation in contract terms and also examined the role of shocks to income or collateral value (e.g., Einav, Jenkins and Levin (2012); Foote and Willen (2018); Garmaise, Jansen and Winegar (2025)). We help connect work on drivers of default to the abovementioned work on modifications and other dimensions of collateralized debt contracting discussed below, with our novel insights on the contracting implications that arise when liquidity creates an additional borrower incentive compatibility constraint and effort and repayment responses can diverge.

We also contribute to the voluminous literature on incentive problems and debt overhang (e.g., Myers (1977); Lamont (1995); Hennessy (2004); Diamond and He (2014)), by adding liquidity constraints to the standard framework while accounting for repossession risk. Our focus on liquidity

[9] Per Ganong and Noel (2022, 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."

[10] 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).

constraints is similar in spirit to He and Xiong (2012), which theoretically models the debt market for large corporations and highlights how market-level liquidity shocks can generate credit risk and exacerbate debt overhang problems. Our focus on the role of repossession risk builds on theory and empirics identifying incentive effects of collateral in various settings (Bester 1985; Chan and Thakor 1987; Tirole 2006; O'Malley 2021; Jack, Kremer, de Laat and Suri 2023; Gertler, Green and Wolfram 2024; Collier, Ellis and Keys 2025). Our framework challenges the standard intuition that more stringent collateral requirements necessarily improves borrower incentives, by showing that repossession risk, when induced by liquidity constraints, can reduce effort in a manner similar to traditional debt overhang. The intuition is straightforward: if liquidity constraints can trigger the loss of a critical business asset and the inefficient termination of the firm, entrepreneurs exert less effort ex ante.

We also contribute to work on how financial frictions shape entrepreneurs' decision making (e.g., Kerr and Nanda (2011); Buera, Kaboski and Shin (2015)), including equipment financing (e.g., Ma, Murfin and Pratt (2022)), by focusing on how liquidity constraints mediate effort responses to contract incentives. Our linked data on financing and effort, unusual in the study of closely-held businesses, is key here. Many studies have of course examined whether and how liquidity constraints constrain small firm expansion, in developing countries and elsewhere. That work includes examination of the marginal returns to additional units of capital and labor (e.g., de Mel, McKenzie and Woodruff (2008, 2019); Banerjee and Duflo (2014)).[11] Our contribution is to show that liquidity constraints can depress utilization of inframarginal units of capital and labor, thereby suggesting that liquidity constraints contribute to the increasingly well-documented slack in input utilization (Bassi, Muoio, Porzio, Sen and Tugume 2022; Walker, Shah, Miguel, Egger, Soliman and Graff 2024).

In sum, our study is novel in several respects. We enrich a standard debt overhang model with liquidity constraints, repossession risk, and their interactions with each other and standard debt overhang effects. This enriched theoretical framework generates four distinct predictions that we test empirically. We consider voluntary debt modification by a lender, not the policy-driven modifications that have been the focus of related literatures thus 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 and help connect the various abovementioned literatures.

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

[11] See also Aydin and Kim (2025), which implements a RCT to examine how changes in debt capacity affect firms' borrowing and investments.

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 (Panel (a), 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).[12]

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 (Panel (b), Figure A.1), 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.

Services on a given route are governed by one of about 1,200 informal taxi associations. Associations are membership-based, with membership comprised of firms licensed to operate on a given route. Through strictly enforced rules, associations control entry through permitting, and further limit competition by limiting each driver to a single primary route, setting pricing for the entire length of the route, and only rarely changing prices. Each association controls one or more routes, and each route is controlled by one association. Casual empiricism suggests that associations optimize as monopsonists; in any case, minibus taxi operators 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 A.4 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

[12] 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.

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 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.[13] 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). Indeed, R 1.87 trillion of household debt and R 0.4 trillion of small business debt in South Africa 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).

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% 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% of the loans and 68.4% 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.

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% 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 range 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.[14] Our lender rejects approximately 65% 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 is common even among borrowers in good

[13]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), and in the minibus sector in Kenya studied in Kelley, Lane and Schönholzer (2024).

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

standing (Figure A.5).

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%. 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.[15] Thus far, the lender has primarily used GPS to locate vehicles in the event that a repossession of vehicle is warranted. We use this data to measure borrower's entrepreneurial effort (as detailed in the next sub-section).

Figure A.6 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 600,000 range, with a median loan size of approximately R 485,000 (average loan size of R 487,000 and s.d.= R 67,000). 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 (s.d = 10 months). There are no prepayment penalties, yet prepayment is uncommon; e.g., only 3.5% 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 A.7 shows the distribution of loan-to-value (LTV) at origination.[16] The debt service on these loans is substantial relative to income, as illustrated in Panel (b) of Figure A.7, 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 income at baseline (median = 0.42 and s.d. = 0.31).[17]

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 A.6 shows that the contract interest rate varies between 13% and 28.5%, with the average rate being 21.6% (s.d. = 3.5%). The share of loans 90+ days delinquent stood at 18% at the start of 2021, gradually increasing to about 22% by mid-2023.

These default rates are high despite mandatory property and liability insurance on the collat-

[15] 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.

[16] 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.

[17] We estimate the monthly income for operators by multiplying our estimate of monthly trips made by the operator by an average income of R 112 per trip. To arrive at the average income of R 112 per trip, we first use the average passenger trip fare of R 17, 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 204. From this we subtract the marginal cost of 45% per trip which includes fuel costs, toll costs and other associated costs.

eral,[18] vigorous collection efforts by the lender, and several incentives to repay for borrowers.[19] 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.

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. In general, we pre-registered monthly and 12-month versions of each outcome. For stock variables, like loan performance or balances, the 12-month versions are defined as the snapshot of the measure at the 12th-month. Appendix Section C.1 provides details on construction of these measures and choices regarding data cleaning based on our pre-registered rules. Appendix Table A.1 documents the pairwise correlations separately for each of the indices and their associated underlying components defined below.

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 normalized values of three equally-weighted component measures: (1) a delinquency indicator, defined as having R 100 or more past due after the payment due date; (2) (negative of) arrears amount; and (3) (negative of) arrears amount scaled by the required monthly payment.

Credit Bureau Outcomes. We use data from Experian, one of the major credit bureaus in South Africa,[20] to help measure outside borrowing, repayment on outside debt sources, total lever-

[18]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.

[19]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.

[20]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

age, and overall credit access for estimating various treatment effects of loan modifications on outside debt. For example, Section 5.1.2 presents estimates of randomized loan modifications on borrowers' credit access and borrowing from outside debt sources. And Section 5.3 presents estimates of heterogeneous treatment effects by borrowers' likelihood of being less liquidity constrained ex-ante.

Measuring entrepreneurial effort. We use driving data to measure effort, the key borrower choice variable in debt overhang models. Such models, including ours in Section 3, conceptualize effort broadly as an activity to produce income that could in turn be used to service debt.

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, implicitly, the resulting income generation).

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 non-work trips: (1) distance driven in kms.; (2) number of days worked in the month (i.e., number of days with non-zero trips were made); and (3) 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).

Observational data shows a very strong association between effort reductions and sharp declines in repayment performance. Borrowers who stay current maintain stable levels of driving per our effort index, while borrowers who fall behind do so in tandem with sizable reductions (about 0.3 standard deviations on average) in driving (Figure A.8).

Conceptually, the association between driving and income generation is likely even stronger than between driving and repayment (see Sections 3.5 and 5.4 for theory and empirics on when effort and repayment diverge). Driving is minibus taxi firms' only income-generating activity. It of course requires both labor (the driver) and capital (the vehicle). That is, the key inputs are strong complements (perhaps even in the Leontief sense): labor utilization requires vehicle utilization, and vice versa. As such, our effort measure spans utilization of the borrower's key inputs, which aligns with how debt overhang models conceptualize income generation, at least in the short-run. One also expects that more productive firms (e.g, firms with a more reliable vehicle) at any point in time will drive more at any point in time, and that those higher marginal products of input utilization will translate into more income. As such our effort measures likely reflect ongoing capital investment to at least some extent (e.g., maintenance required to keep the vehicle running), although the possibility of deferred maintenance does complicate the mapping from our data on input utilization to income over longer horizons.

Another attractive feature of our effort measure is that it captures margins of business activity over which borrowers have the most control, and likely also the most potential elasticity with

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.

respect to changes in debt contract terms. Recall that individual firms have no control over prices, and little control over where they drive. Consequently, when and how much they drive are key margins of adjustment. And there are ample reasons to think there is room for adjustment on the margin: fixed costs of capital and labor acquisition, institutional features of our product market (e.g., queuing up for passengers), and empirical evidence of slack in input utilization (Walker, Shah, Miguel, Egger, Soliman and Graff 2024) spanning decades and countries (Taubman and Gottschalk 1971).

In sum, our effort measure maps well into the theoretical object of interest, both empirically and conceptually.

We are also interested in risky driving, as a potential source of negative externalities (Section 5.5). We again construct a standardized summary index by averaging the following equally-weighted component measures, each aggregated to the monthly level following our pre-registered rules described in Appendix Section C.1: (1) number of accidents (based on insurance claims filed with the Lender);[21] and (2) number of instances speeding over 120 km per hour.

3 Debt Overhang Models Without and With Liquidity Constraints

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. Although highly stylized, the framework captures the hypothesized mechanisms we aim to test empirically. Appendix B works through some extensions that leave the qualitative insights unchanged.

3.1 Preliminaries: Effort choice without debt

To start, we consider a simple two-period setting in which an unlevered entrepreneur chooses the level of effort e to exert in running a business in the first period. As discussed in Section 2.3, e summarizes all business inputs, in keeping with, for example, corporate finance's focus on investment broadly defined. e accordingly determines first-period profits, through a standard strictly concave production function $f(e)$, with $f' > 0$ and $f'' < 0$. In the second period, the business is sold at a price that depends on the first-period profits: $V(f(e))$, where $V' > 0$ and $V'' \leq 0$.[22] This setup reflects the importance of effort broadly defined: an entrepreneur's current actions affect both the immediate payoff from operating the business and its continuation value in the future. The entrepreneur discounts future payoffs with a factor $\beta < 1$ and faces a linear cost of effort, and thus chooses e to maximize the total discounted value of current and future returns minus the cost

[21] As noted above, insurance is required per loan convenants and 92% of the vehicles in our sample are insured with the Lender.

[22] For instance, an interesting special case (which is empirically relevant in many corporate valuation applications) is where V is the multiple of recent earnings at which a business can be sold (i.e., V is just a linear function).

of effort:

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

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

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

This condition highlights that the entrepreneur of course chooses effort to equate its marginal cost to its marginal benefit, with the latter including its effects on both immediate profits and future valuation.

3.2 Standard debt overhang: no liquidity constraints

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.[23] In our context and many others, D is collateralized by and finances a productive or otherwise valuable asset (a firm's minibus taxi in our setting).

The entrepreneur retains the option to default in either period (i.e., to not pay D_t), at the cost of losing V. For now we make two simplifying assumptions about the cost of default. One is that the loss of V entails the loss of all equity in the business, including any equity in its vehicle (this tends to hold in our setting, due to repossession costs that pass through to the borrower; regardless, Appendix B shows that our model's results hold under more general formulations). Another simplifying assumption is that there are no additional costs of default (we relax this assumption in Section 3.5). This loss of V is directly tied to the importance of *repossession risk* in our setting and many others: borrowers cannot default, thereby losing their financed and pledged asset, and still operate the business. In other words, the continuation value $V(f(e))$ can be realized if and only if the borrower remains in good standing on the loan.[24]

The entrepreneur now 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. We assume the borrower first decides on the effort level e, before making the sequence of payment decisions P_1, and then P_2. This simple framework delivers the classical debt overhang effect, as in Myers (1977): if D is too high, incentive compatibility is lost because the entrepreneur no longer captures sufficient returns to their effort. Specifically, the entrepreneur decides to exert first-best

[23] To be clear, this is not a model of optimal lending, and we place no structural restrictions on D_1 and D_2. One way this maps to loan modification situations is if the loan was originated under different conditions (e.g., different expectations about future cash flows) which no longer hold due to a subsequent shock. Another way this maps to loan modification situations, including ours, is if a nonperforming loan is reset to current status by capitalizing arrears, and the lender is unsure about the optimal modification contract. More generally, this setup captures any stage of the contracting game where the lender is unsure about the optimum and interested in how changes to the contract or the borrower's business affect the borrower's behavior.

[24] In contrast, default on an unsecured loan is less likely to preclude continued operation of the business, given unsecured debtor protections (e.g., bankruptcy options for borrowers and limited recourse for lenders) and substantial costs of trying to enforce contracts through the legal system.

effort and repay in full if and only if the discounted continuation value exceeds the debt burden:

$$\beta V(f(e^{FB}) - D \geq 0 \tag{1}$$

When this condition fails to hold, effort falls below the first-best level to e^{SB} (which is implicitly defined by $f'(e^{SB}) = 1$), since the entrepreneur no longer fully internalizes the continuation value.

In this standard debt overhang framework, a reduction in debt obligations D can improve both repayment and effort. (Moreover, those improvements move in tandem, as we detail in Section 3.5.) Importantly, what matters is the overall size of the reduction to D, not how it is distributed between short- and long-term obligations. For instance, a lender could relax the debt overhang constraint by reducing the long-term obligations D_2 while keeping the short-run payment D_1 unchanged, or vice versa. This equivalence will no longer hold once we introduce a liquidity constraint, as we do next.

3.3 Incorporating liquidity constraints

We now add a liquidity constraint, which is absent from standard debt overhang models despite its evident importance in our setting (see Section 2 for details) and many others (e.g., Adams, Einav and Levin (2009); Ganong and Noel (2022); Low (Forthcoming)). The liquidity constraint introduces an additional driver of default, and the entrepreneur's decisions are now shaped by the combined effects of the standard model's strategic concerns and short-term cash flow limitations. This mechanism amplifies the repossession risk problem, as the borrower may be effectively forced to shut down the business even when its continuation value exceeds the outstanding liabilities.

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.[25] The entrepreneur now exerts low effort e^{SB} if *either* the overall debt burden is too large (as in equation (1)) *or* the liquidity constraint is binding:

$$\underbrace{\beta V(f(e^{FB})) - D < 0}_{\text{Debt overhang constraint}} \quad \vee \quad \underbrace{f(e^{FB}) - C - D_1 < 0}_{\text{Liquidity constraint}} \tag{2}$$

The intuition is that liquidity constraints effectively reduce the returns to effort, as they can lead to inefficient liquidation of the business: the entrepreneur no longer reaps the future benefit of today's effort e increasing tomorrow's valuation V if C precludes making the payment D_2 require to realize V.[26]

[25] Our framework thereby assumes that entrepreneurs are constrained to use only the cash generated by their business (net of C). Although this assumption may be overly restrictive in some settings, it holds to a first approximation in many settings, including ours (as documented in Section 2) and even in large swaths of wealthier countries (e.g., consider macroeconomics' recent focus on the high prevalence of "hand-to-mouth" households, and the use of a hard borrowing constraint assumption in many literatures). Moreover, our qualitative findings likely hold even if some marginal financing is available, as long as it is sufficiently expensive.

[26] 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.

This simple enrichment of the standard debt overhang problem immediately produces two striking new implications.

One is that the threat of collateral repossession no longer unambiguously improves incentive alignment between lender and borrower, as in most prior work on the incentivizing effects of collateral. Now the risk of repossession due to liquidity constraints– the risk of a state-of-the-world where the borrower, from a strategic perspective, is incentivized to repay and continue operating the business, but cannot repay– can dampen effort and repayment.

The second new implication is that the lender now has two borrower incentive compatibility constraints to consider, and this changes contracting strategy. Generally, the lender should consider whether *both* constraints are satisfied, since *either* one binding can be sufficient to trigger default. More specifically, the lender now has less assurance, relative to the standard debt overhang framework, that reducing D_2 will improve repayment (and effort). Conversely, reducing D_1 may be necessary. In fact reducing D_1 may be sufficient to achieve incentive compatibility for a *solely* liquidity constrained borrower, even if D remains unchanged.

3.4 Distinct testable predictions

The two simple models with debt presented above imply contrasting predictions about the impacts of different loan modifications on borrower behavior. These predictions motivate our experimental design and related empirical tests, and guide interpretation of test results, and so we summarize and clarify them here for subsequent reference in Sections 4 and 5.

Prediction 1. *In the standard debt overhang model, debt reduction will increase effort and repayments. Conversely, in a model that also incorporates liquidity constraints, debt reduction will not necessarily increase effort and repayments.*

As discussed above, in the standard model it is only high debt burden D that potentially reduces borrower incentives to exert effort and repay. A sufficiently large debt reduction thus improves both margins. Once liquidity constraints are incorporated, however, reducing D may prove ineffective: a borrower with limited cash-on-hand may still be unable to make payments, and the prospect of that liquidity-induced default reduces the borrower's incentives to exert effort and repay.

