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"The Welfare Benefits of Pay-As-You-Go Financing"

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Abstract

Pay-as-you-go (PAYGo) financing is a novel financial contract that has recently become a popular form of credit, especially in low- and middle-income countries (LMICs). PAYGo financing relies on technology that enables the lender to cheaply and remotely disable the flow benefits of collateral when the borrower misses payments. This paper quantifies the welfare implications of PAYGo financing. We develop a dynamic structural model of consumers and estimate the model using a multi-arm, large scale pricing experiment conducted by a fintech lender that offers PAYGo financing for smartphones. We find that the welfare gain from access to PAYGo financing is equivalent to a 5.8% increase in income while remaining highly profitable for the lender. The welfare gains are larger for low-risk and intermediate-income consumers. Under reasonable assumptions about the repossession technology, PAYGo financing consistently outperforms traditional secured loans. For riskier consumers, an intermediate degree of lockout can be welfare maximizing.

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1 Introduction

Consumer lending markets are fraught with economic frictions including moral hazard, adverse selection, and limited enforcement. These frictions ultimately translate to high interest rates for borrowers and limited access to credit. Recently, digital financial products have become increasingly popular, especially in low and middle income countries (LMICs).[1] This growth has been facilitated by rapid technological adoption of mobile phones and digital payment systems as well as better data about borrowers and innovations in financial contracting.[2] Despite this recent growth, little is known about their economic effects. In particular, what are the welfare implications of these new digital products for consumers? To what extent can new technology be used to mitigate the aforementioned economic frictions? Our paper offers an answer to these questions in the context of a novel financial product: pay-as-you-go (PAYGo) financing.

PAYGo financing is effectively a loan secured by the flow services from a durable good. The typical PAYGo contract requires a nominal downpayment to take possession of the good (e.g., a smartphone) followed by frequent, small payments made via a mobile payment system. PAYGo lending crucially relies on an embedded "lockout technology" that allows the lender to remotely disable the good's flow of services for borrowers who have missed payments. PAYGo lending has experienced rapid growth over the last decade[3] and has been used to provide financing for a wide range of consumer durables including solar electricity systems, automobiles, and laptops, as well as follow-up cash loans for consumers who have completed payments on their initial loan.

It is instructive to compare PAYGo lending to secured lending, where the lender repossess the collateral if the borrower defaults. Securing loans with collateral serves three roles: screening borrowers, providing incentives to repay, and providing insurance to the lender (via the value of the repossessed collateral) in case the borrower defaults. PAYGo lending retains the first two roles but foregoes the third. From an economic standpoint, PAYGo financing has both costs and benefits compared to more traditional secured lending. The primary benefit of PAYGo is saving on repossession costs, which is especially valuable when these costs are high relative to the value of the collateral. PAYGo financing also offers

[1] According to the World Bank, in 2021, 76 percent of adults worldwide had an account at a financial institution or through a mobile money provider, up from 51 percent in 2011.

[2] Among LMICs, the number of mobile phone subscriptions per 100 people increased from 4.06 in 2000 to 103.4 in 2020. Similarly, the number of registered mobile money accounts increased from 4 million in 2006 to 866 million in 2018. Source: `https://ourworldindata.org/`, date accessed: August 19, 2022.

[3] For example, the share of PAYGo products out of total solar electricity systems sales volume has risen from 22% in 2018 to 38% in 2021, and African PAYGo solar companies enjoy 72% of the sector's investment. Source: Off-Grid Solar Market Trends Report 2022 by GOGLA.

a more flexible repayment schedule than a traditional secured loan, which is likely to be attractive to borrowers who face large and frequent income shocks. The main disadvantages are the costs of installing and maintaining the lockout technology, foregoing the insurance from repossession, and the ex-post inefficiency associated with locking the good.

Our objective is to quantify the welfare implications of PAYGo lending. In particular, we are interested in the extent to which borrowers are better off from having access to PAYGo financing, as well as how the welfare effects of the PAYGo contract compare to more traditional financial contracts. We develop a dynamic model of consumer lending that features stochastic income, endogenous contract selection, and strategic dynamic repayment. We estimate this model using a large-scale randomized experiment conducted by a fintech lender in Mexico that offers PAYGo financing for smartphones. The experiment involved random variations in both markups (i.e., financing cost) and required minimum downpayments, which allow us to credibly estimate borrowers' preferences and income dynamics. We use the estimated model to quantify the welfare gains brought by PAYGo financing, and perform several counterfactual analyses that shed light on the underlying economic frictions.

Our partner for this study (the lender) is one of the leading PAYGo lenders for smartphones in developing countries, which targets low-income individuals, many of whom are excluded from standard credit markets.[4] The lender offers borrowers a menu of four contracts, corresponding to four maturities (3, 6, 9 and 12 months). For each maturity, a contract specifies a markup (i.e., a financing cost), which increases with maturity, and a minimum required downpayment, which depends on a risk score assigned to consumers based on coarse demographic information. Our empirical analysis exploits an experiment conducted with roughly 30,000 consumers, who were assigned to one of 4×2 treatment arms: four arms with different markups and two arms with different minimum downpayments. The experimental data reveals important stylized facts about consumer behavior that guide our modelling choices. First, there is considerable heterogeneity across risk-scores. The demand of low-risk consumers is highly elastic to markups. In contrast, high-risk consumers respond to higher markups by opting for longer maturity contracts. Second, there is evidence of asymmetric information and moral hazard. Higher markups lead to significantly lower repayment rates, especially for high-risk consumers. Similarly, higher minimum downpayments significantly increase repayment rates for all but the safest consumers. Finally, we observe clear evidence of selection on maturity choice: repayment is significantly lower on longer maturity contracts.

To account for these facts, we develop a structural model of contract choice and repayment. Consumers are rational agents whose income follow a mean-reverting process. Agents differ ex ante along two dimensions: income and initial liquidity. These characteristics are

[4] For example, 79% of the consumers in the pricing experiment do not have credit cards.

privately observed, which generate adverse selection, both in terms of contract take-up and maturity choice. Longer maturity contracts, which carry lower per period payments, are more appealing to consumers with lower income or higher income risk. Repayment decisions are driven by income shocks: when making a repayment decision, consumers trade off the flow services of the good for (other forms of) consumption; negative income shocks increase the marginal utility from consumption and decrease the likelihood of repayment.

We estimate the model using Simulated Method of Moments (SMM). A key feature of our estimation procedure is that we target moments related to take-up, maturity choices, and repayment decisions observed in the pricing experiment. In other words, the model is estimated to replicate how consumers respond to markup and downpayment variations in the pricing experiment. We use four arms of the pricing experiment for estimation and leave the other four for model validation. Given the observed heterogeneity in the reduced-form evidence, we allow the structural parameters to vary across risk scores. For each risk category, we target a total of 52 moments to estimate 13 structural parameters. We provide an exhaustive analysis of model fit. With a few exceptions, our relatively simple model matches the behavior of consumers –take-up, maturity choice, downpayment choice and repayment– in the experiment well, both in and out-of-sample and across risk-scores. The estimates imply that that the average consumer has a mean income close to the minimum wage, faces significant income risk, has a high consumption value for the phone, and is liquidity constrained. There is considerable heterogeneity in income both within and across the risk scores.

We conduct several counterfactuals to better understand the economic consequences of PAYGo financing. First, we quantify the welfare gains for consumers from access to PAYGo financing. Our first counterfactual compares consumer welfare in the estimated model relative to a no-financing benchmark. To the extent that consumers have access to other forms of financing, this counterfactual provides an upper bound on the welfare gains. We measure the welfare gain of PAYGo financing as the percentage increase in income over a two-year period (i.e., the expected lifespan of the smartphone) that would deliver the same utility to the consumer as they enjoy from having access to the menu of PAYGo contracts.

Our findings suggest a sizeable welfare gain, corresponding to a 5.8% increase in income on average across risk scores. These welfare gains are larger for less risky consumers and those with intermediate levels of income. Despite large welfare gains for consumers, PAYGo financing is also highly profitable for the lender with annualized rates of return ranging from 143-201% across risk scores, with a higher profitability for low-risk customers. These high profits suggest that part of the potential welfare gains from PAYGo financing might be dissipated through imperfect competition. We thus consider a competitive pricing counterfactual, whereby markup and downpayment for each risk score are set so that the lender's rate of return is 25%. The reduction in markups under competitive pricing is significant ($\approx$ 15%), but the reduction in the minimum downpayment is even more notable ($\approx$ 80%). The welfare gains under competitive pricing are roughly three times larger than under the lender's current pricing. The higher welfare gains stem from both the intensive margin – takers pay lower markups – and the extensive margin, as take-up increases among more liquidity constrained borrowers. Most of the additional welfare gains for high-risk consumers come from the extensive margin, whereas the intensive margin is relatively more important among low-risk consumers.

Our second welfare exercise compares consumer welfare in the estimated model with PAYGo to a counterfactual where consumers have instead access to a traditional secured loan, where the lender repossesses smartphones of delinquent consumers. We do not observe such contracts being offered for smartphones in practice (presumably because they are unprofitable), but their consideration allows us to also provide a lower bound on the welfare gains. We find the competitive prices of secured loans under a range of assumptions about the repossession technology available to the lender. We then compare consumers under competitive pricing for both contracts and find that PAYGo consistently delivers higher welfare. Under reasonable assumptions about the repossession technology, the welfare gain of PAYGo is equivalent to a 3-5% increase in income.

In our empirical setting, the phone is effectively unusable when locked, i.e., the locking technology is strong. Yet, it is conceivable that a weaker locking technology, that provides some access to the phone's services when consumers miss payments, could improve welfare. Holding prices fixed, decreasing the lock strength benefits consumers by providing better insurance against income shocks. However, it also hurts lender's profit, leading to higher competitive prices. We explore the role of the strength of the locking technology in two counterfactuals.

First, we examine how lender's profit vary as the lock becomes weaker while holding price fixed. A weaker lock affects lender's profits through two channels: screening (i.e., riskier consumers start taking up) and incentives (i.e., existing consumers have less incentive to repay). We find that the lender's profit is concave in the lock strength. Starting from a very strong lock, a small reduction in lock strength leads only to a small reduction in lender's profit. For intermediate lock strengths, a further reduction leads to a more significant decrease in profit, which can be roughly equally attributed to screening and incentives. For weaker lock strengths, lending is unprofitable. In this region, most of the reduction in profit is due to weaker ex post incentives.

Second, we calculate the welfare-maximizing locking technology. To do so, we compute competitive prices for various levels of lock strength and evaluate consumer welfare for each technology. For low-risk consumers, welfare is strictly increasing in lock strength as the benefit of lower prices outweighs the foregone insurance. However, for high-risk consumers, consumer welfare is hump-shaped in the lock strength and maximized at an intermediate lockout strength. Relative to a perfect lock, welfare is about 30% larger with the optimal weaker lock. This finding suggests that the welfare gains from optimally designing financial contracts using lockout technology could be significantly larger than what we estimate from PAYGo financing. We believe this is an important direction for future research.

Related Literature Our paper relates to the empirical literature studying contracting and frictions in credit markets, and, in particular to the literature that exploits exogenous variations in contract terms to quantify the extent of information asymmetries. A first strand of this literature relies on reduced-form evidence (e.g., Karlan and Zinman 2009, Hertzberg et al. 2018, Indarte 2023, Agarwal et al. 2010, Dobbie and Skiba 2013, Gupta and Hansman 2022, Stroebel 2016, Indarte 2023). Closer to us, a second strand analyzes these variations through the lens of structural models of the credit market (e.g., Adams et al. 2009, Einav et al. 2012, Xin 2023, DeFusco et al. 2022, Cuesta and Sepulveda 2021). Our paper contributes to this literature by shifting the focus away from standard loan contracts and toward a novel financial contract, PAYGo. Methodologically, our model allows borrowers to make endogenous decisions regarding not only loan take up, but also but also downpayment and maturity, and our estimation relies on a large-scale, multi-arm experiments.

Our analysis of PAYGo financing complements Gertler et al. (2023), who show that, compared to an unsecured loan, PAYGo loans reduce both moral hazard and adverse selection and increase lender profitability. While Gertler et al. (2023)'s findings suggest that PAYGo financing improve welfare, our paper offers a quantitative assessment of such welfare gains. Beyond PAYGo, our paper also contributes to the literature evaluating how financial technology affects household welfare in developing countries.[5] Prior research emphasizes that access to mobile phone-enabled FinTech such as mobile money improves risk-sharing, employment outcomes, and household resilience (Jack and Suri, 2014; Suri and Jack, 2016; Suri et al., 2021), and stimulates entrepreneurship in developing countries (Apeti et al., 2023). More generally, FinTech has been shown to create positive spillovers on economic activity (Higgins, 2022; Agarwal et al., 2020b) and to provide a remedy against financial repression (Buchak et al., 2021).[6] Our paper emphasizes the role of a novel technology, lockout, and how it is

[5] For an introduction on FinTech developments in other settings, we refer the readers to Berg et al. (2022) and Boot and Thakor (2024).

[6] Through its focus on a novel financial technology, our paper is also related to the literature that analyzes the screening and monitoring efficiency of fintech lenders (Agarwal et al., 2020a; Buchak et al.,

used in financial contracting. While we focus on the smartphone market, increasing credit supply for smartphone purchases is likely to generate positive externalities as they allow to access mobile money, platform-based business models, mobile investing, or online learning.