Prediction 2. *In the standard debt overhang model, reducing short-run payment obligations without affecting the present value of debt has no effect on effort or repayment. In contrast, when liquidity constraints are present, reducing short-run payments may stimulate higher repayment and greater effort.*

As discussed above, in the standard debt overhang model the only relevant quantity affecting borrower decisions is the present value of the debt D.[27] Hence, lowering D_1 affects behavior only if it changes D. But if liquidity constraints bind, then reducing the short-term payment (e.g.,

[27] We are glossing over different NPVs for the borrower and lender, due to different discount rates, because in our setting both discount rates are high enough to make the difference between them immaterial for our qualitative predictions.

by extending maturity to lower the monthly payment as is commonly done in modifications) can increase repayment and effort, even if the present value of the debt D remains unchanged. This response reflects that, for some borrowers, default is driven purely by liquidity.

Prediction 3. *Liquidity constraints interact with the standard debt overhang problem to shape borrower responses to contract terms. E.g., payment reductions will be more effective for borrowers with substantial ex-ante equity, while debt reductions will be more effective for those whose liquidity constraints are less severe.*

This prediction follows directly from the presence of two potentially binding incentive compatibility in equation (2). Lowering payments relaxes liquidity constraints and increases effort for borrowers who do not face a binding debt overhang constraint. Similarly, reducing the debt burden D is more likely to be effective for borrowers who do not face a binding liquidity constraint. Conversely, if both constraints bind, modifications that treat only liquidity constraints or D will not be effective, with the latter prediction implicit in the second half of Prediction 1.

3.5 When effort and repayment diverge, and an additional prediction thereon

As we discuss in Appendix B, the entrepreneur's effort and repayment decisions endogenously move together in the two models with debt presented above: they are qualitatively interchangeable. But it turns out that this tight link depends on the assumption of no additional default costs beyond losing the continuation value V.

We illustrate this in Appendix B by adding a common specification of additional default costs, specifically an immediate fixed default cost ϕ.[28] This extension leaves Predictions 1-3 qualitatively unchanged but does introduce a new dynamic: in some cases, a borrower may decide to repay while staying at a second-best effort level. The intuition is that the benefit of postponing the immediate fixed cost of default – $(1-\beta)\phi$ – may exceed the cost of continuing to make the regular payment D_1, thereby inducing short-term repayment even if the borrower plans to strategically default in the long run. This mechanism operates only when borrowers are not liquidity constrained; if the constraint binds, then they effectively have no choice over repayment. As such we now have:

Prediction 4. *If there are significant immediate costs of default in addition to lost continuation value, repayment and effort responses may diverge. This mechanism arises only when borrowers are not liquidity constrained.*

Taking this prediction to the data helps address two important questions and thereby helps illustrate the value of effort data. First, it can help identify whether additional default costs are important driver of borrower behavior, which is an important question for quantitative modeling, policy, and mechanism design (e.g. for credit reporting). Second, it is essential for addressing the question of whether repayment behavior is a summary statistic for effort. As mentioned above, in

[28] This specification is meant to capture stigma, stress, and/or adjustment costs (e.g., moving in the mortgage setting, finding different work in our setting). One can think of it as also capturing the NPV of a flow of future costs from default; e.g., lost relationship value with the lender and/or reduced access to credit more generally.

some cases a borrowers may find optimal to pay in the short-run to delay costly default, even if they are exerting second-best effort. Accordingly, improved repayment does not necessarily indicate the absence of debt overhang. More broadly, when the two actions diverge, effort (which affects real output) is likely a better social welfare proxy than repayment (which is a transfer).

3.6 Empirical research design implications

The four predictions developed above motivate our research design and empirical tests. In design terms, each of the predictions motivates comparing effects of a modification that reduces debt to one that alleviates liquidity constraints while leaving the total debt obligation unchanged. They also highlight the value of doing so in a setting where one can measure effort as well as repayment. In terms of specific empirical tests, Predictions 1 and 2 suggest estimating average treatment effects (ATEs) of the two different approaches to loan modification, while Predictions 3 and 4 suggest three key tests for heterogenous treatment effects (HTEs) that we detail in Sections 5.2, 5.3, and 5.4.

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.[29] 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 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. 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.[30] Anecdotally, other minibus taxi

[29] 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.

[30] 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.

lenders typically take a similar approach to modifications and other forms of debt restructuring were less common.

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.

Despite being standard practice, the baseline mod does not seem particularly attractive from either a theoretical or empirical perspective. Theoretically, it neither alleviates liquidity constraints nor reduces debt burden.[31] 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 the new loan that resulted from any desired debt reduction on any loan contract had to be at least 14%.[32] The mechanics are as follows: in November 2023, we worked with the lender to identify 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).[33] The randomization conditions on eight strata pertinent for the constrained randomization and heterogeneous treatment effect estimation.[34]

[31] Modifications do potentially change repayment incentives through reporting to credit bureaus, although any effect is likely modest for most borrowers. The modification itself 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.

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

[33] 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.

[34] Specifically, we stratify on all combinations of indicators for: whether the loan would receive an above-median

The constrained randomization produced an actual treatment reduction lower than the intended one of 20% in 93% of cases in the debt reduction arm and 72% 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 debt reduction modification arm. The last row corresponds to the payment reduction modification arm. Figure A.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.

Table 2: Illustrative Example of Randomized Treatments

Treatments		Loan characteristics			
Debt Reduction (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 debt reduction modification arm. Row 3 corresponds to the payment reduction modification arm. Column (1) shows the average reduction in interest rate (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.

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.10 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% in the control arm, 1.3% in the payment reduction arm, and 1.2% 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

interest write-down amount if assigned to that arm × whether the loan would receive an above-median reduction in monthly payment if assigned to that arm × above-median baseline debt-to-income ratio.

several other criteria.[35] For each of these loans we then estimated the what the actual modification 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. The face value of the total debt outstanding for the sample was R 1.4 billion.

Table A.2 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% of borrowers in the baseline group are men, are 51 years old and have about 1.37 active loans with the lender. 69% of the borrowers took out loan with the lender to finance a new 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%, the annual monthly payment is R 12,996 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 debt reduction and payment reduction treatments, respectively, on the baseline characteristics, conditional on randomization strata fixed effects. The prevalence of significant correlation between the number of deals that borrower has with the lender and assignment to the debt reduction (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 control 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-D is 0.53 for the debt reductions (column 2) and 0.81 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 debt reduction and monthly payment reductions as follows:

$$y_{it} = \alpha + \beta^{DR}\ 1(\text{debt reduction})_i + \beta^{PR}\ 1(\text{payment reduction})_i + \Gamma_t'\ \alpha_{s(i)} + \epsilon_{it} \tag{3}$$

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 loan level which is our unit of randomization.

We begin our estimation by quantifying the first-stage effects on contract terms. Table 3 does this by estimating equation 3 on contracts terms in the 12-month period after the loan modifiction. These estimates capture the net effects of the randomization constraints (described in Section

[35]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; or (v) had a vehicle with GPS device that stopped reporting telematics data.

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 percentage point (s.e. = 0.095%) lower in the debt reduction group compared to the baseline modification control group (which has an average interest rate of 24%). It is unchanged in the payment reduction group, as intended. Column 2 shows that the monthly installment is lower by R 1,392 (s.e. = R 76.5) in the payment reduction group (control mean = R 12,784). It is unchanged in the debt reduction 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 (s.e.= 0.67 months) in the debt burden reduction arm (row 1), and increases by 19.25 (s.e.= 0.89 months) in the payment reduction group (row 2).

The lender committed to leave the randomly assigned modifications in place for at least 12 months (hence our pre-registration of a 12-month horizon for estimating treatment effects), and month-by-month first-stage estimates confirm that effects on the key contract terms are largely unchanged over this horizon (Figure A.11).

These loan modifications are economically significant (Table 3). On average, borrowers receiving a payment reduction see their monthly required debt installment shrink by the above-mentioned %. Over a year, this corresponds to about R 20,000 in lower payments, or about 6% of the average annual national income.[36] By construction, this intervention is NPV-neutral for the borrower when discounted at the loans' average baseline APR 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 borrower's perspective, we estimate that the intervention reduces loan NPV by about R 53,000.[37] This reduction is large in absolute terms (R 53,000 is about two months' income for a typical firm in our sample) and relative terms (a 12% reduction relative to the mean baseline D = (outstanding principal + arrears)). It is also large, or at least comparable to, modifications studied in prior work. Dobbie and Song (2020) report that the credit card RCT they examine generates a *maximum* interest reduction of about 11.8% of the lender's NPV (presumably this would be substantially in terms of the borrower's NPV and average NPVs). Aydin (2024) does not report treatment size estimates in NPV terms, but we infer that the mean interest rate reduction is about one-fourth (24%) of the baseline APR. The comparable estimate in our RCT is 27%. In the quasi-experimental literature on consumer mortgage modifications, Ganong and Noel (2020) studies a policy intervention that generates a nominal reduction in loan balances of about 20% (no present value adjustment reported).

5 Results

This section analyzes intent-to-treat (ITT) effects of loan modifications using specifications based on equation (3), with a focus on implementing tests of the model predictions laid out in Section 3.4.

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

[37] The lender's NPV cost is higher, at around R 83,000, when discounted at its cost of funds

We begin by presenting average treatment effects (ATEs) on repayment and effort, and then test for heterogeneous treatment effects (HTEs) by proxies for strengths of debt overhang and liquidity constraints. We conclude with estimates of effects on some potentially key externalities.

5.1 Average Treatment Effects

5.1.1 Minibus Loan Performance

ATE estimates of effects on minibus loan repayment provide a first test of our model's Predictions 1 and 2. Per our pre-registered specifications, Table 4 presents estimates on loan performance snapshots taken 12-months after treatment assignment, and Figure 1 presents month-by-month estimates. Recall from Section 2 that we selected the loan performance measures in consultation with lender to capture its key metrics of loan performance, and normalize each of them such that TE estimates are in standard deviation (SD) units (see Appendix Section C.1 for details on variable construction).

Starting with Prediction 1, the first row of Table 4 shows no evidence that debt reduction changes repayment behavior. The point estimates are each small (0.02 SD or less), and the maximum effect size contained in the confidence intervals is about 0.1 SD. This pattern is inconsistent with the standard debt overhang model's prediction that substantial debt reduction should induce improved repayment. It is thus a first piece of evidence from TE estimates suggesting that the standard debt overhang model is missing something.

Turning to Prediction 2, the second row of Table 4 shows evidence of substantial improvement in repayment performance from payment reduction. E.g., our summary index improves by 0.13 SD (s.e. 0.04). This is another piece of evidence that the standard debt overhang model is missing something, and the first piece suggesting that our model with liquidity constraints better captures the reality of our setting.

Figure 1 plots month-by-month versions of Table 4 for the minibus loan repayment summary index, and it yields similar inferences. There is no evidence that debt reduction improves repayment in any month, while payment reduction improves performance in every month except for perhaps the first month of the intervention.

5.1.2 Additional results on minibus loan repayment, and on outside liquidity

Before turning to our estimates of ATEs on effort, we present some additional ATEs on borrower repayment behavior that help characterize the role of liquidity constraints. The additional tables and figures discussed here report estimates for both modifications (as in our main tables and figures), but we focus our discussion here on payment reduction, since the additional estimates on debt reduction here straightforwardly corroborate our inference of its ineffectiveness.

Appendix Table A.3 considers ATEs on additional measures of minibus loan repayment. We did not pre-register these and have added them in response to presentation comments.

Panel A unpacks our main result that payment reduction improves the summary index of the

lender's key repayment metrics, which emphasize avoiding delinquent states. Columns 1-4 suggest that the improvement is driven by decreases in late payments and increases over-payments (relative to the new, lowered installment amount), not by any increase in paying the exact new installment amount.[38] This is consistent with our payment reduction design intent to give borrowers flexibility to pay somewhat less than their original installment amount, and the accompanying prior that not every borrower would exercise that option. It accordingly suggests heterogeneity in the degree to which liquidity constraints bind (see Section 5.3 for more evidence on this), and indeed Columns 4 and 5 suggest that many borrowers' preferred repayment amount lies between the pre-experiment and post-payment reduction required installments. Panel B shows that payment reduction reduces the amount repaid in the 12th month (Columns 1 and 2), and cumulatively over the 12 months (Columns 3 and 4).

Taken together, Panels A and B suggest that payment reduction generates a tradeoff for the lender: it improves the likelihood that a borrower remains current, but reduces to the total amount repaid relative to the control group over our 12-month horizon. Although the lender was of course hoping there would be no tradeoff, it was neither surprised nor concerned about the finding there is one. There are several reasons for this view, starting with the ancillary benefits of prioritizing current repayment status: it aligns with funder, regulator, and analyst preferences, subject to the constraints on maturity length that our payment reduction adheres to (as detailed Section 4) and are designed to ensure sufficient repayment amounts at any point in time. One underpinning of this view is the strong prior that current status (and even paying anything at all) bodes well for future full repayment. This prior aligns with our model's insight that current status (or, roughly conversely, lowering the probability of defaulting) reduces the present value of the debt from the borrower's perspective, thereby relaxing the standard debt overhang constraint and inducing repayment.

Besides making it more feasible for the borrower to stay current (and thereby better aligning its incentives with the lender's), payment reduction might also free up cash for other productive uses. One such use, and one we can observe using the credit bureau data described in Section 2.3, is reducing expensive outside borrowing for working capital (most outside borrowing takes the form of unsecured credit lines, and as such is almost surely even more expensive the minibus taxi loan). Accordingly we pre-registered estimating ATEs on two summary indices of outside borrowing. Table A.4 Columns 1 and 2 present these results, which do in fact indicate modest (0.05 SD) but potentially meaningful reductions. Column 3 suggests that this reduction in outside borrowing does not come at the expense of reduced access, as measured by our pre-registered summary index. That is, we do not find evidence that payment reduction changes outside options to borrow (although the point estimates do not rule out economically meaningful effects in either direction). Following our pre-registration, we also present month-by-month estimates for each of the outcomes in this table (Figure A.12), in the interest of completeness.

All told, these additional results on minibus loan repayment and outside borrowing sharpen

[38] We define "exact" as falling within a 1% bandwidth around the required installment amount, and define the underpayment and overpayment indicators in Columns 2 and 4 relative to that benchmark.

and strengthen the inference that liquidity constraints strongly shape how borrowers respond to debt contract terms.

5.1.3 Entrepreneurial Effort

ATE estimates of effects on entrepreneurial effort provide a second test of our model's Predictions 1 and 2, and some initial hints regarding Predictions 3 and 4. Following our pre-analysis plan, we measure effort as detailed in Section 2, considering both month-by-month totals (Figure 2) and 12-month average of those totals (Table 5).

As with repayment, we find no evidence of debt reduction on effort. The point estimates for both the 12-month average and each month are close to zero. The confidence intervals do include economically meaningful effects in either direction (of up to $|0.1|$), but ultimately the full picture of our theoretical and empirical results will lead us to weigh the point estimates heavily when making inferences. For now, we note simply that the lack of empirical evidence for effort responding to debt reduction is consistent with the second part of Prediction 1, and provides another piece of evidence suggesting that the standard debt overhang model is missing something.

Table 5 and Figure 2 also report ATE estimates of the payment reduction on effort, showing imprecisely estimated modest increases (e.g., about 0.05 SD on the 12-month measures). As such, whether these results shed light on Prediction 2 (that payment reduction can increase effort, in contrast to the standard debt overhang model) depends greatly on the strength of one's priors. The lack of a sharp inference here makes sense in light of the first part of Prediction 3, which suggests that inconclusive ATEs could mask a strong HTE for those with a nonbinding debt overhang constraint (combined with a null effect for those with a binding one). We will implement that test in the next sub-section.

Before turning to HTE estimation, note that comparing payment reduction ATEs on effort vs. repayment provides our first piece of suggestive evidence supporting Prediction 4. For example, the 12-month effect on the effort index is 0.08 SD (s.e.=0.03) lower than the on repayment index ATE in Table 4 (0.05 vs. 0.13), suggesting that effort and repayment responses do in fact diverge when liquidity constraints are less binding (here due to payment reduction). Section 5.4 will provide a sharper test, based on HTEs.

5.2 Heterogeneous treatment effects by baseline equity

We now detail how we implement and interpret our sharpest test of the first part of Prediction 3: payment reduction will be more effective for borrowers with high-enough equity (more specifically, high-enough continuation value). This is due to model's more general prediction that both liquidity and standard debt overhang constraints must be non-binding for a change in contract terms to induce repayment and effort.

One issue in mapping from the model's Prediction 3 to our data is measuring equity. Equity in our model is important as an input to V, the continuation value from not defaulting on the debt D. Consequently equity in the model, as applied to our setting, is most synonymous with the

value of the business. We do not directly observe business value and proxy for it with the value of the vehicle, net of D (more specifically, we use of loan-to-value, per common practice in research, business, and policy). This is a good proxy because the minibus is the borrower's main productive asset, and all we need from a qualitative perspective is that the V is increasing in vehicle value (i.e., decreasing in LTV). One way to see that this assumption almost surely holds is to consider how the vehicle's LTV would affect business' liquidation value: all else equal, a buyer will pay more for a business with a more valuable productive asset. We estimate the asset value for each vehicle using market data, as detailed in Appendix C.2.

A second issue in mapping from model to data is how much equity is "high enough". Since our model is qualitative, it does not provide clear guidance on this question. We accordingly define our cutoff based on convention and hopes of maximizing statistical power: high (low) equity borrowers are defined as those with less than or equal to- (above-) median LTV in our sample.

A third issue is the timing of equity measurement. Given our two-period model and the potential for our treatments to causally affect vehicle equity, we measure equity at baseline (i.e., at random assignment).

Putting together our solutions to these three issues, we pre-registered estimating HTEs on our measure of vehicle LTV at baseline. We report these estimates in Table 6, Figure 3, and Figure A.14. We focus our discussion below on the 12-month repayment and effort index outcome measures for brevity, and on payment reduction TEs for mapping to first part of Prediction 3.

Consistent with Prediction 3, Column 1 shows a larger point estimate on the repayment index for higher- than lower-equity borrowers (0.16 vs. 0.10), although the p-value on the 0.06 SD difference is too high at 0.38 to merit strong inference without strong priors. Column 2 shows stronger evidence of an HTE on the effort index, with point estimates of -0.04 for lower-equity and 0.14 for higher-equity, and a p-value on the 0.18 SD difference of 0.04. We see two alternative explanations for the stronger HTE on equity. One is that, statistically speaking, we simply fail to detect a larger true HTE on repayment. Another is that the repayment HTE is in fact weaker or non-existent, and that this is consistent with Prediction 4's focus on how repayment and effort responses can diverge. It could be that liquidity drives repayment decisions in the presence of additional default costs, while that effort responds only when both the debt overhang constraint is nonbinding to due high-enough equity and liquidity constraints are relaxed due to payment reduction.

One issue for inference is whether these HTEs are causal and capture the effects of variation in equity *per se*. Even if not, they are still useful in two respects. First, they still speak to our model's descriptive and predictive value, so long as our measure of equity is correlated with whatever causally drives borrower behavior. Second and similarly, they are still useful for practice and policy in identifying an observable characteristic (equity position in the collateralized asset) that can be used for targeting payment reduction to borrowers who are most likely to respond to it (Adelino, Ferreira and Oliveira 2025).

If the HTEs do capture causal mediating effects of equity, they have an additional application beyond testing model predictions and providing guidance on how to target payment reduction.

Specifically, causality would imply that one can also use our theory and empirics to make inferences about how borrowers respond to shocks to equity; e.g., from shocks to collateralized asset value, which has been a big point of emphasis in the home mortgage literature.

Although it is of course difficult to definitively pin down the mechanism(s) producing an HTE on a baseline characteristic, we find some circumstantial evidence supporting a causal interpretation. To get a sense of potential alternative interpretations and how to address them empirically, we start by using an R-squared decomposition model (Huettner and Sunder 2012) of baseline LTV. This exercise estimates the contributions of a rich set of vehicle, borrower, and loan characteristics at origination and at baseline (see Appendix C.2 for details).

The R-squared decomposition estimates that remaining maturity at baseline explains 51% of the variation baseline LTV. None of the other variables explains more than 13%. The one surprise to us here is that the new vs. used vehicle distinction at origination does not contribute more. But otherwise the decomposition results reflect the lack of major variation in other vehicle characteristics, contract terms (including downpayment), and borrower characteristics that we document in Section 2. Remaining maturity could indeed proxy for unobserved business characteristics that drive our HTE results, rather than or in addition to equity *per se*. Borrowers with shorter remaining maturity are those who defaulted later in the life of the loan (conditioning, as we do on maturity at origination), and so they might for instance be higher-quality entrepreneurs.

As such we take the approach of testing the robustness of our main, pre-registered specification– and specifically of our key result on effort in Table 6 Column 2– to controlling for remaining maturities under various functional form assumptions (see Appendix C.2 for details).[39] Tables A.6 and A.7 report these robustness checks. Their HTEs are similar qualitatively (p-values actually fall a bit relative to our main specification) and larger quantitatively (our four new estimates imply HTEs ranging from 0.22 to 0.31, vs. 0.18 in our main specification).

These results provide suggestive evidence that a causal interpretation is warranted. Future research would do well to directly examine what we see as the main additional application of a causal interpretation; namely, how borrower behavior responds to exogenous shocks to collateralized asset value under different debt burdens and liquidity conditions.

5.3 Heterogeneous treatment effects by baseline liquidity (repayment probability)

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 (second part of Prediction 3). The flip side of our model is that we should expect a reduction in

[39] We did not pre-register these tests because we of course did not know ex-ante whether we would find an HTE on baseline equity. Nor had we identified that, conditional on finding a HTE, that there was causal-specific application– making inferences about how borrowers respond to shocks to equity– that would actually create a material distinction between correlational and causal interpretations of a HTE.

debt burden to be effective when borrowers 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.[40]

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 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.[41]

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.[42] 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 $\hat{\mathcal{L}}_i \equiv \hat{\mathcal{L}}(Z_i)$.[43] 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 2020; Chernozhukov, Demirer, Duflo and Fernández-Val 2023). Appendix Section D 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

[40] 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.

[41] 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.

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

[43] 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 D.

for borrowers with a high ex-ante probability of remaining current on their loans. In other words, it 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. Therefore, we expect debt reduction to have positive effects — for both repayment and effort — within this sample of borrowers.

We report the results for repayment outcomes in column 1 of Table 7. 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. Second, and more importantly, we find that debt reduction increases repayment for borrowers with a higher ex-ante likelihood of staying current on the loan. This result is consistent with our initial hypothesis and suggests that the policy improves repayment, but only for those borrowers less likely to face a binding liquidity constraint during the experimental period. 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 to 5 of Table 7, 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 debt reduction 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.[44]

5.4 Effort versus repayment

In Section 5.1, we documented positive average treatment effects of payment reduction on repayment but null effects on effort. Indeed, this divergence between repayment and effort is consistent

[44]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.

with Prediction 4. Recall that per this prediction, when borrowers are not liquidity constrained, repayment and effort responses may diverge when borrowers have strong incentives to postpone (strategic) default when they face significant immediate default costs.

This prediction can be more formally tested by analyzing the repayment and effort responses in a subsample in our experiment population: borrowers for whom debt overhang constraint binds, but liquidity constraint is relaxed (or was not binding ex-ante). Within the context of our HTE tests described above, these borrowers map to two subgroups in our experimental sample. The first subgroup consists of borrowers with low baseline equity (i.e., for whom debt overhang constraint is likely to bind) receiving a payment reduction (i.e., for whom liquidity constraints are relaxed). Our results in Table 6 are consistent with Prediction 4 — while we observe an increase in minibus repayment for low baseline equity borrowers receiving payment reduction (column 1), the effect on effort is muted (column 2-5).

The second subgroup consists of borrowers who either received a payment reduction or were less likely to face liquidity constrain at baseline within our control group. Because these borrowers did not receive any debt reduction, debt overhang constraint is likely to bind for them. However, these borrowers are less likely to face liquidity constraints because either our experiment relaxed their liquidity constraint or the liquidity constrain were less binding to start with. Table A.8 analyzes the effects on repayment and effort for this subgroup and — together with results presented above — echoes our Prediction 4 that effort and repayment may diverge in absence of binding liquidity constraints when there are significant immediate costs of default.

5.5 Key externalities

Although a full welfare analysis lies beyond the scope of this paper, we also consider how the intervention affects stakeholders beyond our borrowers and lender. As pre-registered, we examine two externalities: repayment to other lenders and driving behavior. The corresponding results are presented in Appendix Table A.5.

In the first two columns, we examine the impact on repayments to other lenders. As before, this measure is constructed as a standardized index, combining information collected from the Credit Bureau. We present this outcome in raw form (column 1) and in winsorized form (column 2). Across both treatments, we fail to find strong evidence that our intervention had a significant effect on repayment to other lenders.[45] In the next two columns, we examine the effect on driving behavior, particularly risky driving, which could negatively affect the communities where these borrowers operate. To capture this, we measure the number of insurance claims filed (column 3) and the number of speeding alerts recorded by the GPS tracker (column 4). Across both measures, we find no significant change in driving behavior following the intervention.

The main message from this analysis is that the positive impact of payment reduction docu-

[45] More precisely, estimates for debt reduction are generally larger than those for the payment reduction, with one specification showing a statistically significant decline in repayment at the 10% level. Even then, however, the effect is quantitatively small.

mented earlier does not come at the expense of other stakeholders, at least in terms of repayment of other debts and driving behavior. More broadly, these tests suggest that the externalities imposed by this experiment are likely modest.

6 Discussion

Our theory and empirics suggest several implications for modeling, practice, policy, and future research opportunities. We also discuss external validity and key caveats.

6.1 How and why liquidity constraints are key

Our theory and empirics point to various mechanisms through which liquidity constraints (LCs) affect collateralized borrower behavior. Underlying each of these mechanisms is the fundamental result that a binding LC introduces another borrower incentive compatibility constraint, in addition to the standard debt overhang (DO) constraint, that principals should take in account.

In particular, our results highlight that LCs do more than simply depress repayment by reducing ability-to-pay: they can, and in our setting do, tend to dampen the standard DO effect (Prediction 1) and drive behavior even if the standard DO constraint is not binding (Prediction 2). They can also depress effort, even in the short-run, when borrowers anticipate that failing to repay in the short-run increases their repossession risk in the longer-run. This reduces incentives to exert short-run effort that produces subsequent payoffs (i.e., reduces incentives to invest, broadly defined). Our results related to Prediction 4 moreover highlight that the incentivizing effects of higher default costs apart from repossession are limited by LCs: there will be cases where a strategic borrower would repay in the short-run, effectively exercising the option to delay incurring the extra default costs, *if* they had or could get the liquidity to do so without exerting additional effort. Further investigation of these dynamics is a promising line of future research.

6.2 A new role for repossession risk?

Our theoretical and empirical results add nuance to the long-held and empirically-validated prediction that repossession risk, and the incentive effects of collateral more broadly, reduce default. We show that there can be a countervailing force when both LCs and standard DO bind. The first half of our Prediction 3 speaks to this indirectly, and future work could test a sharper prediction with the help of exogenous variation in repossession risk: an increase in said risk actually could reduce effort and repayment for borrowers with binding LCs and low equity in the collateralized asset.

6.3 Standard debt overhang remains key

Our theoretical and empirical results related to Predictions 1 and 3 show that failures of debt reduction to "move the needle" on effort and repayment (as is the case with our average treatment effects) need not imply that the standard DO effect is absent. Rather, they may be signatures

that both LCs and the standard DO constraint are binding, as our heterogeneous treatment effect results indicate.

6.4 Implications for loan restructuring practice and policy

Although our work here does not speak to optimal contracting (see our caveats discussion below), our results do suggest a pecking of sorts for lender (and policymaker) modification strategy, in light of lenders' understandable revealed preference for NPV-neutral maturity extensions (payment reduction, leaving debt owed unchanged) over NPV-reducing debt reduction.[46] First, lenders should generally err on the side of offering payment reduction in settings where liquidity constraints likely bind. Second, lenders should consider trying to target payment reduction to borrowers with sufficiently high continuation value, as proxied for example by sufficiently high equity positions in their collateralized asset (or in their business more broadly). Third, debt reduction alone may be sufficient to induce effort and repayment from borrowers with non-binding LCs, and debt reduction and payment relief in tandem may be required to induce the desired changes in borrowers with both low equity and binding LCs (i.e., borrowers for whom both LCs and the standard DO constraint bind).

Our empirical results also could serve as estimates of several parameters one might include in a quantitative model used for welfare and policy analysis: elasticities of borrower behavior with respect to contract terms (or to changes in liquidity and equity positions more generally), and any externalities these responses create for other lenders, insurers, and road users.

6.5 External validity

We consider three dimensions of external validity here, and a fourth in the caveats disussion further below.

First, we posit that several features of our setting provide external validity for loan originations and well-performing loans, even though our randomized variation is on loan modification terms. As noted above, one feature of our design is that everyone in the experiment gets a baseline modification that brings their loan current. As such, one can interpret our results as applying to non-delinquent borrowers who are close to the margin of default. Most borrowers likely are close to that margin in our setting — recall that 57% of our lender's loans originated in 2016-2017 entered delinquent status at some point — and many other non-prime lending markets. Another feature is that our model and empirics each speak to comparative statics that are important for any stage of loan (re)contracting: how borrower behavior responds to changes in liquidity, or to their equity position in their collateralized asset.

Second, we posit external validity to many other collateralized debt markets. Binding liquidity constraints seem to be more the rule than the exception for small businesses and consumers worldwide. More specifically, our market has much in common with the U.S. subprime consumer

[46] Another reason lenders and policymakers may want to avoid debt forgiveness is that it seems to create greater dynamic, reputational concerns than do NPV-neutral modifications.

vehicle market that has attracted much research and policy scrutiny (Adams, Einav and Levin (2009); Jansen, Kruger and Maturana (Forthcoming)). Our setting also shares important characteristics with household mortgage markets. 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 (2022, 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 taxi markets across the world when driver strikes impede economic activity (Eaglin (Forthcoming)).

Third, we speculate that our model will be useful for studying unsecured debt markets as well. Our intuition is that the absence of repossession risk leads to lower continuation value (lower V in our model), making the standard DO problem more likely to bind in unsecured markets. This conjecture could help explain why loan modification RCTs on unsecured debt do find ATEs on debt reduction (Dobbie and Song 2020; Aydin 2024), while we do not. It also seems plausible that one-time default costs (in our model, additional default costs outside of V) are lower in unsecured markets, which could generate the testable prediction that borrower effort and repayment decisions are more tightly aligned in unsecured than secured markets. Properly investigating these intuitions is a promising line of future research.

6.6 Caveats

One potentially key caveat is that we lack empirical estimates beyond a 12-month horizon. We posit that at least two features of our study mitigate this concern and conversely argue in favor of external validity for longer horizons and contracting parties' decision making generally. First, the parties have high discount rates. This is evident in their financing costs of course: borrowers' costs for collateralized debt averaged 24% per year and our lender's cost of capital stood at 13% per year. It is further validated by our various results on how liquidity constraints shape borrower behavior, and by our lender's planning horizon– they would have preferred an even shorter horizon for treatment effect estimation, and indeed the research team had to expend substantial internal political capital to convince the lender that keeping the randomization in place for at least 12-months was worthwhile. Second, our lack of an ATE on debt reduction mitigates any concern that any short-term benefits the lender (or market) gleans from that modification might be offset by longer-term costs from signaling lack of commitment to contract enforcement.

Another key caveat, as noted above, is that neither our theory nor empirics speak to optimality. They do however potentially provide some guidance on how to structure models that one could use for welfare analysis, and some estimates of key parameters that one might include in a quantitative model.

7 Conclusion

Understanding the drivers of default and repayment behavior is crucial for designing optimal loan modification strategies. This study leverages a unique RCT 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 debt reduction through 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 a debt reduction 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 nuanced. 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 debt reduction increased both repayment and effort for borrowers that were ex-ante less likely to be liquidity constrained.