Finally, our paper contributes to the emerging literature in applied microeconomics that combine randomized control trials (RCT) with structural modeling (see Todd and Wolpin, 2023 for a survey). RCT data have been used in two ways to enhance the credibility of structural methods. First, for model validation purposes, using one either the treatment group or the control group as holdout samples in performing out-of-sample model fit tests.[7] A second way to combine an RCT with a structural model is to rely on variations in treatment induced by the RCT to identify and estimate key structural parameters.[8] Our paper combines both approaches. Our experiment contains 4 pricing arms and 2 minimum required downpayment arms. We exploit 4 of these arms for estimation and use the remaining four to assess model fit. We also use our structural model to provide counterfactuals assessing the welfare effects of PAYGo financing in the smartphone market in Mexico.

2 Reduced-Form Evidence

2.1 Institutional Background

Smartphones have become a critical tool for economic development. For instance, they facilitate access to mobile money and digital banking services, which can bring poor households into the formal financial system and foster both savings and borrowing for entrepreneurial activity (Suri and Jack (2016)). However, most mass-market smartphones remain expensive for households in developing countries. Our partner in this study is a FinTech lender that offers PAYGo financing to households looking to purchase a smartphone, with a specific focus on the underbanked population that lack access to traditional forms of financing. To do so, the lender installs a lock on the phones it finances. When users are late on a payment, the lock prevents them from using the phone until they make their payment, which instantly restores functionality. This feature fosters repayments and thus allows the firm to serve consumers who would otherwise be excluded from traditional credit markets.

The lender offers financing contracts, which are characterized by (1) a maturity T, which corresponds to the required number of weekly payments, (2) a minimum downpayment D,

2018; Di Maggio and Yao, 2021; Fuster et al., 2019).

[7] See, e.g., Todd and Wolpin (2006) and Duflo et al. (2012) in an education context, Kaboski and Townsend (2011) in a microfinance setting, and Keane and Wolpin (2010) on labor supply and welfare programs.

[8] See, e.g., Attanasio et al. (2011) on school attendance and child labor and Bellemare and Shearer (2011) on worker effort.

and (3) a multiple θ. If a customer puts down $D_i \geq D$, and the phone price is p, she finances an amount $L_i = p - D_i$, and she has to pay back T weekly installments of $\theta L_i / T$ to the lender. Missing a payment locks the phone until a payment is made, but leaves the total number of payments due, and their amount, unchanged. After the customer makes T payments, she owns the phone and the locking system is disabled. Customers interested in financing a smartphone are offered a menu of contracts (T, D, θ), which consists of 4 possible maturities: 13, 26, 39 or 52 weeks. The multiples are the same for all customers, but they vary across maturities, with longer maturities facing higher multiples. The minimum downpayment D is the same for all maturity, but depends on a risk score $R \in \{1, 2, 3, 4\}$ attributed by the lender based on personal information provided by the consumer (demographics, occupation, financial conditions).

The lender operates in numerous countries around the globe, including Mexico, Brazil, Colombia, India, Kenya, and South Africa. Our paper exploits a large-scale pricing experiment conducted by the lender in Mexico in 2018-19.

2.2 Experimental Design and Data

The pricing experiment we analyze was conducted from November 2018 to June 2019. Customers expressing interest were randomly assigned to one of 4×2 treatment groups: 4 arms with different multiples θ, and 2 arms with different minimum downpayments D. Table 1 details the term of each arm. Panel A shows the details of the four multiples arms. The Control arm corresponds to the baseline contract. The Medium and High arms shift upward multiples across maturities, while keeping constant the relative price of different maturity. The Steep arm makes longer maturities relatively more expensive. Panel B shows the details of the two downpayment arms as they depend on risk score. The Low downpayment arm reduces the minimum downpayment across risk scores, by five percentage points for risk score one, two and three, and by 10 percentage points for risk score four. The allocation of customers across pricing arms was uniform. Customers had a 60% chance of being assigned to the Control downpayment arm, and a 40% chance of being assigned to the Low downpayment arm.

Our dataset contains information about customers in the experiment, including some basic demographics, their treatment arm, whether they accept a contract, and if so, which contract they accept, as well as their repayment behavior over a two-year period following the experiment. 28,786 customers are subjects in the pricing experiment (Table 1). The typical customer is 32 years old, and is mostly male (85%). 57% of them have a bank account, 21% have a credit card, and more than half of them work in the formal, private sector. 24% are assigned to the safest risk score (1), 30% to risk score 2, 27% to risk score 3, and 20% to risk score 4.

52% of the customers in the experiment accept one of the offered contracts, and we refer to them as "takers" (Table A1). The average phone price they purchase is \$206.1.[9] 29% of takers opt for a three month contract, 38% for a six month contract, 22% for a nine month contract and 11% for a 12 month contract. The minimum downpayment requirement appears binding for most customers: over 80% of takers put down exactly the minimum required downpayment (Figure A1). Across risk scores, takers put down on average 31% of the purchase price, and thus finance \$142. They face an average multiple of 1.70, which implies a weekly payment of \$9.8 on an average maturity of 28 weeks.

Repayment is far from perfect. Only 37% of borrowers have fully repaid the amount owed at maturity. 74% of takers repay their loan in full within two years of origination, but it takes them on average 116% of the contract's maturity to reach full repayment. The average taker repays 73% of the total amount owed to the lender. 62% of takers miss at least one payment. Panel B of Figure 2 shows a histogram of the share of promised payments missed across maturity. The figure highlight the borrowers' inconsistent repayment behavior. 22% of borrowers have missed 50% or more of the promised payments at contract maturity. This figures rises to almost 40% for borrowers in the 12-month contract.

The interest rate implied by the PAYGo contracts in our sample is high. Across all treatment groups, the implied Annualized Percentage Rates (APR) range from 142% to 360%. However, because the nominal payment amount is fixed, a peculiar feature of the PAYGo contract is that the longer the borrower takes to repay, the lower is the effective interest rate. For example, the six-month maturity contract in the control arm has a multiple of 1.54, which corresponds to a weekly interest rate of 3.49% or an APR of 182% (i.e., $3.49\% \times 52$) for on-time payers. A consumer who makes their weekly payment only every other week, and therefore takes one year to repay a six-month contract, pays a *bi-weekly* interest rate of 3.49%, which corresponds to an APR of 91%.