Overall, our results highlight the important interplay between liquidity and strategic concerns, and their implications for both default and effort behavior. 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.[47]

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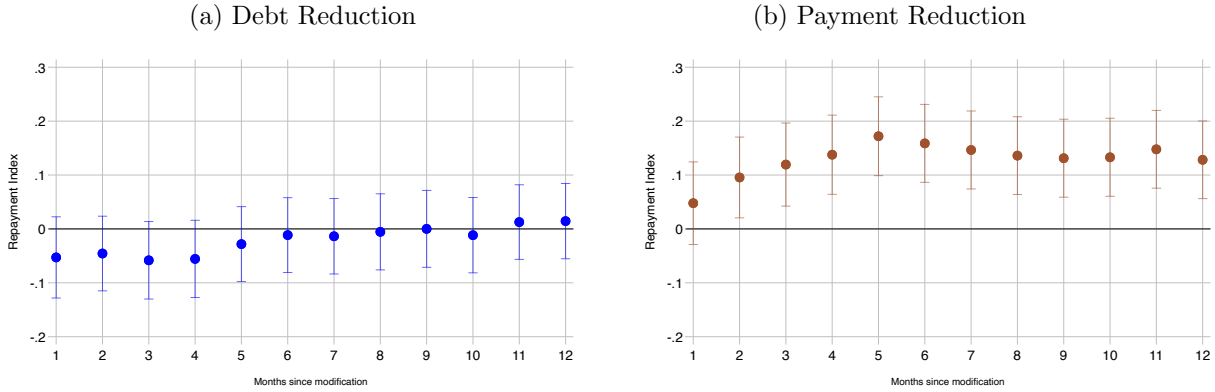
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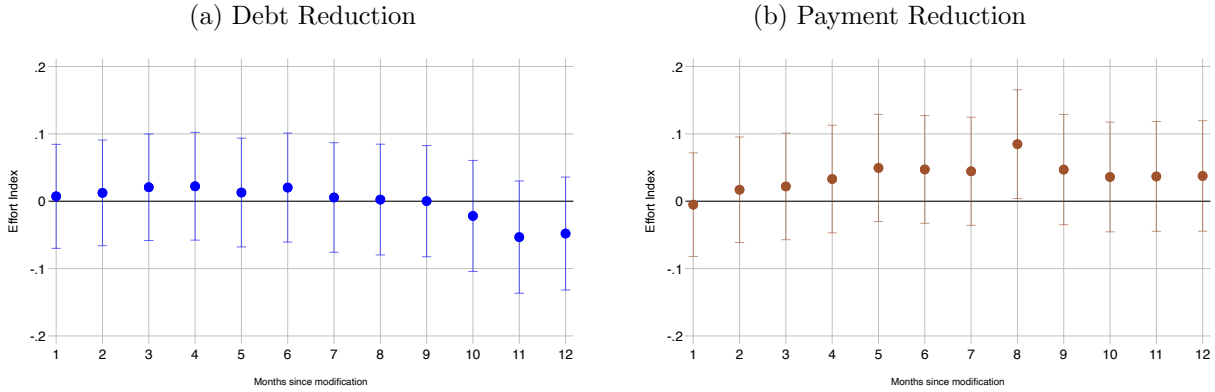
Figures and Tables

Figure 1: Month-by-month effects of loan modifications on minibus loan repayment



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 normalized measures 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. Normalized measures are constructed by subtracting the mean and dividing by the standard deviation for the variable. Panel (a) reports the monthly estimates for the debt reduction modification relative to the baseline modification. Panel (b) 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 2: Month-by-month effects of loan modifications on entrepreneurial effort

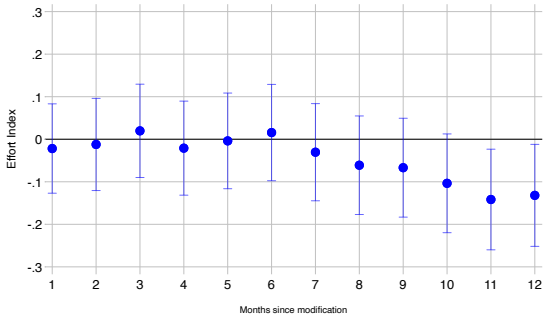


Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on borrowers' effort. The index is defined as equal weighted average of normalized measures of: (i) total distance covered by the vehicle (ii) total number of days worked in the month (iii) the number of hours on the job. Normalized measures are constructed by subtracting the mean and dividing by the standard deviation for the variable. Panel (a) reports the monthly estimates for the debt reduction modification relative to the baseline modification. Panel (b) 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.

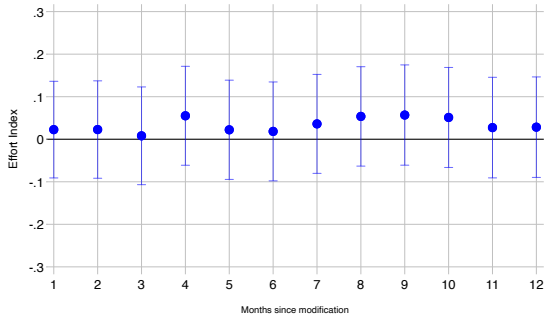
Figure 3: Month-by-month effects of loan modifications on effort, by baseline equity

Panel A. ... following debt reduction

(a) borrowers with low baseline equity

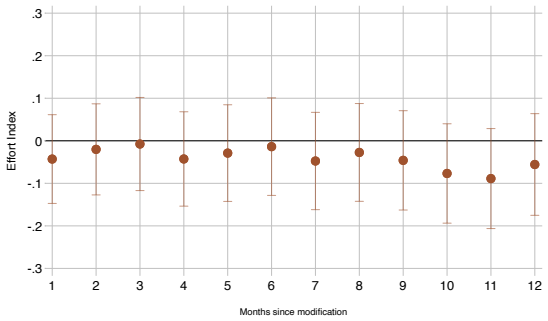


(b) borrowers with high baseline equity

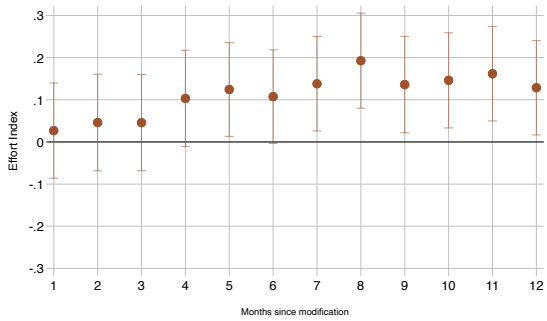


Panel B. ... following payment reduction

(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 effort index is defined as equal weighted average of normalized measures 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. Normalized measures are constructed by subtracting the mean and dividing by the standard deviation for the variable. The top panel reports the monthly estimates for the debt reduction 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; 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 3: First-stage: Impact on contract terms

	Interest Rate (%) (1)	Monthly Installment (2)	Remaining Maturity (3)
β^{DR} : 1(debt reduction)	-6.579***	87.177	-11.108***
	(0.095)	(77.283)	(0.670)
β^{PR} : 1(payment reduction)	-0.122	-1,391.940***	19.241***
	(0.102)	(76.553)	(0.898)
Observations	3,186	3,186	3,186
R-squared	0.713	0.268	0.484
Control mean	23.90	12,784.09	54.85
p-value[$\beta^{DR} = \beta^{PR}$]	0.00	0.00	0.00
Strata f.e.	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of debt reduction and payment reduction on contract terms. Column (1) reports the changes to the annual interest rate (%); Column (2) reports the changes to the monthly loan 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Results on minibus loan repayment

	Repayment Index (1)	1(current) (2)	Arrears Amount (3)	Arrears (Scaled) (4)
β^{DR} : 1(debt reduction)	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[$\beta^{DR} = \beta^{PR}$]	0.00	0.00	0.00	0.21
Strata f.e.	✓	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of debt reduction 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 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: Results on entrepreneurial effort

	Effort Index (1)	Distance driven (2)	Time Spent on job (3)	Total days driven (4)
β^{DR} : 1(debt reduction)	-0.002	-0.013	-0.003	0.010
	(0.044)	(0.048)	(0.047)	(0.046)
β^{PR} : 1(payment reduction)	0.052	0.035	0.052	0.069
	(0.044)	(0.049)	(0.046)	(0.046)
Observations	3,178	3,178	3,178	3,178
R-squared	0.026	0.009	0.035	0.035
Control mean	-0.02	-0.01	-0.02	-0.03
p-value$[\beta^{DR} = \beta^{PR}]$	0.20	0.30	0.22	0.19
Strata f.e.	✓	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of debt reduction 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 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: Heterogeneous Treatment Effects by Baseline Equity

	Repayment Index (1)	Effort Index (2)	Distance driven (3)	Time Spent on job (4)	Total days driven (5)
β^{DR+LE}: 1(debt reduction)	-0.033	-0.053	-0.056	-0.074	-0.028
× 1(low baseline equity)	(0.050)	(0.061)	(0.068)	(0.064)	(0.063)
β^{DR+HE}: 1(debt reduction)	0.069	0.042	0.023	0.060	0.042
× 1(high baseline equity)	(0.050)	(0.064)	(0.069)	(0.067)	(0.067)
β^{PR+LE}: 1(payment reduction)	0.099**	-0.039	-0.039	-0.063	-0.014
× 1(low baseline equity)	(0.050)	(0.061)	(0.069)	(0.064)	(0.063)
β^{PR+HE}: 1(payment reduction)	0.164***	0.138**	0.104	0.161**	0.147**
× 1(high baseline equity)	(0.053)	(0.063)	(0.069)	(0.066)	(0.066)
1(high baseline equity)	0.187***	-0.226***	-0.221***	-0.274***	-0.183***
	(0.055)	(0.068)	(0.075)	(0.071)	(0.071)
Observations	3,186	3,178	3,178	3,178	3,178
R-squared	0.093	0.030	0.013	0.041	0.037
Control mean	-0.05	-0.02	-0.01	-0.02	-0.03
$p[\beta^{DR+LE} = \beta^{PR+LE}]$	0.01	0.81	0.80	0.85	0.83
$p[\beta^{DR+HE} = \beta^{PR+HE}]$	0.07	0.12	0.22	0.12	0.10
$p[\beta^{DR+HE} = \beta^{DR+LE}]$	0.15	0.29	0.41	0.15	0.45
$p[\beta^{PR+HE} = \beta^{PR+LE}]$	0.38	0.04	0.14	0.01	0.08
Strata f.e.	✓	✓	✓	✓	✓

Notes: The table reports the heterogeneous treatment effects of debt reduction 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 less than or equal to the 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 at baseline. 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 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 an average over the 12 months following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: 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(debt reduction)	-0.072	-0.094	-0.110	-0.102	-0.069
	(0.049)	(0.063)	(0.068)	(0.066)	(0.067)
1(debt reduction) × high $\hat{\mathcal{L}}_i$	0.171**	0.179**	0.189**	0.194**	0.155*
	(0.070)	(0.089)	(0.097)	(0.093)	(0.092)
1(payment reduction)	0.096*	0.033	0.022	0.024	0.054
	(0.050)	(0.062)	(0.069)	(0.065)	(0.064)
1(payment reduction) × high $\hat{\mathcal{L}}_i$	0.082	0.035	0.022	0.054	0.029
	(0.073)	(0.088)	(0.098)	(0.092)	(0.092)
high $\hat{\mathcal{L}}_i$	0.265***	-0.052	-0.063	-0.071	-0.022
	(0.053)	(0.066)	(0.074)	(0.069)	(0.069)
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	-0.02	-0.01	-0.02	-0.03
Strata f.e.	✓	✓	✓	✓	✓

Notes: The table reports the heterogeneous treatment effects of debt reduction 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 calculated using machine learning algorithm described in Appendix Section D. 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 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), (negative of) arrears Amount and (negative of) scaled Arrears, and is reported at the 12th-month snapshot. 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 from Column (2) to (5) — measures of entrepreneurial effort — are measured as an average over the 12 months following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A Appendix Figures and Tables (Online Appendix)

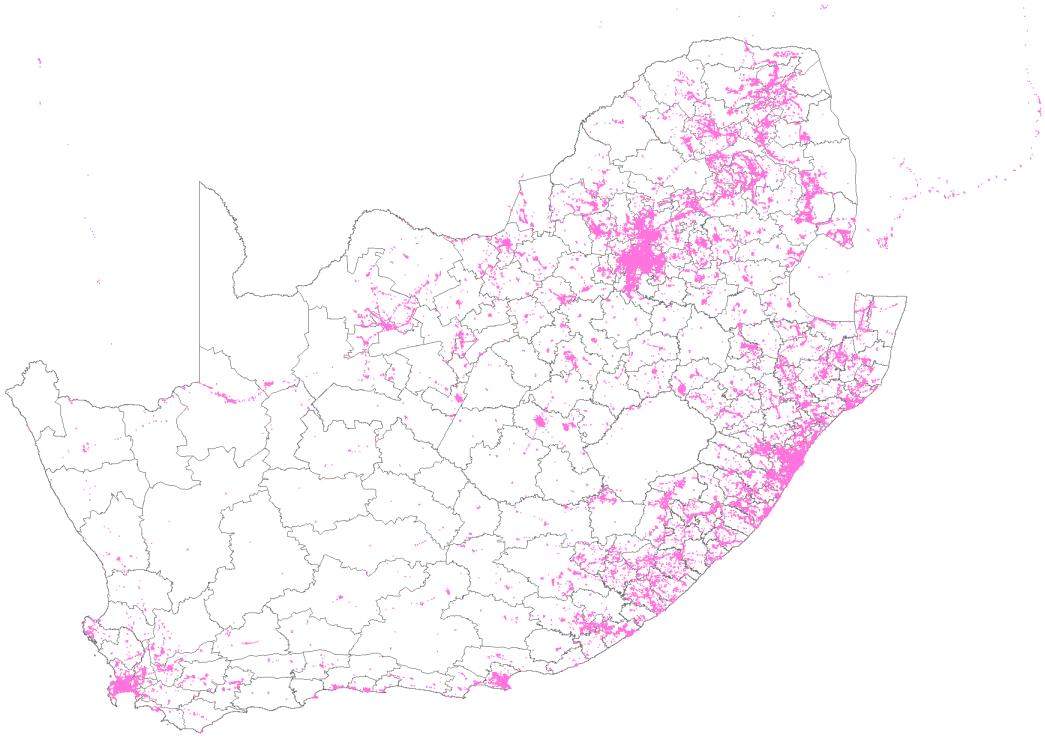
Figure A.1: A Toyota Quantum Minibux Taxi





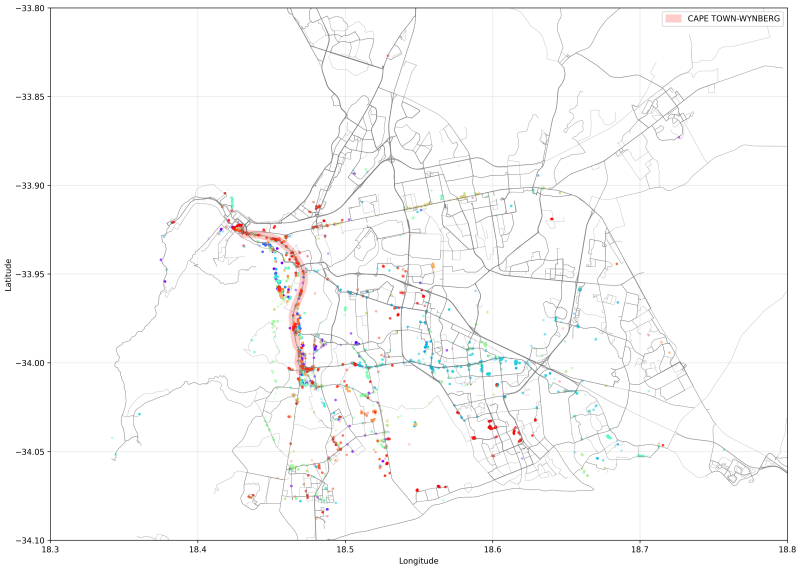
Notes: Panel (a) of the figure shows the 16-seater minibus from Toyota that constitute 80% of the collateralized vehicles in our sample. Panel (b) of the figure shows the example of a taxi rank.

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.