During the experiment (2018-2019), the company was also offering financing for phones that had a "weaker" lock system: these devices came with a similar PAYGo technology, but the lockout feature could be circumvented by borrowers. These weak lock systems are installed on different phones: the phones in our experiment are Samsungs while the weak lock phones are Motorolas, which are slightly cheaper (about \$180 vs. \$203 for Samsungs). Contract terms were also different: the weak lock phones could only be purchased with 3 or

[9]Table A1 documents some heterogeneity in the price of smartphones purchased: the standard deviation of smartphone prices among takers is \$77. Since the experiment we exploit only provides random variations in financing terms, our structural model abstracts away from the choice of the phone's model and assumes a constant cash price for all smartphones of \$200.

6 months loans and carried higher downpayment requirements (40% vs. 25% in the Control downpayment arm). Despite their lower price and higher downpayment requirements, we observe significantly higher default rates for weak lock loans: for instance, the share of customers with a three-month contract who have missed at least one payment after three months is 25% in our data, but 41% for weak lock phones. This result suggests that the lockout technology significantly increases repayment. Unfortunately, this evidence is essentially qualitative: while the lockout could be circumvented, we have no data on the cost or difficulty of doing so, nor the extent to which borrowers were aware that the lock could be circumvented at the time of purchase. This prevents us from mapping this evidence to the model we develop below.

2.3 Reduced-Form Evidence

The structural estimation we present in Section 4 aims to reproduce consumer behavior (in terms of take-up, contract choice, downpayment choice and repayment) across four treatment arms of the pricing experiment. The other four arms are used to validate the estimated model. In this section, we summarize the main features of consumer behavior observed in the experiment. We do so by presenting simple reduced-form estimates that measure how consumers with different credit score causally adjust their decisions in response to changes in contract terms.

We estimate the following model using OLS for each risk score R separately:

$$Y_i^R = \alpha^R + \beta^R \cdot \log(\text{Average multiple}_i) + \gamma^R \cdot \mathbb{1}_{i \in \text{low min down}} + \epsilon_i^R.$$

Average multiple$_i$ corresponds to the average multiple faced by customer i in her assigned pricing arm. $\mathbb{1}_{i \in \text{low min down}}$ is a dummy equal to one if customer i is assigned to the Low downpayment arm. We exclude the Steep pricing arm for this estimation since it does not shift multiples across maturity in a uniform way. We estimate this equation for four outcomes of interest (Y_i^R): (i) loan take-up, (ii) log-loan maturity, (iii) log-downpayment, (iv) the log-share of the total amount owed to the lender repaid at maturity.

Higher multiples significantly reduce loan take-up, with an average semi-elasticity across risk scores of -0.24 ($t = -5.1$). This semi-elasticity increases with risk score, from about -0.5 and highly significant for low-risk customers to about zero and insignificant for high-risk customers (Panel A, Figure 1). Higher-risk borrowers (risk scores 3 and 4) respond to increased loan cost by shifting to longer maturity loans (Panel B). While longer maturity loans have higher multiples, they also imply lower weekly payments. However, despite the shift to longer maturity loans, the net effect of higher multiples on weekly payments remain positive:

across risk scores, the elasticity of weekly payments to higher multiples is 0.60 ($t = 9.9$). While take-up and downpayment significantly respond to higher multiples, downpayment choices do not (Panel C). Finally, takers facing higher multiples repay a lower share of the total amount owed to the lender at maturity. Across risk scores, the elasticity of the share of the loan repaid at maturity to the average multiple is -0.70 ($t = -44.5$). This elasticity is negative and significant across all risk scores. It decreases with risk scores, from about -0.65 for low-risk customers to -0.80 for high-risk customers. Since high-risk customers' demand is not elastic to multiples (Panel A), their lower repayment elasticity cannot be driven by adverse selection. In contrast, the demand of lower-risk customers (risk scores 1 and 2) is highly elastic to multiples, but their maturity choice is not. Their lower repayment rates in response to higher multiples are thus likely driven either by adverse selection or by the higher weekly payments induced by higher multiples.

We also evaluate the effect of minimum downpayment requirements on take-up, contract choice and repayment by estimating the following equation using OLS:

$$Y_i^R = \alpha^R + \beta^R \cdot \log(\text{min down}_i) + \sum_{l=1}^{4} \gamma_l^R \cdot \mathbb{1}_{i \in \text{price arm } l} + \epsilon_i^R,$$

where $\mathbb{1}_{i \in \text{price arm } l}$ is a dummy equal to one if customer i is assigned to pricing arm $l \in \{\text{Control, Medium, High, Steep}\}$. The elasticity of actual downpayment to the minimum required downpayment is close to one and significant for all risk scores (Panel G, Figure 1). This result is not surprising since, for all risk scores, more than 80% of takers select exactly the minimum downpayment. Higher downpayment requirements lead to significantly lower take-up rates (Panel E), especially for riskier customers who are more likely to be liquidity constrained. On average, customers facing higher downpayments shift to significantly lower maturity contracts (Panel F), which carry lower multiples. The overall effect of higher minimum downpayments on weekly payments is a priori ambiguous: it reduces the financed amount, which mechanically decrease weekly payments; it also lead takers to select lower maturity, which leads to increased weekly payments. Overall, the former effect dominates. Across risk scores, the elasticity of weekly payments to minimum downpayment is -0.40 ($t = -25.6$). Since higher minimum downpayments potentially induce positive selection and lead to reduced weekly payments, we find that they also lead to increased repayment rates across risk scores (Panel H).

Finally, Panel A of Figure 2 shows how repayment rates vary over time by maturity. While weekly payments decrease with maturity, repayment rates at maturity are significantly lower for longer maturity contracts. Panel B of Figure 2 shows the distribution of the fraction of weeks in default. Together with the evidence of Panel B in Figure 1, Figure 2 shows that maturity choice is a potentially important channel of selection in this market, a feature we will incorporate into our structural model.

3 Model

3.1 Model Overview

A single firm produces a good that delivers a flow utility to consumers and offers a menu of PAYGo loan contracts to consumers, which vary by maturity and interest rate. Consumers have heterogeneous private income that follows a mean reverting process. Household must decide whether to accept a contract and if so, which contract to accept. If the consumer accepts one of the contracts then it must make the requisite downpayment in order to take possession of the device. In subsequent periods, consumers decide whether to make the payment in that period after privately observing their realized income. During repayment, the device locks if the consumer misses a payment. If and when the consumer completes the number of payments specified by the contract, the device is permanently unlocked.

3.2 Consumers

Consumers (indexed by i) are expected utility maximizers. They have time-separable, quasi-linear utility over the consumption good and the flow of services from the device, $u(c_{it}) + q_{it}$, where c_{it} denotes the consumption of consumer i in period t and q_{it} denotes consumer i's flow utility from the device at date t. Consumers have CRRA utility for the consumption good, $u(c) = \frac{1}{1-\gamma}c^{1-\gamma}$, where γ denotes the degree of relative risk aversion. Consumers' discount factor is denoted by β.

Consumer i has long-run mean income, $\bar{y}_i$ and per-period income follows a log AR(1) process with constant drift. In addition to date 0 income, consumer i has some initial wealth (or "liquidity"), which we denote by L_i, that can be used for the downpayment or date 0 consumption.[10] Residual liquidity that is not used for a downpayment or date 0 consumption can be "saved," which delivers a payoff proportional to consumer i's shadow value for liquidity. Consumers do not have access to an external borrowing or savings technology.

[10]Initial wealth at the date of purchase is both plausible (i.e., consumers save to make the purchase) and necessary to simultaneously match both take-up and repayment data in the pricing experiment. If the downpayment was funded solely by date 0 income then, in order to match the take-up rates, consumers would be too rich to match their repayment decisions.

3.3 The PAYGo Contract

A PAYGo contract is summarized by the triple $\Gamma \equiv (D, T, \theta)$, where D denotes the minimum downpayment, T denotes the total number of payments required (i.e., the maturity), and θ denotes the markup. If consumer i accepts a contract Γ for a phone of price p, and makes a downpayment of $D_i \geq D$, then the loan amount is $L = p - D_i$ and the per-period payment amount is $m = \theta L/T$. When consumer i makes the required payment in period t then the device is "unlocked" and the consumer enjoys the flow utility from the good, $q_{it} = v_{it}$. If the consumer does not make the required payment, then the device is locked and the consumer receives flow utility $q_{it} = (1 - \lambda)v_{it}$, where λ parameterizes the effectiveness of the lockout technology. A perfectly effective lockout technology corresponds to $\lambda = 1$: consumers derive no utility from the device when locked. An unsecured loan corresponds to $\lambda = 0$: consumers derive the same utility from the device regardless of whether they make a payment. Once the consumer has made T payments, the consumer owns the device, and it is permanently unlocked.

All consumers experience an initial flow utility from the device upon purchasing it, $v_{i0} = \bar{v}$. In each period, the good depreciates with probability ϕ. If depreciation materializes for consumer i in period t then $v_{it} = \max\{v_{it-1} - \bar{v}/N_v, 0\}$, where N_v corresponds to the number of depreciation shocks the good can experience before being worthless.

The firm offers each consumer a menu of PAYGo contracts, which vary in their maturity, markup, and minimum downpayment. Payments are made on a weekly basis.[11]

3.4 The Consumer's Problem

Consumers make several decisions in the model. Firs, they have to decide which, if any, of the contracts to accept. If the consumer does not accept any of the contracts, it retains the option to purchase the device with cash at any future date. If the consumer accepts one of the offered contracts, it must choose how much to put down. Each period, after (privately) observing their realized income and depreciation, the consumer chooses whether to make a payment.

In what follows, we formalize the consumer's problem and characterize its solution as follows. First, taking the contract as given, we solve for he optimal repayment policy of the consumer. Next, we characterize the consumer's ex-ante value for a given contract. Then, after describing the consumer's outside option, we solve for consumers' optimal downpayment, maturity and take-up decisions.

[11] Consumers have the ability to prepay for future weeks. However, doing so increases the effective interest rate and is rarely observed in the data.

Repayment Decisions Fixing a contract Γ and downpayment D_i, the payoff-relevant state variable is $x_{it} = (v_{it}, y_{it}, n_{it}, m_i)$, where n_{it} denotes the number of payments remaining on the loan and m_i denotes the weekly payment amount. Let $U_i(x_{it}; \Gamma)$ denote the continuation value of consumer i under the contract Γ (henceforth, the latter argument is regularly suppressed).[12] While in repayment (i.e., for $n_{it} \geq 1$), the Bellman equation for consumer i is

$$\begin{aligned} U_i(x_{it}) = \max \Big\{ & v_{it} + u(y_{it} - m_i) + \beta \mathbb{E}\left[U_i(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i) | x_{it}\right], \\ & (1-\lambda) v_{it} + u(y_{it}) + \beta \mathbb{E}\left[U_i(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i) | x_{it}\right] \Big\}. \end{aligned} \tag{1}$$

Therefore, the optimal policy of consumer i is to make the payment if

$$\underbrace{\lambda v_{it}}_{\uparrow \text{ flow utility}} + \beta \underbrace{\mathbb{E}[U_i(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i) - U_i(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i) | x_{it}]}_{\uparrow \text{ in future expected utility from principal reduction}} \geq \underbrace{u(y_{it}) - u(y_{it} - m_i)}_{\text{disutility from } \downarrow \text{ consumption}}$$

In words, the consumer optimally makes a payment if the extra flow utility from being unlocked plus the discounted expected value of having one less payment to make in the future outweighs the disutility associated with lower consumption today. We denote the solution to the consumer's repayment decision as $A_i(x_{it})$.

The ownership boundary condition is

$$U_i(v_{it}, y_{it}, 0, m_i) = \Pi_i(v_{it}, y_{it}) \tag{2}$$

where Π_i is the expected utility from ownership (i.e., being permanently unlocked),

$$\Pi_i(v_{it}, y_{it}) = v_{it} + u(y_{it}) + \beta \mathbb{E}[\Pi_i(v_{i,t+1}, y_{i,t+1}) | x_{it}]. \tag{3}$$

Value of a Contract A contract, Γ_j, is *feasible* for consumer i if they can afford to make the minimum downpayment. Given a feasible contract, the consumer must choose how much to put down as well as how much to consume in that period subject to (1) their budget constraint, (2) the downpayment constraint, and (3) the constraint that the consumers cannot save more than their liquid wealth. The solution to this problem yields housholds i's ex-ante value for contract Γ_j, which we denote by $W_i(\Gamma_j)$. Let $m(d_i)$ be the weekly payment on the contract given a downpayment d_i ($m(d_i) = \frac{\theta \times (p - d_i)}{T}$). Then, the

[12]The i subscript on the value function indicates its dependence on variables specific to consumer i that are constant over time and not included as state variables (e.g., long-run mean income).

consumer's value for any feasible contract Γ_j is given by:

$$\begin{aligned} W_i(\Gamma_j) = \max_{c_{i0}, w_i, d_i} \; & v_{i0} + u(c_{i0}) + \mu_i w_i + \beta \mathbb{E}[U_i(v_{i1}, y_{i1}, T, m(d_i)) | v_{i0}, y_{i0}] \\ s.t. \quad & c_{i0} + w_i + d_i \leq y_{i0} + L_i, \\ & d_i \geq D_j, \\ & w_i \leq L_i, \\ & c_i, w_i \geq 0. \end{aligned} \tag{4}$$

The term $\mu_i w_i$ captures the consumer i's value from retaining w_i units of liquidity, where μ_i can be interpreted as the consumers shadow value for a unit of liquidity.[13] This specification ensures consumers face a trade-off between using wealth for a downpayment or saving it without incorporating a full consumption/savings problem into the model.