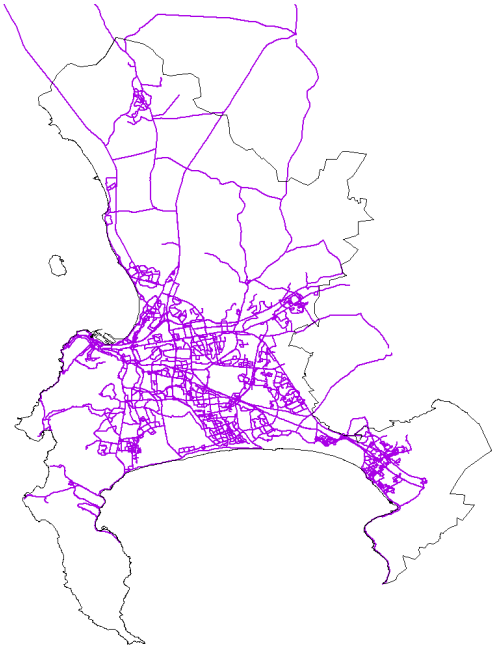
Figure A.3: Example of a minibus route in Cape Town



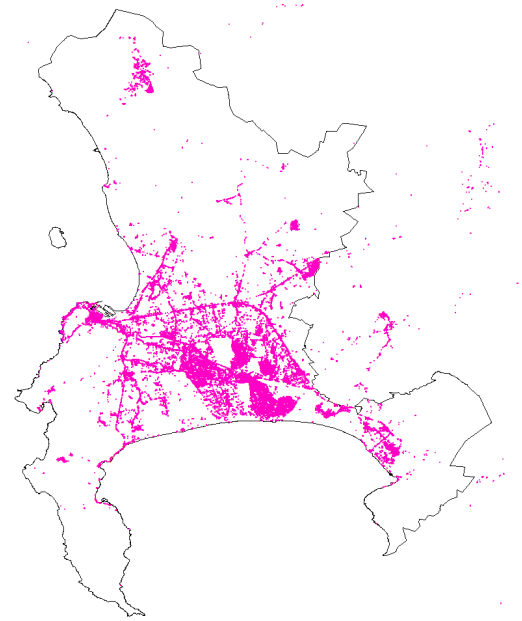
Notes: The gray lines indicates the official routes; the red shaded thick line represents the official route of Cape Town CBD to Wynberg (and back); the dots represents the coordinates of various vehicles determined to operate on the Cape Town CBD - Wynberg Route Jan'24 to Feb'25, with each color of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

Figure A.4: 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

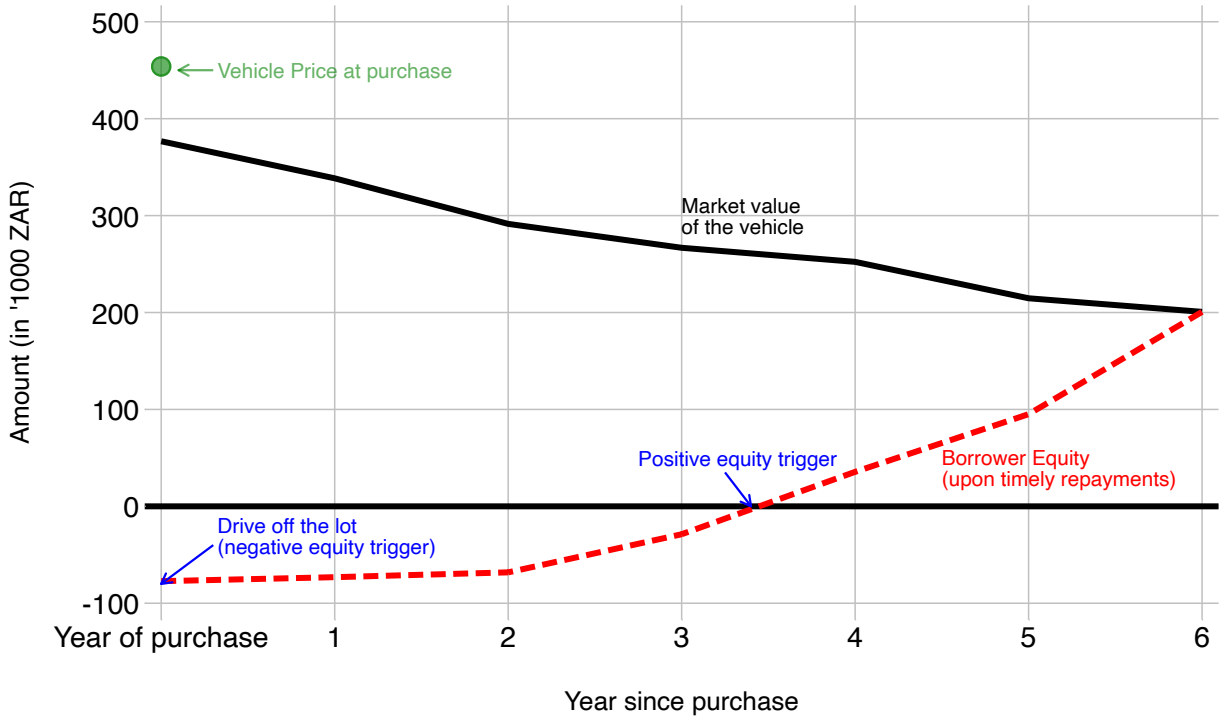


(b) Geo-coordinates of operators in experiment



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.

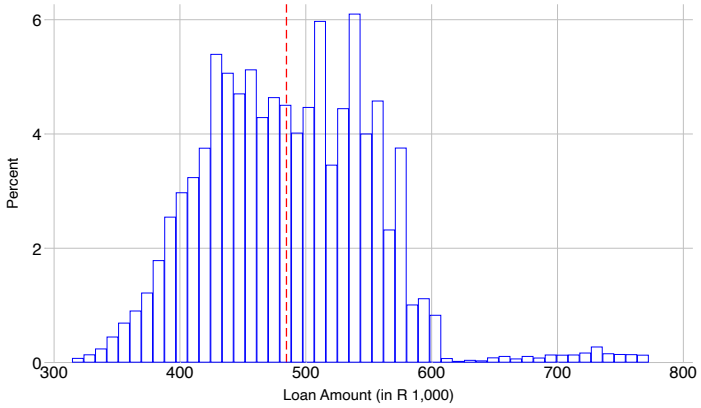
Figure A.5: Evolution of equity over time for new borrowers



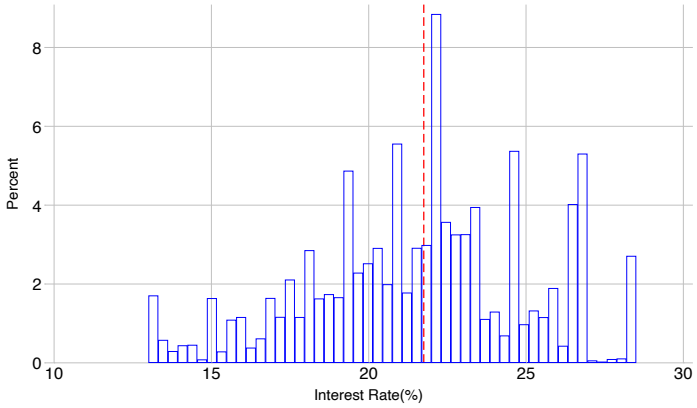
Notes: The figure provides an example of the evolution of equity (red dashed line) for borrowers that make timely repayment on loan with a newly collateralized vehicle. The black solid line represents the market value of a new minibus (Toyota Quantum 16 seater in this example). The green dot represents 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 A.6: Distribution of loan terms in the Lender's portfolio

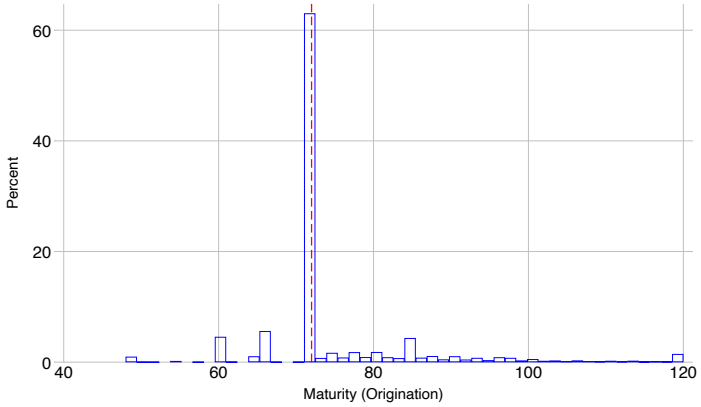
(a) Loan Amount (in R 1,000)



(b) Interest Rate (%)



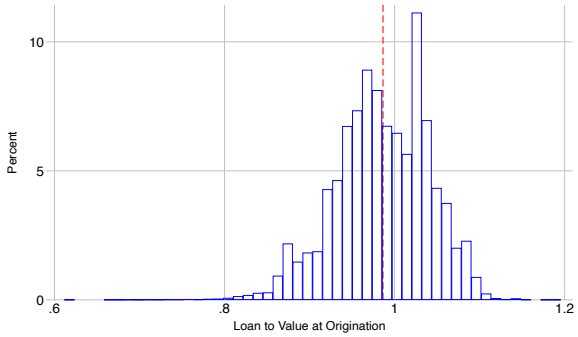
(c) Maturity in months (at Origination)



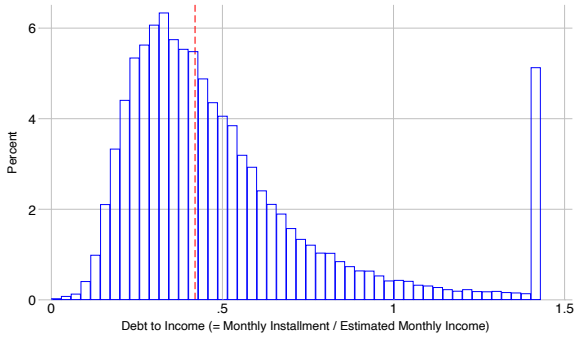
Notes: The figure plots the distribution of loan characteristics as observed at origination of the loan. The sample is all the accounts active with the lender as of October 2023 (the month before the experiment rollout). The red vertical lines on each subplot corresponds to the median value for the reported 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 = 32,000)

Figure A.7: Distribution of loan-to-value (at origination) and debt-to-income

(a) Loan to Value (LTV) at origination

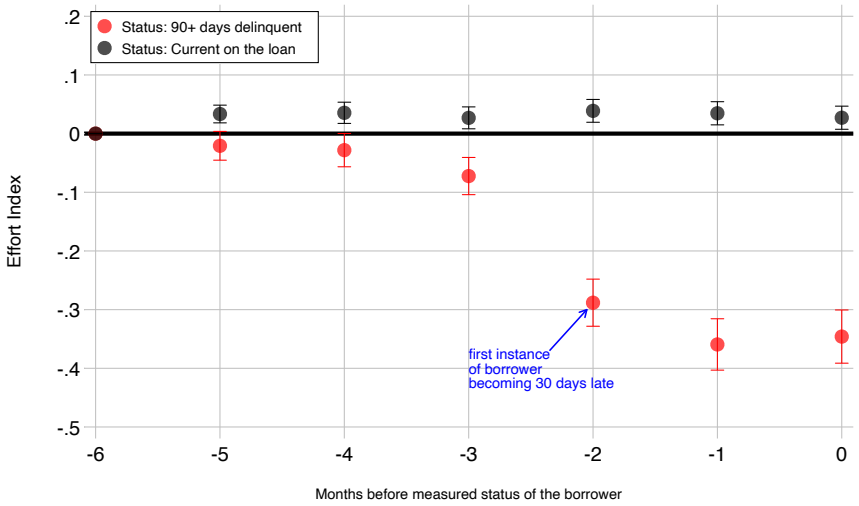


(b) Debt to Income (DTI) at baseline



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)

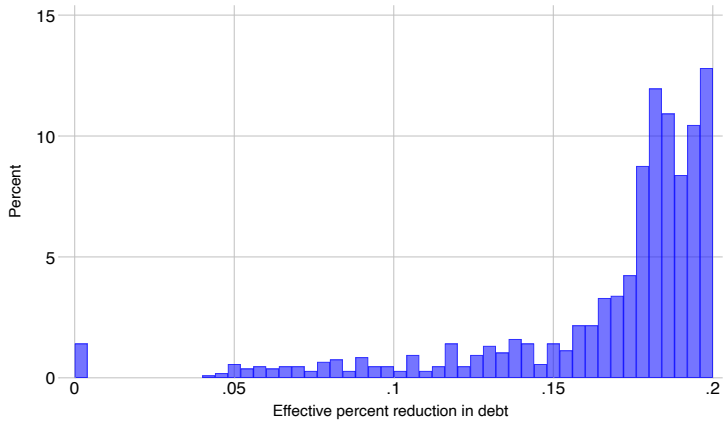
Figure A.8: Co-evolution of Entrepreneurial Effort and 90+ Day Delinquency



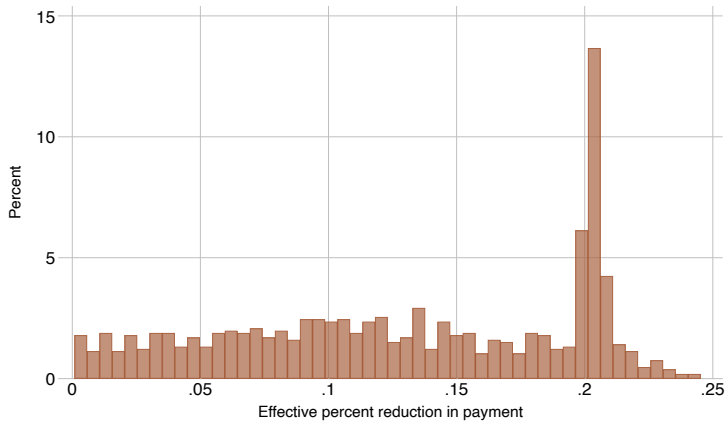
Notes: Black and red (or gray, in black and white) dots plot the point estimates β^i from separate regressions for each of two repayment statuses i in month t: Effort Index$_{i,t} = \alpha_i + \alpha^i_{t_0} + \sum_{k=0}^{-5} \beta^i_k \cdot \mathbf{1}(t = t^i_0 + k) + \epsilon_{it}$. Vertical bars show 95% confidence intervals on β^i. Repayment status is {1(current) or 1(90+ days delinquent)}. The unit of observation is the measurement of i taken in each month t_0 = [June 2024, January 2025], with the analysis corresponding to our experiment window because the June 2024 observations look back through December 2023. Min k=-5, because the omitted month is month 6 before t_0. For each account that is ever 90+ days delinquent in the June 2024-January 2025 window, we only include the observation from the month in which the account is first observed as 90+ days past due. For accounts current as of t_0, we include only those that have also been current in each of the preceding six months. For accounts that are current multiple times in the June 2024 to January 2025 window, we randomly select one of those monthly observations to include in the regression sample. Standard errors are clustered at the account level. We exclude accounts that neither current nor seriously delinquent, and/or that are in our experimental sample, because here we are interested in estimating the typical correlation between effort and repayment status rather than anything particular to or inclusive of modifications.

Figure A.9: Effective treatment intensity

(a) Debt Reduction

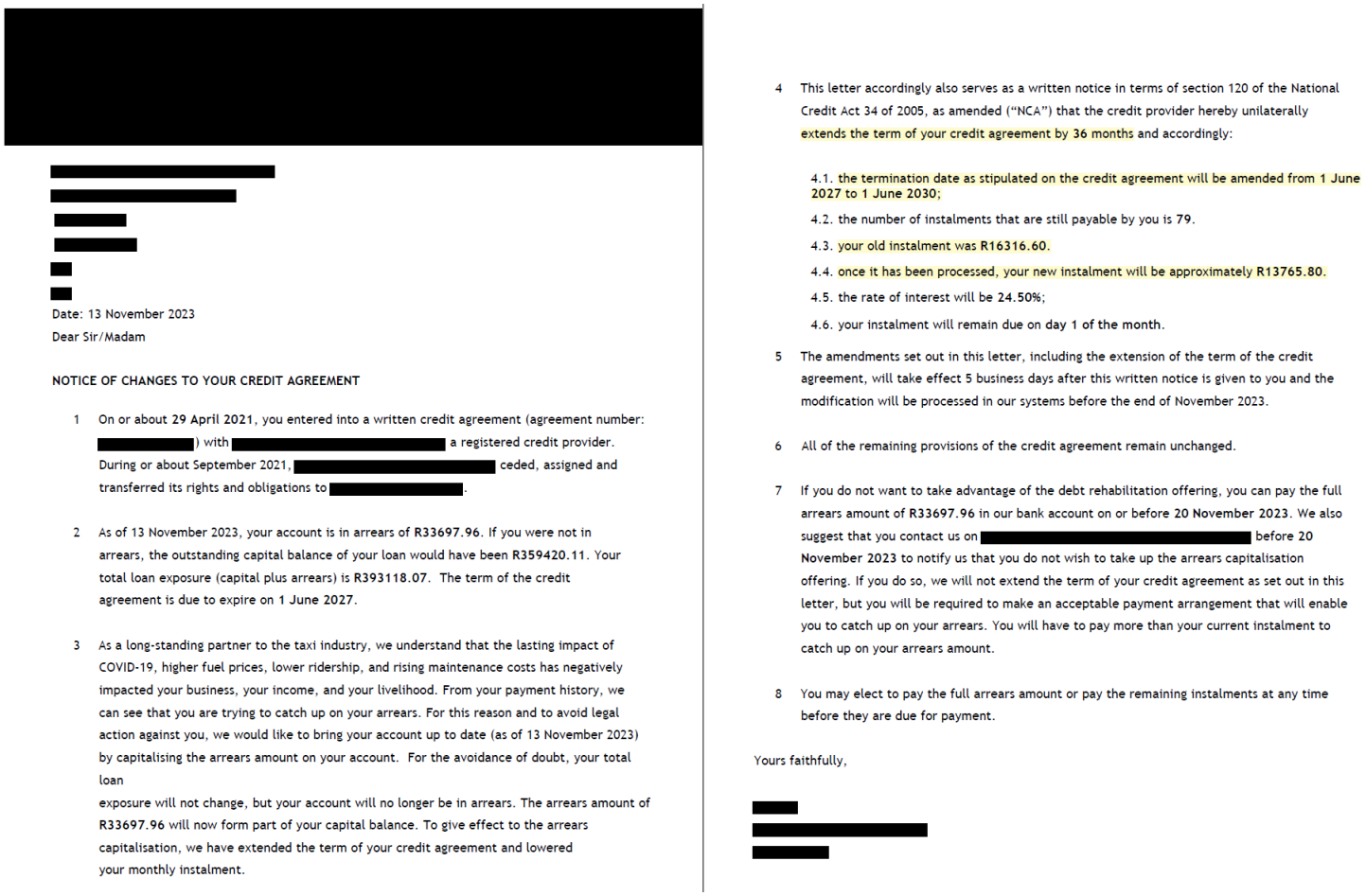


(b) Payment Reduction



Notes: These panels report the distribution of effective treatment intensity separately across the two treatment arms. Panel (a) reports the effective reduction in total debt amount owed (in percentage points) by the borrowers assigned to the debt reduction treatment group. Panel (b) reports the effective reduction in monthly payments (in percentage points) for the borrowers assigned to the payment reduction treatment group.