Outside Option If households do not accept one of the contracts, they have the option to purchase the device with cash for price p at any date t. Thus, households' outside option is a real option, which includes the option to never purchase the device. The value of this outside option, which includes retaining all of their liquidity, is given by:

$$O_i(y_{it}) = \mu_i L_i + F_i(y_{it}) \tag{5}$$

where F_i is the value of the real option, which is the maximum of the value from buying with cash (denoted by G_i) or retaining the option to buy with cash in the future.

$$F_i(y_{it}) = \max \Big\{ u(y_{it}) + \beta \mathbb{E}[F_i(y_{i,t+1}) | y_{it}], G_i(y_{it}) \Big\}. \tag{6}$$

Household i can only buy with cash at date t if they can afford the cash price. Conditional on buying with cash, the household must forego some of their liquidity and choose how much to consume. Therefore, the value from buying with cash is given by:

$$\begin{aligned} G_i(y_{it}) = & \max_{c_{it}, w_i} v_0 + u(c_{it}) - \mu_i (L_i - w_i) + \beta \mathbb{E}[\Pi(v_{i1}, y_{it+1}) | y_{it}] \\ \text{s.t. } & c_{it} + w_i + p \leq y_{it} + L_i \\ & w_i \leq L_i \\ & c_{it}, w_i \geq 0. \end{aligned} \tag{7}$$

[13] In our empirical specification below, we assume that the marginal value of liquidity is higher for poorer consumers. Formally, we let μ_i be proportional to the consumer's marginal utility at its long-run mean income, i.e. $\mu_i = \mu \times u'(\bar{y}_i)$.

If $y_{it} + L_i > p$, then buying with cash at date t is not feasible and we let $G_i(x_{it}) = -\infty$.

Maturity Choice: Contract Selection Each consumer faces a menu of contracts $\mathcal{M}^i = \{\Gamma_j^i\}_{j \in J}$, where the j subscript corresponds to the maturity of the contract (i.e., the number of payments). Contracts with a greater number of payments involve a lower weekly payment, but a higher markup. Household's contract choice is a two-stage process. First, consumer identify the set of contracts that dominate their outside option. Denote this set by $\mathcal{M}_i^* \equiv \{\Gamma \in \mathcal{M}^i : W_i(\Gamma) \geq O_i(x_{i0})\}$. If $\mathcal{M}_i^* = \emptyset$, then consumers select the outside option. Next, if $\mathcal{M}_i^*$ is non-empty then consumers draw a random utility shock ω_{ij} for each $\Gamma_j \in \mathcal{M}_i^*$. The consumer then selects the contract from $\mathcal{M}_i^*$ that delivers the highest value inclusive of the utility shock, which we denote by Γ_i^*, where

$$\Gamma_i^* = \arg \max_{\Gamma_j \in \mathcal{M}_i^*} W_i(\Gamma_j) + \omega_{ij}. \tag{8}$$

These maturity-choice shocks are necessary to match the observed maturity selection in our pricing experiment. When consumers have low discount rates, their maturity choice is largely driven by the contract's multiple, which is always lower for three-month maturity contracts. Higher discount rates push consumers towards longer maturity contracts as they trade off lower weekly payments against higher multiples. In our pricing experiment, while the multiple on the three-month contract is by far the lowest multiple, the multiple on the six-month contract is only slightly lower than the nine-month contract. This pricing makes the six-month contract effectively dominated by the three and nine-month alternatives. Yet, in the data, 37% of takers select a six-month contract. To account for this choice, we follow the discrete choice literature and introduce random utility shocks. These shocks capture the unobserved heterogeneity in consumers' preferences for contract maturity, which is not explained by other sources of heterogeneity in the model.[14]

3.5 Firm Profit

Let $V_i(x_{it}, \Gamma)$ denote the firm's expected gross profit from consumer i under contract Γ and given state variables x_{it}. It is defined recursively by

$$\begin{aligned} V_i(x_{it}; \Gamma) = & A_i(x_{it})\big(m_i + \delta \mathbb{E}[V_i(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i)|x_{it}]\big) \\ & + (1 - A_i(x_{it}))\delta \mathbb{E}[V_i(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i)|x_{it}] \end{aligned} \tag{9}$$

[14] In the appendix, we estimate a version of our baseline model that does not include maturity-choice shocks (see Table A6 for parameter estimates). Figure A5 shows the estimated model fails to match the large observed take-up rate for 6-month contracts.

where δ is the firm's discount rate. The terminal boundary condition is

$$V_i(v_{it}, y_{it}, 0, m_i, \Gamma) = K \tag{10}$$

where K is the life-time value of a consumer that has fully repaid.[15] On date 0, the firm's expected net present value (NPV) from lending to consumer i under contract Γ is

$$\text{NPV}_i(\Gamma) = d_i + \delta\mathbb{E}[V(x_{i1}, \Gamma)|x_{i0}] - c, \tag{11}$$

where c is the marginal cost to the firm of producing and selling the device. Notably, we assume that the firm incurs no fixed costs.

4 Estimation

This section describes the model's estimation. We fit our model using a Simulated Method of Moments (SMM) that targets moments related to take-up, downpayment choices, maturity choices and repayment decisions observed in the pricing experiment. We use four arms of the pricing experiment for estimation and leave the other four for model validation. We estimate the model separately for each risk score.

4.1 Methodology

To take our model to the data, we make four parametric assumptions:

1. Income follows an AR(1) process

$$\log\left(\frac{y_{it}}{\bar{y}_i}\right) = \rho \log\left(\frac{y_{i,t-1}}{\bar{y}_i}\right) + \epsilon_{it} - \frac{\sigma_\epsilon^2}{2(1+\rho)}, \tag{12}$$

   with $\epsilon_{it} \sim \mathcal{N}(0, \sigma_\epsilon^2)$ and $\rho \in (0,1)$. At date 0, consumers draw their income from its steady-state distribution: $\log(y_{i0}/\bar{y}_i) \sim \mathcal{N}(-\frac{\sigma_\epsilon^2}{2(1-\rho^2)}, \frac{\sigma_\epsilon^2}{1-\rho^2})$.[16]

2. Consumers long-run mean income, $\bar{y}_i$, is log-normally distributed: $\log(\bar{y}_i/\bar{y}) \sim \mathcal{N}(-\frac{\sigma_{\bar{y}}^2}{2}, \sigma_{\bar{y}}^2)$.

[15] K derives from future business between the firm and consumer that are facilitated, which might also utilize the device as digital collateral. For example, the firm in our study issue subsequent cash loans that also leverage the lockout technology to customers who have successfully repaid their initial loan and obtained ownership.

[16] The term $-\frac{\sigma_\epsilon^2}{2(1+\rho)}$ in equation 12 ensures that there is no drift in the average income of consumers over time. Since consumers draw their initial income from the steady-state distribution, the cross-sectional distribution of income is the same every period.

3. Household liquidity is log-normally distributed: $\log(L_i/\bar{L}) \sim \mathcal{N}(-\frac{\sigma_L^2}{2}, \sigma_L^2)$.

4. The random maturity shocks are normally distributed: $\omega_{ij} \sim \mathcal{N}(0, \sigma_{\omega_j}^2)$ and i.i.d. across consumers and contracts. We normalize $\sigma_{\omega,12}$ to 1.

We also make a few assumptions that are useful for identification purposes. First, we assume that the lockout technology is perfectly effective (i.e., $\lambda = 1$). While some customers might be able to circumvent the lockout technology, this is unlikely to be a concern in practice.[17] Second, we assume that consumers have log-utility (i.e., $\gamma = 1$). While maturity choices are informative about consumers' discount rates, it is not clear how to separately identify the discount rate and risk aversion given the sources of variations in our data. Third, we assume that the device loses all of its value when depreciation materializes (i.e., $N_v = 1$). Depreciation shocks thus correspond to damage to the smartphone that renders it unusable, which is the most common source of smartphone depreciation over a two-year horizon.[18] Finally, since we do not have any data on the firm's profit after loans have been repaid, we assume that the lifetime value of a fully repaid household to the firm is zero (i.e., $K = 0$). Note that this assumption does not affect the model's estimation and only affects our counterfactual analyses.

These assumptions leave 13 parameters for estimation: $\bar{y}$ (long-run mean income), $\sigma_{\bar{y}}$ (dispersion of long-run mean income across consumers), σ_ϵ (volatility of income shock), ρ (persistence of income), $\bar{L}$ (average initial liquidity), σ_L (dispersion of initial liquidity across consumers), v_0 (initial device value), ϕ (probability of depreciation each week), β (weekly discount rate), μ (value of savings), $\sigma_{\omega,3}$ (size of random shock for the 3 month contract), $\sigma_{\omega,6}$ (size of random shock for the 6 month contract), $\sigma_{\omega,9}$ (size of random shock for the 9 month contract). We denote by Θ the set of these 13 structural parameters.

We estimate the model using SMM for each risk score separately. The estimation targets a total of 52 moments for each risk score, which correspond to 13 moments estimated across each of the four treatment arms of the pricing experiment. The first set of moments captures take-up and maturity choices: the share of customers selecting each maturity. The second set of moments relates to the repayment behavior of customers: the share of the amount owed repaid at maturity for each contract. The third set of moments captures the overall dynamics of repayment: the share repaid in the first half of the contract compared to the second half, the share of buyers who have fully repaid their loans at maturity, the probability of resuming

[17] The lender uses a patented Android technology, which is typically built into the smartphone by the device manufacturer.

[18] Surveys show that the average lifespan of smartphones in Mexico during our sample period is approximately 24 months, which is within the range of the expected lifespan implied by our estimated ϕ. The main reasons why people replace their smartphones are device failures (47.5%), the model being obsolete (22.9%), and loss or theft (7.3%).

payments in week t conditional on missing a payment in week $t-1$, and the share of buyers who stop paying within two years of origination. Finally, we inform downpayment decisions by targeting the share of buyers who put exactly the minimum required downpayment.

We now summarize our estimation procedure and refer readers to Section A.1 in the Online Appendix for details. We start from an arbitrary value for structural parameters Θ. We discretize the state space $x_{it} = (v_{it}, y_{it}, n_{it}, m_i)$ as well as the initial decision set: the downpayment decision d_i and initial consumption and saving choice, c_{i0} and w_i. We set the contract terms to Γ_j, one of the contracts in the menu $\mathcal{M}$ offered in the pricing experiment. We start consumers at an arbitrary downpayment d_i and consumption c_{i0}. Using value function iteration (VFI), we solve consumers' value function U_i (Equation 1) on the x_{it} grid.[19] This step delivers consumers' optimal repayment decision for each possible value of the state space $A_i(x_{it})$. We then find consumers' date-0 optimal value in the contract, $W_i(\Gamma_j)$, which delivers consumers' optimal downpayment choice $d_i(x_{i0})$. We reiterate this procedure for all the contract Γ_j in the menu $\mathcal{M}$. Using VFI to solve the outside option O_i (Equation **??**), we can then obtain consumers' preferred contract Γ^* (Equation 8) in the menu $\mathcal{M}$ given an initial state x_{i0}.

We then simulate a sample of 10^6 consumers. These consumers chose from one of the 8 menus $(\mathcal{M}_l)_{l\in\{1,8\}}$ offered in the pricing experiment. Their initial income is drawn from the steady-state distribution $\mathcal{N}(-\frac{\sigma_\epsilon^2}{2(1-\rho^2)}, \frac{\sigma_\epsilon^2}{1-\rho^2})$ and their initial liquidity is drawn from $\mathcal{N}(\bar{L}, \sigma_L)$. We also simulate a household-level time-series of income y_{it} and device value v_{it} that follow the law of motions described in Section 3. Using consumers' optimal policies, we can create a simulated sample that provides, for each household, the contract they would choose in the menu $\mathcal{M}_l$ (which may include not purchasing, i.e. $\varnothing$), their downpayment choice given the selected contract, and their optimal repayment behavior. Repeating this procedure for each of the 8 menus in the experiment, we can estimate the 52 targeted moments $m(\Theta) = m_1 - m_{52}$ on the simulated dataset.

The estimation minimizes the distance between simulated moments $m(\Theta)$ and empirical moments m:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}}\, (m(\Theta) - m)' W (m(\Theta) - m), \tag{13}$$

where we use the identity matrix as the weighting matrix W.[20] Details on the algorithm used to estimate Θ can be found in Section A.4 in the Online Appendix.

[19]We cannot use backward induction since the contract's terminal date depends on the household's repayment behavior.

[20]We also conducted robustness analysis using alternative weighting matrices, including $W = (K_{\mathbf{mm}})^{-1}$, where $K_{\mathbf{mm}}$ is the variance-covariance matrix of data moments and obtained via bootstrapping using the actual sample.