Figure A.10: 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,

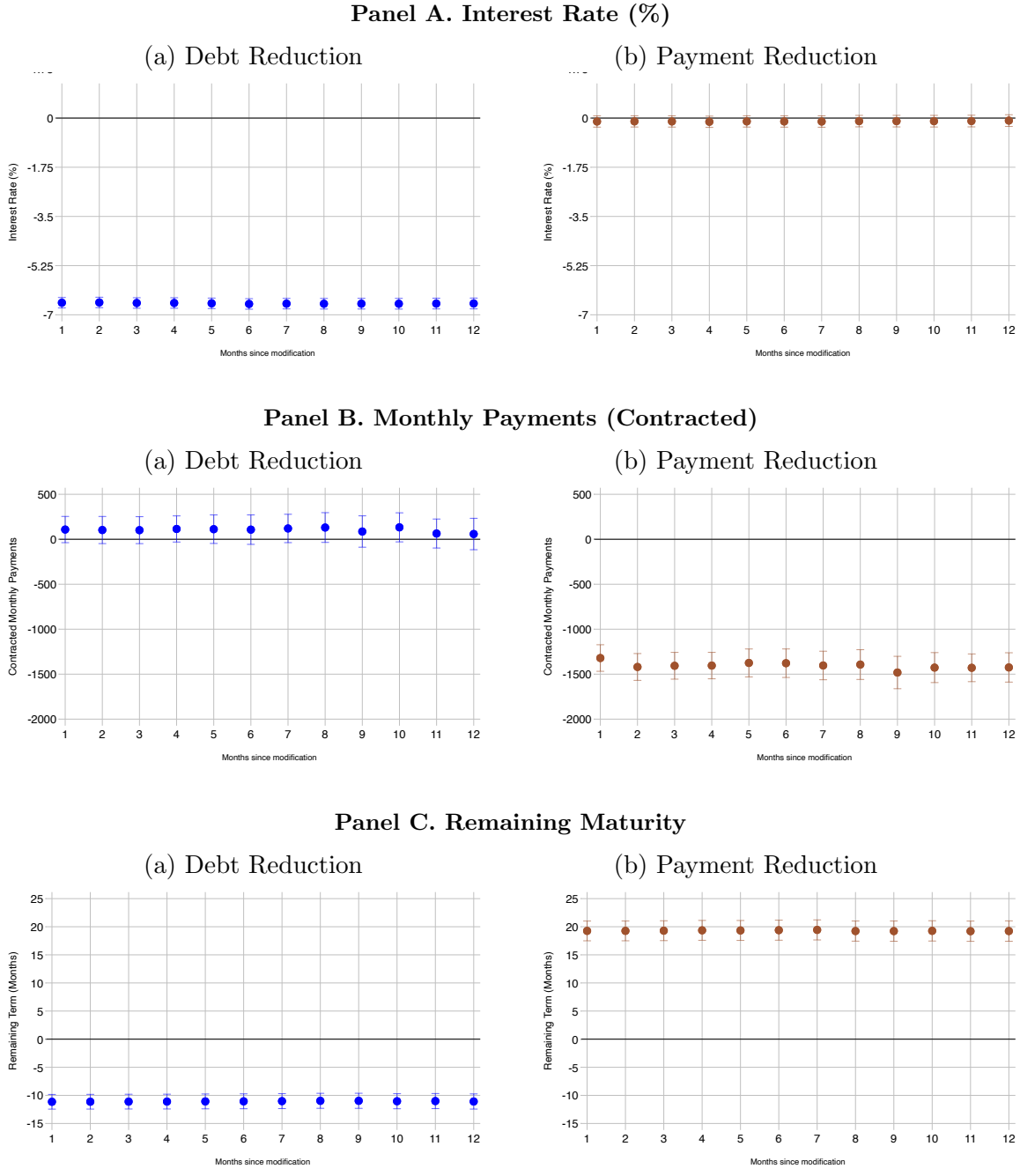
[redacted]

[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.11: First-stage: Impact on contract terms across treatment arms

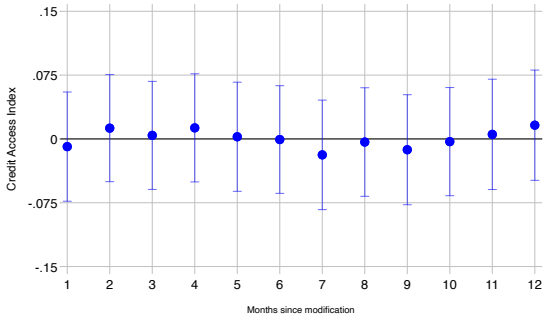


Notes: These panels report the month-by-month estimates on contract terms — Interest Rate (Panel A), Contracted Monthly Payments (Panel B), and the outstanding maturity (Panel C) — in the twelve months after the loan modifications (November 2023) relative to the baseline modification. For each panel, the left column reports the contract terms under the debt reduction 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.

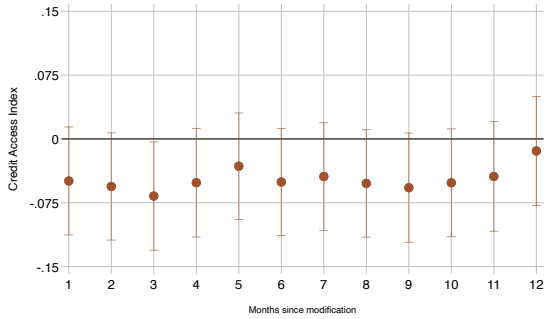
Figure A.12: Dynamics effects of loan modifications on outside debt

Panel A. Credit Access Index

(a) Debt Reduction

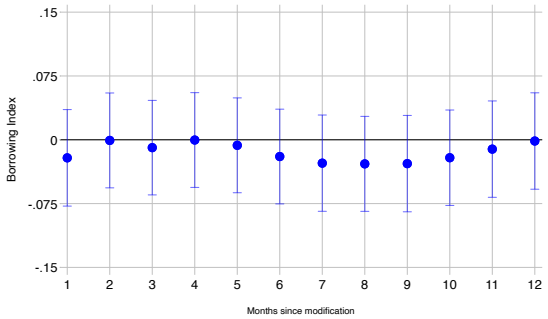


(b) Payment Reduction

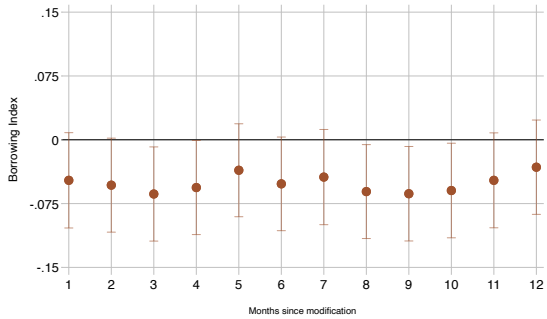


Panel B. Borrowing Index

(a) Debt Reduction

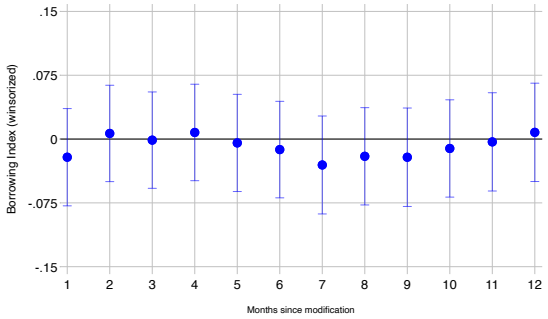


(b) Payment Reduction

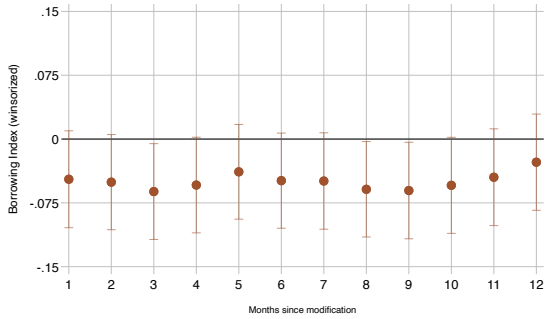


Panel C. Borrowing Index (winsorized)

(a) Debt Reduction

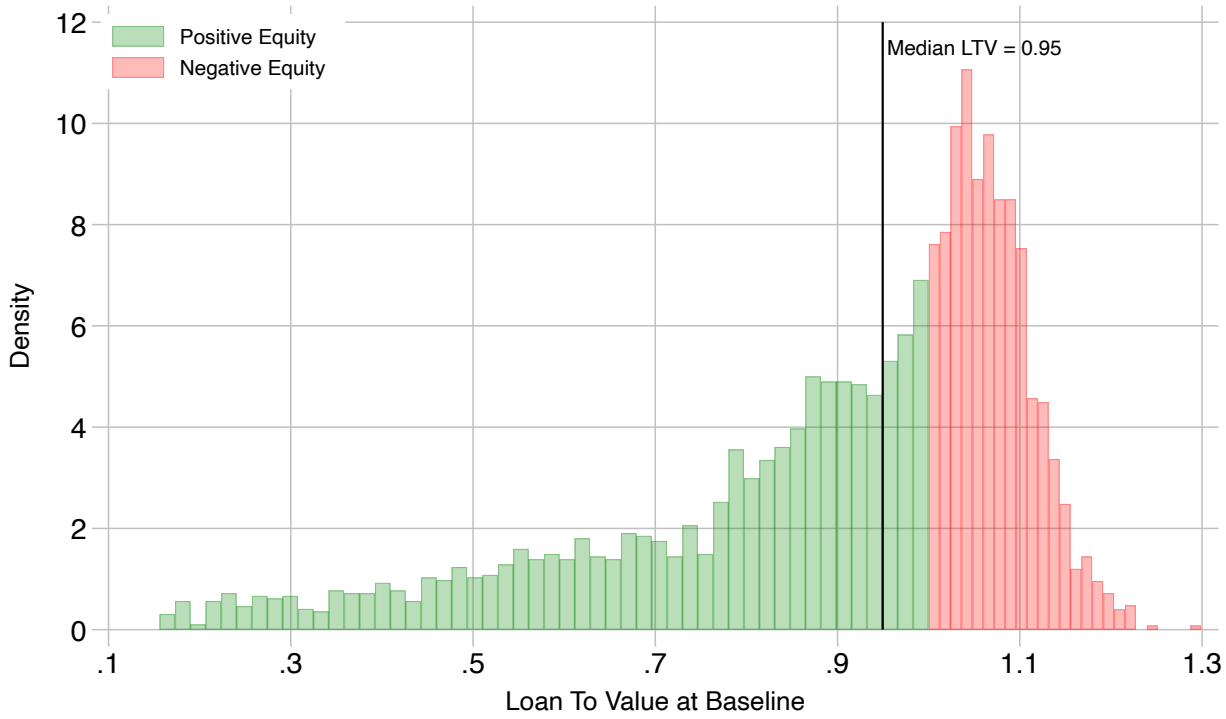


(b) Payment Reduction



Notes: These panels report month-by-month reduced-form estimates of the impact of loan modifications on two indices measuring performance on outside debt: credit access index (panel A); borrowing index (panel B); borrowing index - winsorized (panel C). For each month t, the indices are defined as follows:
1. *Credit Access Index*$_t$= (1(has credit card)$_t$ + 1(has credit line)$_t$ + (Total amount on credit lines)$_t$ + 1(has installment loan)$_t$)/ 4
2. *Borrowing index*$_t$= (1(outside debt $>$ 0)$_t$ + (Line Utilization)$_t$ + (Total Amount Owed on Outside Debt)$_t$)/3
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 debt reduction 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 A.13: Distribution of Baseline LTV in the experimental sample

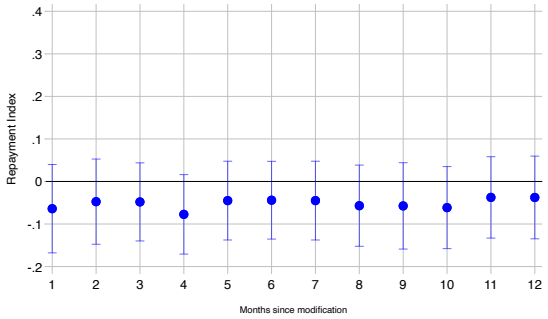


Notes: The figures plots the distribution of LTV (loan-to-value) across borrowers in our experimental sample at baseline month of October 2023. LTV is defined as the outstanding loan balance (sum of principal and any outstanding arrears) divided by the estimate of the market value of the underlying collateralized 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)

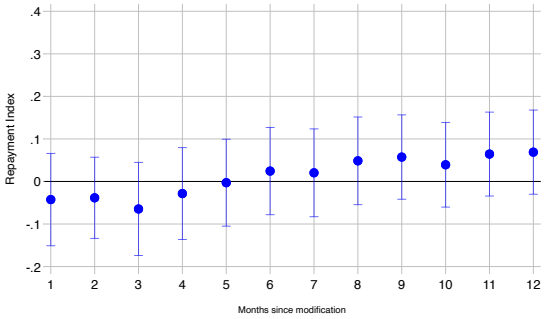
Figure A.14: Month-by-month effects of loan modifications on minibus loan repayment, by baseline equity

Panel A. ... following debt reduction

(a) borrowers with low baseline equity

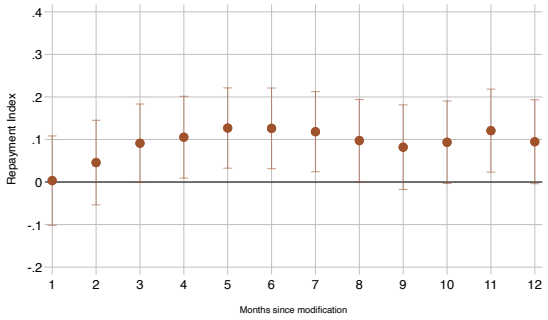


(b) borrowers with high baseline equity

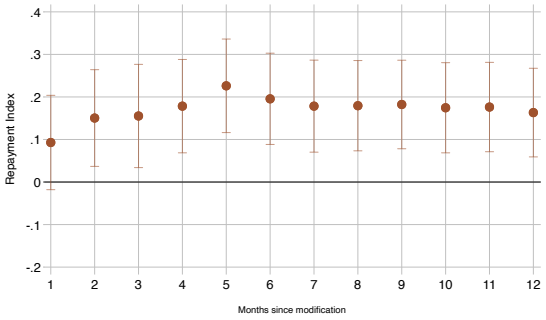


Panel B. ... following payment reduction

(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 debt reduction 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 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	Time in job (hours)	Total days driven
Effort Index	1			
Distance Driven	0.890	1		
Time in job (hours)	0.959	0.763	1	
Total days driven	0.945	0.723	0.916	1

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

Table A.2: Summary Statistics and Balance

Sample: *All Baseline: 3,186 loans*	**Control mean** (1)	**Debt Reduction** (2)	**Payment Reduction** (3)
Panel A. Borrower characteristics:			
Credit Score	592.194	0.001	0.000
		(0.000)	(0.000)
1(male)	0.761	–0.006	0.010
		(0.020)	(0.020)
Borrower's Age	51.098	–0.000	0.000
		(0.001)	(0.001)
No. of deals with lender	1.374	–0.023**	0.005
		(0.010)	(0.011)
Panel B. Loan characteristics:			
1(vehicle is new)	0.690	0.008	–0.016
		(0.033)	(0.032)
Age of the Vehicle	3.412	0.002	–0.000
		(0.007)	(0.007)
Loan Principal (R 1,000)	388.570	–0.001	0.000
		(0.000)	(0.000)
Arrears (R 1,000)	54.040	0.000	–0.000
		(0.001)	(0.001)
Maturity in months (Origination)	73.952	–0.003	0.003
		(0.002)	(0.002)
Loan to Value (Origination)	0.999	0.240	–0.132
		(0.235)	(0.236)
Loan to Value (Baseline)	0.879	0.025	0.098
		(0.180)	(0.178)
Panel C. Baseline contract terms:			
Interest Rate	0.240	–0.892	–0.235
		(0.627)	(0.617)
Installments (R 1,000)	12.996	0.023	0.000
		(0.015)	(0.015)
Remaining Maturity (in months)	47.492	0.003	–0.003
		(0.003)	(0.003)
Panel D. Baseline outcomes (normalized):			
Repayment Index	0.010	0.012	–0.007
		(0.020)	(0.022)
Effort Index	–0.007	0.001	0.002
		(0.010)	(0.010)
Credit Access Index	0.013	0.021	–0.025
		(0.021)	(0.021)
Borrowing Index	0.011	–0.003	–0.000
		(0.024)	(0.024)
p-value (joint F-test)	—	[0.530]	[0.808]
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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.3: Other Results on Repayment

	Repayment metrics ...			
	Total Payment	1(Payment in Full)	1(Under Payment)	1(Over Payment)
	(1)	(2)	(3)	(4)
β^{DR} : 1(debt reduction)	-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[$\beta^{DR} = \beta^{PR}$]	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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.4: Results on credit access and borrowings (outside debt)

	Credit Access Index	Borrowing Index	Borrowing Index (Winsorized)
	(1)	(2)	(3)
β^{DR} : 1(debt reduction)	0.016	-0.015	-0.009
	(0.033)	(0.026)	(0.026)
β^{PR} : 1(payment reduction)	-0.014	-0.051**	-0.050*
	(0.033)	(0.025)	(0.026)
Observations	3,186	3,186	3,186
R-squared	0.027	0.070	0.073
Control mean	-0.00	0.02	0.02
p-value[$\beta^{DR} = \beta^{PR}$]	0.36	0.14	0.11
Strata f.e.	✓	✓	✓

Notes: The table reports the estimates on the intent-to-treat estimates of debt reduction 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%). Credit Access Index is measured as of month 12 following the intervention, and is an equal-weighted average of: 1(has credit card), 1(has credit line), Total amount on credit lines,(has installment loan). Borrowing index is measured as an average over the 12 months following the intervention, and is an equal-weighted average of: 1(outside debt > 0), Line Utilization, Total Amount Owed on Outside Debt. All index components are normalized by subtracting the mean and dividing by the standard deviation for every month. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.5: Results on Key Extenalities

	Repayment Index (1)	Repayment Index (Winsorized) (2)	# of insurance claims filed (3)	# speeding alerts (> 120 km/hr) (4)
β^{DR} : 1(debt reduction)	-0.048	-0.059*	0.026	0.002
	(0.033)	(0.033)	(0.018)	(0.033)
β^{PR} : 1(payment reduction)	-0.004	-0.014	0.031	-0.018
	(0.032)	(0.033)	(0.019)	(0.031)
Observations	2,947	2,947	2,913	3,176
R-squared	0.025	0.025	0.003	0.009
Control mean	0.09	0.10	-0.00	0.00
p-value$[\beta^{DR} = \beta^{PR}]$	0.15	0.17	0.79	0.47
Strata f.e.	✓	✓	✓	✓

Notes: This table reports the estimates of loan modifications on key externalities. Column (1) reports the effects on repayment index (non-winsorized) on outside debt; and Column (2) reports the effects on repayment index (winsorized at 5%) on outside debt; Column (3) reports the effects on the number of insurance claimed filed with the lender. Column (4) reports the estimates on the number of speeding alerts, defined as the alerts received when the vehicle crosses speed of 120 km/hr. Repayment index is defined as equal-weighted average of normalized value of the following variables: 1(any account past due), number of accounts past due, 1(any account in default), number of accounts in default, balance that is past due, balance that is in default. Only accounts active at baseline considered for the construction of repayment index measure. Normalization is done by subtracting the mean and dividing by the standard deviation for every month. All dependent variables are measured as a average over the 12 months following the intervention. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level.$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.6: Robustness on Subsample Analysis: Effect on entrepreneurial effort

	Effort Index	
	(1)	(2)
Panel A. Z_i = Normalized baseline remaining maturity		
β^{DR+LE}: 1(debt reduction)	-0.053	-0.076
× 1(low baseline equity)	(0.061)	(0.076)
β^{DR+HE}: 1(debt reduction)	0.042	0.065
× 1(high baseline equity)	(0.064)	(0.081)
β^{PR+LE}: 1(payment reduction)	-0.039	-0.104
× 1(low baseline equity)	(0.061)	(0.077)
β^{PR+HE}: 1(payment reduction)	0.138**	0.202***
× 1(high baseline equity)	(0.063)	(0.078)
1(high baseline equity)	-0.226***	-0.245**
	(0.068)	(0.096)
Observations	3,178	3,178
R-squared	0.030	0.031
Control mean	-0.02	-0.02
$p[\beta^{DR+LE} = \beta^{PR+LE}]$	0.81	0.70
$p[\beta^{DR+HE} = \beta^{PR+HE}]$	0.12	0.08
$p[\beta^{DR+HE} = \beta^{DR+LE}]$	0.29	0.28
$p[\beta^{PR+HE} = \beta^{PR+LE}]$	0.04	0.02
Strata f.e.	✓	✓
1(debt reduction) × Z_i	✓	✓
1(payment reduction) × Z_i	✓	✓
Panel B. Z_i = Quartiles of baseline remaining maturity f.e.		
1(debt reduction)	-0.053	-0.035
	(0.061)	(0.095)
1(debt reduction)	0.094	0.205
× 1(high baseline equity)	(0.089)	(0.138)
1(payment reduction)	-0.039	0.041
	(0.061)	(0.096)
1(payment reduction)	0.176**	0.292**
× 1(high baseline equity)	(0.088)	(0.134)
1(high baseline equity)	-0.226***	-0.352***
	(0.068)	(0.101)
Observations	3,178	3,178
R-squared	0.030	0.039
Control mean	-0.02	-0.02
Strata f.e.	✓	✓
1(debt reduction) × Z_i	✓	✓
1(payment reduction) × Z_i	✓	✓

Notes: The table reports the robustness of heterogeneous treatment effects of debt reduction 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 6. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.7: 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^{DR+LE}: 1(debt reduction) $\times$ 1(low baseline equity)	-0.060	-0.055
	(0.068)	(0.066)
β^{DR+HE}: 1(debt reduction) $\times$ 1(high baseline equity)	0.045	0.041
	(0.073)	(0.091)
β^{PR+LE}: 1(payment reduction) $\times$ 1(low baseline equity)	-0.063	-0.057
	(0.068)	(0.067)
β^{PR+HE}: 1(payment reduction) $\times$ 1(high baseline equity)	0.152**	0.195**
	(0.069)	(0.087)
1(high baseline equity)	-0.202***	-0.210**
	(0.074)	(0.084)
Observations	2,534	2,185
R-squared	0.027	0.025
Control mean	0.04	0.03
$p[\beta^{DR+LE} = \beta^{PR+LE}]$	0.97	0.98
$p[\beta^{DR+HE} = \beta^{PR+HE}]$	0.12	0.08
$p[\beta^{DR+HE} = \beta^{DR+LE}]$	0.29	0.40
$p[\beta^{PR+HE} = \beta^{PR+LE}]$	0.03	0.02
Strata f.e.	✓	✓

Notes: The table reports the robustness of heterogeneous treatment effects of debt reduction and payment reduction on entrepreneurial effort by baseline equity after removing the outlier values of remaining maturity (measured at the start of the experiment). 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 6. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.8: 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(debt reduction)	-0.072	-0.094	-0.110	-0.102	-0.069
	(0.049)	(0.063)	(0.068)	(0.066)	(0.067)
1(debt reduction) × high $\hat{\mathcal{L}}_i$	0.411***	0.132**	0.133**	0.128*	0.136**
	(0.049)	(0.063)	(0.068)	(0.067)	(0.066)
1(payment reduction) |	0.247***	0.002	-0.015	-0.010	0.032
(1(control) × high $\hat{\mathcal{L}}_i$)	(0.043)	(0.053)	(0.059)	(0.055)	(0.055)
Observations	3,178	3,178	3,178	3,178	3,178
R-squared	0.100	0.026	0.010	0.036	0.035
Control mean	-0.05	-0.02	-0.01	-0.02	-0.03
Strata f.e.	✓	✓	✓	✓	✓

Notes: The table reports the heterogeneous treatment effects of debt reduction and payment reduction on minibus repayment and 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 calculated using machine learning algorithm described in Appendix Section D. Variables definition are same as Table 7. All specifications control for eight strata fixed effects. Standard errors are clustered at the loan account level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B Model Appendix: Alternative assumptions about default costs (Online Appendix)

Section 3 presents two stylized models 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. In this Appendix, we expand that discussion and present the more general versions of these model, and highlight how the presence of different assumptions qualitatively alter our results. The baseline and the standard debt-overhang case are presented in Section 3 but we include them here so that the appendix is self contained.

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 $V'' \leq 0$. We adopt this interpretation for simplicity. Alternatively, the model can be viewed as one in which an entrepreneur chooses effort today, considering its effect on both current profits and the business's future continuation value.

The entrepreneur discounts future payoffs with a factor $\beta < 1$ and incurs a linear cost of effort.[1] 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

Setting Consider an entrepreneur facing a fixed debt burden with a short-term payment D_1 and a long-term payment D_2, giving a present value of $D = D_1 + \beta D_2$. Default may occur at any time, but we assume it is triggered immediately upon a missed payment. Thus, if the entrepreneur fails to make D_1, repossession follows in the second period regardless of subsequent actions.

[1] Our results would be qualitatively unchanged if we take a more general approach and assume a standard increasing and convex cost function $c(e)$.

In this model, the borrower chooses three actions: the effort level e and the two repayments P_1, P_2. We assume the borrower first selects the effort level e (period zero), then makes the first payment decision P_1, and finally makes the second payment decision P_2.

In the paper, we have focused on the simple case where we assume that default leads to the full loss of the business. We now consider a more general assumption. In particular, we now consider two costs related to default:

- In case of default, the asset is repossessed and sold by the lender. We assume that this action leads to a loss of equity for the borrower: in particular, the borrower only receives a share $1-\gamma$ of the equity.

- On top of the future asset loss, default leads to an immediate non-monetary cost ϕ for the borrower. For instance, this cost can capture the utility cost related to having a default flag in the credit report. This cost affects the borrower's utility at the time of default.

To be clear, we note that the case discussed in Section 3 focuses on the special case where $\gamma = 1$ and $\phi = 0$.

Solution Before discussing the solution, it is important to make a simple observation: in this model, there is no room for partial payments. Once a payment is partially missed, the borrower has no incentive to pay more than zero in the future. One implication of this observation is that there are only three possible realizations for payments: (a) $P_1, P_2 = D_1, D_2$, (b) $P_1, P_2 = D_1, 0$, and (c) $P_1, P_2 = 0, 0$.

We solve the model by backward induction, beginning with the optimal choice of P_2 given e^* and P_1. If the borrower skips the first payment ($P_1 = 0$), then $P_2 = 0$ necessarily. If the first payment is made in full ($P_1 = D_1$), the borrower pays $P_2 = D_2$ only if:

$$V(f(e^\star)) - D_2 \geq -\phi + (1-\gamma)(V(f(e^\star))) \tag{B.3}$$

The logic is straightforward: by repaying D_2, the borrower retains full equity; by defaulting, she forfeits a share γ of equity and incurs the fixed default cost ϕ. This trade-off reduces to the following condition:

$$\gamma\, V(f(e^\star)) - D_2 \geq -\phi \tag{B.4}$$

In the first period, the borrower will choose whether or not to repay, knowing her future choice P_2. Therefore, we need consider two scenarios, based on equation B.4. If that condition holds, then a borrower that pays in the first period will also pay in the second period. This happens only if the benefit to pay in full outweighs the benefit of avoiding any payments. In other words:

$$f(e^\star) - e^\star - D_1 + \beta(V(f(e^\star)) - D_2) \geq f(e^\star) - e^\star - \phi + (1-\gamma)\,\beta V(f(e^\star)) \tag{B.5}$$

This expression can be re-written as:

$$\beta\gamma(V(f(e^\star))) - D \geq -\phi \tag{B.6}$$

Therefore, a borrower repays the debt in full D if both equations B.4 and B.6 hold. However, it is straightforward to see that equation B.4 always holds whenever equation B.6 holds. Thus, full repayment $(P_1, P_2) = (D_1, D_2)$ requires only that equation B.6 be satisfied.

We then consider the other case, where equation B.4 does not hold. This implies that—regardless of the first-period decision—the borrower will not repay in the second period and will therefore default. [2] In this case, the only benefit of paying in the first period is to postpone default. Hence, the borrower will pay $P_1 = D_1$ if:

$$f(e^\star) - e^\star - D_1 + (1-\gamma)\,\beta V(f(e^\star)) - \phi\beta \geq f(e^\star) - e^\star - \phi + (1-\gamma)\,\beta V(f(e^\star)) \tag{B.7}$$

which can be re-written simply as:

$$\phi \geq D_1(1-\beta)^{-1} \tag{B.8}$$

The implication of this result is that a borrower will $(P_1, P_2) = (D_1, 0)$ if long-term debt is too large (i.e., equation B.4 does not hold) and the benefit of postponing defaults are large enough (equation B.8).

Given these conditions, it is easy to observe when the borrower would completely avoid any payment. In order this to happen, you need the overall debt burden to be too large, which happens if equation B.6. Furthermore, it also has to be true that the conditions for which you have $(P_1, P_2) = (D_1, 0)$ does not hold.

The last step is to determine the optimal effort. If a borrower will make full repayment, then she will not get repossessed, and therefore the objective function is:

$$\max_e \; f(e) \; - D_1 + \; \beta\,(V(f(e)) - D_2) \; - \; e$$

It is easy to observe that this problem is equivalent to the one in the baseline model, and therefore the optimal effort is $e^\star = e^{FB}$.

In the other two cases, the borrower will be repossessed, and therefore the two objective functions are both equivalent to the following:[3]

$$\max_e \; f(e) \; - P_1 + \; \beta(1-\gamma)\,(V(f(e))) \; - \; e$$

[2] In this case, we note that when equation B.4 does not hold, this also implies that equation B.6 will not hold. This is consistent with the idea that in this case paying in full is not optimal.

[3] We stress here the word equivalent: clearly, across the two scenarios, certain parameters of the objective functions will differ (e.g., the role of ϕ). However, these parameters do not affect the marginal incentives to exert effort, and therefore it is equivalent to exclude them.

In this case, we obtain that the optimal effort is e^{SB}, which implicitly defined by $f'(e^{SB})\left(1+\beta\left(1-\gamma\right)V'(f(e^{SB}))\right)=1$. It is easy to observe that $e^{SB}<e^{FB}$ as long as $\gamma>0$.

Summary The key results from this model are the following:

1 The entrepreneur exerts first best effort $e=e^{FB}$ and pay the debt in full $(P_1,P_2)=(D_1,D_2)$ if the overall debt burden is sufficiently low (equation B.6). In other words, the following condition needs to hold: $\beta\gamma(V(f(e^{\star})))-D\geq-\phi$.

2 If the condition above does not hold, the borrower will put $e=e^{SB}$. It is important to note that such that $e^{FB}>e^{SB}$ if $\gamma>0$.

3 Even if the borrower exerts lower effort $e=e^{SB}$, she may still repay in the short run with $(P_1,P_2)=(D_1,0)$. This occurs only if the immediate cost of default is sufficiently large: $\phi\geq D_1(1-\beta)^{-1}$.

Discussion This more general version of the model in Section 3 yields several noteworthy insights. First, as expected, it is important to note that this model reduces to the standard debt overhang framework discussed in Section 3 if equity is completely lost in the event of default (i.e., $\gamma=1$) and there is no immediate default cost (i.e., $\phi=0$).

Second, even in this richer setting, the basic mechanism from Section 3 remains: high debt burdens reduce the net value of continuation, leading to default and underinvestment in effort. The only requirement necessary to deliver the prediction about effort is that $\gamma>0$, which implies that repossession prevents the entrepreneur from fully recovering some of the marginal investment in the business.[4] The precise cutoff for repayment depends on γ and ϕ, but the qualitative result—debt overhang induces lower effort—remains unchanged.[5] The only qualitative change is related to repayment, and it is discussed in the next paragraph.

Third, the framework shows that effort and repayment can diverge in some cases. As discussed above, introducing $\phi>0$ leaves effort incentives qualitatively unchanged: the entrepreneur still reduces effort when the debt burden is high. Repayment, however, may differ. With $\phi>0$, the entrepreneur may repay in the short run while anticipating eventual default, since repayment postpones the immediate penalty. This occurs only if the value of delaying default exceeds the first-period payment, i.e., when $\phi\geq D_1(1-\beta)^{-1}$.

We view $\phi>0$ as a realistic assumption, reflecting reputational or legal costs associated with missed payments.[6] We conjecture that this mechanism becomes especially important in more

[4] We believe that this assumption is relatively mild in our setting. However, we can also think of our experiment as a way to test this assumption: if γ were zero, there is no debt overhang and changes in loan characteristic should not affect effort. Our results clearly suggest the opposite.

[5] To be clear, we are not claiming that these assumptions are unimportant: from a quantitative standpoint, pinning down the most accurate specification of default costs is probably crucial to match the data. However, our model is designed to have a purely qualitative interpretation.

[6] As we discuss in Section 5, some of our results are consistent with this assumption: for instance, we find that low-equity borrowers are more likely to remain current in response to a payment reduction, though they do not change

realistic multi-period settings with uncertainty, where delaying default resembles exercising the option to continue earning profits from the business—or, more generally, utility from the pledged asset.

As discussed in the main text, this case illustrates why it is essential to focus on effort rather than solely on repayment behavior. When $\phi > 0$, full repayment in the short run does not necessarily imply that debt overhang is no longer binding. This nuance is important for interpreting the loan modification results. For instance, a payment reduction may ease liquidity constraints and raise short-run repayments, yet such an increase could still be consistent with debt overhang depressing effort incentives while high default costs make continued repayment optimal in the short run. We return to this point when discussing the model with liquidity constraints.

B.3 Debt overhang with liquidity constraints

Setting 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:

$$f(e) - C - P_1 \geq 0 \tag{B.9}$$

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. Apart from this change, we keep all the other assumptions made earlier.

Solution The inclusion of the liquidity constraints create an extra condition in the problem discussed above. In particular, we now have to consider three possibilities. The first option is that the liquidity constraint is not binding, even if the borrower makes the full payment D_1 in the first period. In other words, we have:

$$f(e^{SB}) - C - D_1 \geq 0 \tag{B.10}$$

When this condition holds, the solution of the model is exactly equivalent to the one discussed above. In other words, the conditions under which we observe effort and payment choices remain exactly as described earlier.

The second case to consider is one where liquidity is sufficient only if first effort is exerted. In other words:

$$f(e^{SB}) - C - D_1 < 0 \ \wedge \ f(e^{FB}) - C - D_1 \geq 0 \tag{B.11}$$

In this case, the model's solution is similar to the one discussed above, but with a crucial distinction. In this case, it is not possible for the borrower to pay in the first period unless she puts

effort.

first best effort. This implies that the partial payment case (i.e., $(P_1, P_2) = (D_1, 0)$) is not possible anymore. In this case, the borrower will pay nothing $(P_1, P_2) = (0, 0)$ and exert second best effort, as soon as the main debt overhang condition (i.e., equation B.6) does not hold.

The last case to consider is one where the liquidity constrained is binding, irrespective of the borrower's effort. In other words:

$$f(e^{FB}) - C - D_1 < 0 \tag{B.12}$$

In this case, the borrower is unable to make the payments, even if she exerts first-best effort. As a result, the borrower will only make zero payments $(P_1, P_2) = (0, 0)$ and set $e = e^{SB}$.

Discussion. 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:

$$\gamma\beta V(f(e^{FB}) - D < 0 \ \vee \ f(e^{FB}) - C - D_1 < 0 \tag{B.13}$$

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

In particular, the presence of liquidity constraints changes the type of intervention necessary to increase effort. 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.

Before concluding, it is important to note two things. First, as expected, this model is equivalent to the simpler version discussed in Section 3. Second, the presence of liquidity adds another interesting nuanced to the possibility of divergence between effort and payments, discussed earlier. As in the standard debt overhang model, a high ϕ may induce borrowers to repay in the short run, even while exerting suboptimal effort. It is important to note that this behavior can arise only when the liquidity constraint is not binding: if $f(e^{SB}) - C - D_1 < 0$, a borrower with high immediate default cost would still rationally pays zero, since making the payment D_1 is not an option.

C Data Appendix (Online Appendix)

C.1 Variable Definitions and Construction

This appendix details the definitions of key variables and the construction of outcome indices used in our analysis, and largely follows the choices made and definitions provided in pre-analysis plan available at: https://www.socialscienceregistry.org/trials/13052 (while pointing to deviation from the pre-analysis as they happen). Unless otherwise noted, all continuous are standardized to have zero mean and unit variance prior to aggregation into a summary index. Both monthly and 12-month measures are defined. For stock variables, like loan performance or balances, the 12-month versions are defined as the snapshot of the measure at the 12th-month; for others we use the average (or sum) over 12 months. We provide these details below.

C.1.1 First-Stage Outcomes

We describe the three measures of our first-stage outcomes — interest rate, monthly payment, and remaining maturity. First-stage outcomes are calculated only for months when the loan remains on the books, and no imputation is applied. Thus, if loans exit the lender's books (e.g. due to repayment in full, pre-payment, repossession, or maturity). These outcomes are considered as is (i.e. no standardization is performed).

(i) *Monthly Installment Owed.* The contractual installment owed by the borrower on the loan (based on the total loan amount owed at experiment baseline) in a given month.

(ii) *Interest Rate.* The current contractual interest rate applicable to the loan in a given month.

(iii) *Remaining Maturity.* The outstanding maturity (in months) for the loans in a given month.

For 12-month definition, we average the outcomes variable for each borrower for the period they are on the lenders' book.

C.1.2 Minibus Loan Repayment Index

The index is the equally weighted average of three standardized components (mean zero and standard deviation 1) defined below:

$$\text{Repayment Index}_t = \frac{1(\text{current})_t - \text{Arrears Amount}_t - \text{Scaled Arrears}_t}{3}$$

The components are defined as:

(i) *1(Current).* We following the defintion used by the lender to define current borrower, which is equal to one if arrears are less than or equal to 100 ZAR in the month (arrears defined as obligations $>$ 30 days late). For loans that went off-books, if account is paid in full it is

coded as current with zero arrears. If the account is not fully repaid, then it is coded as not current with the last observed arrears carried forward.

(ii) *Arrears Amount.* Total amount (in R) of the unpaid past loan amount (i.e. the total past loan payments that is in delinquency).

(iii) *Scaled arrears.* Total arrears amount divided by the monthly owed installment in that month.

For monthly definition we utilize the snapshot at each month. For the 12-month definition, we utilize the snapshot at the $12th$-month date.

C.1.3 Entrepreneurial Effort Index

The index is constructed as the equally weighted average of the three standardized components (mean 0 and standard deviation 1) defined below derived from GPS data in a given month:

(i) *Distance driven:* Sum of the total distance covered.

(ii) *Days worked:* Count of days with non-zero trips made.

(iii) *Hours on the job.* For each days , we consider this measure to be the duration between the start of the first trip and the end of the last trip during the day. Then for each month, we consider the total hours on the job in that month.

We only have data for drivers while their loan is on the books, leading to an unbalanced panel. We do not impute missing values, given our focus on the principal-agent problem — the lender cares only about driver effort while the borrower is obligated to repay. Finally, 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. For monthly definition we utilize the snapshot at each month. For the 12-month definition, we sum the measure across months and divide by 12 to arrive a monthly index measure.

C.1.4 Credit Access Index

The index is constructed from credit bureau data as the equally weighted average of the following standardized (mean 0 and standard deviation 1) components (from the credit bureau data) in a given month:[7]

(i) Has a credit card or store card.

(ii) Has a credit line.

[7]We pre-register to also include (i) indicator for having a credit score and (ii) credit score (conditional on having one). We were unable to obtain borrowers' credit scores on a monthly frequency after loan origination. The final measure uses in the paper, therefore, does not include these two components that rely on credit score.

(iii) Total number of credit lines.

(iv) Has an installment loan from another lender.

Absence of data is coded as no credit access. For monthly definition we utilize the snapshot at each month. For the 12-month definition, we utilize the snapshot at the $12th$-month date.

C.1.5 Borrowing Index

The index is constructure as equally weighted average of the following standardized (mean 0 and standard deviation 1) components (from the credit bureau data) in a given month:

(i) Indicator for non-zero debt with other lenders.

(ii) Line utilization rate (share of available credit lines drawn).

(iii) Total owed on installment loans from other lenders.

(iv) Total owed on revolving credit lines.

Any absence of data is coded as no borrowing activity. For monthly definition we utilize the snapshot at each month. For the 12-month definition, we average the measure across months.

C.1.6 Outside debt Repayment Index

The index is constructed on outside borrowing as the equally weighted average of the following standarized (mean 0 and standard deviation 1) components (from the credit bureau data) in a given month:

(i) Indicator for any accounts that are 30+ days past due.

(ii) Number of accounts that are 30+ days past due.

(iii) Indicator for any account that are 90+ days past due.

(iv) Number of accounts that are 90+ days past due.

(v) Balances that are past due (30+ days behind on payments).

(vi) Balances that are in default (90+ days behind on payments).

For monthly definition we utilize the snapshot at each month. For the 12-month definition, we average the measure across months. The index is based only on loans outstanding at time of treatment assignment.

C.1.7 Risky Driving Measures

The use the of the following standardized measures in a given month to analyze risky-driving behavior:

(i) *Number of accidents.* Based on insurance claims filed with the lender (for borrowers that had insurance with the lender).

(ii) *Instances of over-speeding.* Count of GPS-recorded trips exceeding 120 km/hr.

For monthly definition we utilize the snapshot at each month. For the 12-month definition, we average the measure across months.[8]

C.2 Equity measurement and decomposition

In Section 5, we discuss several tests that exploit differences in borrowers' baseline equity to test HTEs borne out of the Prediction 3 of our model in Section 3. This Appendix provides details on the construction of the measure of baseline equity and discuss more in detail the factors driving the evolution of borrower equity in our sample.

C.2.1 Measuring baseline equity

We define baseline loan-to-value ($LTV_{i,t=-1}$) for borrower i at experiment baseline ($t = -1$) as:

$$LTV_{i,t=-1} = \frac{\text{Total Loan Amount Owed to the Lender}_{i,t=-1}}{\text{Market Value of the Vehicle Model}_{i,t=-1}}$$

The numerator is the total amount owed to the lender at experiment baseline, and is a sum of total loan principal outstanding and any outstanding arrears. The denominator is the the market value of the vehicle model (based on year of vehicle manufacture, the loan origination year, and the vehicle make-model) as measures in October-2023. We obtain the latter using data on the market value of all vehicle models in South Africa on a quarterly-basis. The lender sources this data for its operation and shared it with us. We define borrowers with high baseline equity as those with baseline LTV less than or equal to the median LTV in our experiment sample. Figure A.13 shows the distribution of baseline LTV 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. We discuss this next.

C.2.2 Decomposition of baseline equity

To quantify factors driving the evolution of borrower equity in our sample, we apply an R-squared decomposition model (Huettner and Sunder 2012; Biasi and Ma 2022), which leverages the Shapley

[8] We pre-specified to construct an index using the two measures. However, also we report results on these measures separately because information on accidents was only available for 92% of the borrowers that has an insurance policy with the lender.

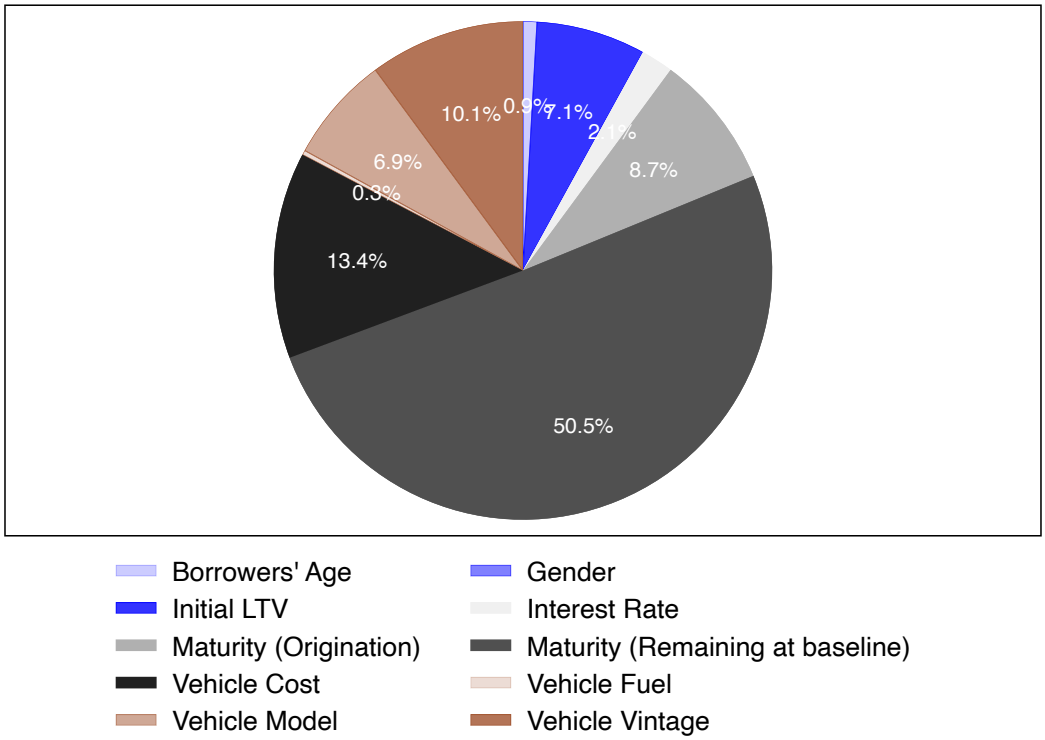
value framework to estimate how much of the variance in LTV is explained by different groups of covariates. The model includes a broad set of vehicle attributes ((log) price paid by borrower at loan origination and dummies for vehicle's make and model, for the vintage, and for whether the engine used 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 C.15, which shows the share of variance in baseline LTV explained by each characteristic.[9] 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 most important variable, the initial cost of the vehicle.[10] 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.

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

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

Figure C.15: 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.

D 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 5.3. 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 (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.

D.1 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.

To implement this approach, we first randomly distribute borrowers across treatment (payment and debt reduction combined) and control groups separately into five sub-groups.[11] 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.

D.2 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

[11] 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.

(we refer to this as $\mathcal{L}_i$ in Section 5.3). 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).

D.3 Machine Learning Methods Considered

We consider four distinct machine learning algorithms, each capturing different aspects of the relationship between covariates (X) and outcomes (y): (i) elastic net regression; (ii) gradient boosting machines (GBM); (iii) principal component neural networks (pcaNNet); (iv) random forest. Elastic Net combines LASSO and Ridge regression penalties, providing both variable selection and coefficient shrinkage. The method is particularly effective when dealing with correlated predictors and performs automatic feature selection. GBM builds models sequentially, where each new model corrects errors from previous models. This ensemble method excels at capturing non-linear relationships and interactions between variables. pcaNNet approach combines dimensionality reduction through Principal Component Analysis with neural network prediction, making it effective for high-dimensional data while maintaining interpretability. Random forests creates multiple decision trees using bootstrap samples and random feature selection. The method provides natural handling of non-linearities and variable interactions while being robust to outliers. We use the libraries in the software `R` for our estimation.

D.4 Algorithm: 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. The algorithm is summarized in Algorithm 2). We provide details on each sub-steps of this algorithm next.

Balanced fold creation. 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 ($\text{Fold}_k = T_k \cup C_k$). The step is summarized in Algorithm 1:

Algorithm 1 Balanced Fold Creation

1: Separate data into treatment (T) and control (C) groups
2: Create K folds for treatment group: $T_1, T_2, \ldots, T_K$ ($K = 5$)
3: Create K folds for control group: $C_1, C_2, \ldots, C_K$ ($K = 5$)
4: **for** $k = 1$ to K **do**
5: $\quad \text{Fold}_k = T_k \cup C_k$
6: **end for**

Cross-Validation Procedure. 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 methods 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.

Algorithm 2 Machine Learning Approach to HTEs by liquidity

Require: Data $\mathcal{D} = \{(L_i, Z_i, T_i)\}_{i=1}^{N}$ where L_i is "current after 6 months", Z_i are baseline covariates, $T_i \in \{0, 1\}$ is assignment; number of folds $K = 5$; learner set $\mathcal{M} = \{\text{Elastic Net (EN)}, \text{GBM}, \text{pcaNNet}, \text{Random Forest (RF)}\}$

Ensure: Out-of-sample predictions $\widehat{L}_i^{(m)}$ for each learner $m \in \mathcal{M}$; median ensemble $\widehat{L}_i$

Split by assignment: $\mathcal{C} \leftarrow \{i : T_i = 0\}$ (controls), $\mathcal{T} \leftarrow \{i : T_i = 1\}$ (treated).
Create balanced folds: Randomly partition $\mathcal{C}$ into $\{\mathcal{C}_1, \ldots, \mathcal{C}_K\}$ and $\mathcal{T}$ into $\{\mathcal{T}_1, \ldots, \mathcal{T}_K\}$.
for $k = 1$ to K **do**
  $\text{Fold}_k \leftarrow \mathcal{C}_k \cup \mathcal{T}_k$
end for
for $k = 1$ to K **do**
  test $\leftarrow \text{Fold}_k$; train $\leftarrow \bigcup_{\ell \neq k} \text{Fold}_\ell$
  for each $m \in \mathcal{M}$ **do**
    Fit $\widehat{g}^{(m,k)} : Z \mapsto L$ on *controls only* in train: $\{(L_i, Z_i) : i \in \text{train}, T_i = 0\}$
    For all $i \in$ test, set $\widehat{L}_i^{(m)} \leftarrow \widehat{g}^{(m,k)}(Z_i)$
  end for
end for
$\widehat{L}_i \leftarrow \text{median}(\widehat{L}_i^{(\text{EN})}, \widehat{L}_i^{(\text{GBM})}, \widehat{L}_i^{(\text{pcaNNet})}, \widehat{L}_i^{(\text{RF})})$
$\{\widehat{L}_i^{(m)}\}_{i,m}$, $\{\widehat{L}_i\}_i$

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