4.2 Estimated Parameters and Model Fit

Estimates Table 2 presents the parameter estimates. For the sake of parsimony, we only report the estimates for risk scores 1 and 4, which corresponds to the safest and riskiest consumers. The parameter estimates for risk score 2 and 3 can be found in Table A2 in the Appendix. Unsurprisingly, the parameter estimates imply that consumers in risk group 4 are poorer and have more volatile income than consumers in risk score 1. The average long-run mean weekly income for risk score 1 is \$35 compared to \$28 for risk score 4. These income levels corresponds to just above and below the Mexican minimum wage during our sample period.[21] The volatility of income for consumers in risk score 1 is 0.36 (i.e., a one-standard-deviation shock corresponds to 36% of their long-run mean income) and their income is almost i.i.d. around its long-run mean. The volatility of income for consumers of risk score 4 is higher (0.43) and their income process is closer to a random walk. As a result, the steady-state distribution of consumers' log-income is more dispersed for consumers in risk score 4. Consumers in risk score 1 have access to about twice the liquidity of consumers in risk score 4 (\$153 vs. \$75).

Consumers in risk score 1 have a device value that is 27 times their marginal utility at $\bar{y}_1$. Combined with a probability of depreciation of about 1.06%, this device value implies that, in the absence of dispersion in income (i.e., $y_{it} = \bar{y}$ for all i and t), consumers in risk score 1 would be willing to pay at most a perpetual rent of about 30% of their weekly long-run mean income to acquire a phone.[22] While this average willingness to pay is high, it conceals significant heterogeneity, in part due to the dispersion in long-run mean income ($\sigma_{\bar{y}}$). For instance, in the absence of income shocks ($\sigma_\epsilon = 0$), about 23% of customers in risk score 1 would not want to purchase a \$200 phone even if the financing rate was the same as their discount rate.[23] This heterogeneity is even larger once we account for the significant variance of income shocks. In practice, financing is costly, and the firm charges

[21]In January 2020, the minimum wage in Mexico was 123.22 Mexican Pesos per working day, or approximately \$32 per week. Source: Comisión Nacional de los Salarios Mínimos.

[22]This calculation assumes that there are no income shocks ($\sigma_\epsilon = 0$) and no dispersion in long-run mean income ($\sigma_{\bar{y}} = 0$), so that consumers earns a constant $\bar{y}$ every period. In this case, the consumer's lifetime value without the phone is $\frac{\log(\bar{y})}{1-\beta}$. She can transfer a perpetual rent t against ownership of the phone, in which case her lifetime value becomes: $\frac{\log(\bar{y}-t)}{1-\beta} + \frac{v_0}{1-\beta(1-\delta)}$, where δ is the phone's probability of depreciation. The perpetual transfer making the consumer indifferent is thus: $t = \bar{y}(1 - e^{-\frac{1-\beta}{1-\beta(1-\delta)}v_0})$. For customers in risk score 1, this implies $t = 0.34\bar{y}$. Once we allow for income shocks and solve numerically, it becomes $t = 0.27\bar{y}$.

[23]This would imply a perpetual weekly payment of \$2.4 for consumers in risk score 1. A consumer at the 23th percentile of the date-0 income distribution in risk score 1 (assuming $\sigma_\epsilon = 0$) earns \$7.2, which implies that she would be willing to pay at most 0.34×\$7.2=\$2.4 every week for the phone and would thus not buy. Once we allow for income shocks, about 27% would not buy.

significant markups.[24] Yet 60% of customers in risk score 1 still purchase the phone, which explains why the estimated device value is large. For consumers in risk score 4, device value is similar (30 times the marginal utility evaluated at $\bar{y}_4$), but depreciation is significantly higher (1.61%). Overall, the average consumer in risk score 4 has a smaller willingness to pay for the phone as a share of their income, and the higher dispersion of income in risk score 4 implies that, all else equal, demand for the phone in this group will be smaller.[25] Note that the higher depreciation rate for risk score 4 consumers contributes to making them significantly riskier.

Both groups share almost the same discount rate (0.988 and 0.990), which corresponds to annual interest rates of about 78%. Such time preferences are in the range of other estimates for poor consumers in developing countries.[26] The marginal value of savings at date 0, μ, is also similar for both groups of consumers (3.92 and 3.83 for risk score 1 and 4 respectively). This μ implies that consumers in our sample face significant liquidity constraints, since they value an extra-unit of savings at date 0 about 4-times as much as an extra unit of consumption. Such large liquidity constraints are qualitatively consistent with the reduced-form literature that evaluates the effect of cash transfers in Mexico (e.g., Gertler et al. (2012)).

Figure 3 in the Online Appendix offers a simple way to summarize some of the differences in parameter estimates across risk scores. For this exercise, we fix the contract menu to the one offered in both control arms to low risk customers, and simulate the model for each risk score. Panels A and B show the dynamics of repayment over time. Therein, we see consumers in risk score 1 and 2 behave quite similarly: after origination, about 10% of consumers miss payments and this fraction increases steadily over the lifetime of the contract to about 35%; repayment at maturity (as a fraction of what is owed) is 75%. Repayment for consumers in risk scores 3 and 4 is significantly worse: after origination, the fraction missing payments is 20%, and it rises to 45% at maturity; repayment at maturity is 60%. Panel C show that the IRR on loans made to consumers decreases significantly with their risk scores: from 174% for consumers in risk score 1 to 65% for consumers in risk score 4.

[24] On a 3-month contract, free financing would imply a multiple of 1.07 for individuals in risk score 1 given their estimated time-preference vs. an average multiple of 1.71 in the experiment.

[25] If $\sigma_\epsilon = 0 = \sigma_{\bar{y}}$, $t = \bar{y}(1 - e^{-\frac{1-\beta}{1-\beta(1-\delta)}v_0} = 0.33\bar{y}$ for consumers in risk score 4. Once we allow for income shocks, however, $t = 0.16\bar{y}$. The large σ_ϵ and high ρ amplifies the deviation in the approximate solution that assumes away income shock. In addition, 31% would not buy under free financing.

[26] For instance, Carvalho (2010) uses poor consumers' consumption responses to randomized transfers in Mexico through the PROGRESA program and estimates, under the assumption of a risk-aversion of 1 and using the actual real interest rate of 5% over his sample period, an annual discount rate of 78%.

Model fit We visually (and exhaustively) assess the fit of the model for consumers in risk score 1 in Figures 4-6. The model fit is qualitatively similar across risk scores. For brevity, we therefore relegate the analysis of model fit for risk scores 4 to the Online Appendix (Figures A2-A4).

Figure 4 plots the average take-up rate for each of the eight arms in the experiment, both overall (Panel A) and for each maturity separately (Panels B-E). The four arms targeted in the estimation appear in solid fonts, and the four validation arms appear in transparent fonts. The empirical take-up rates are in blue, and the simulated ones are in red. The model does an excellent job matching take-up rates both for targeted and untargeted arms. The one exception is that the model fails to precisely match the take-up rate of six-month contract, which is about three percentage points higher in the data than in the estimated model. This is not surprising given the non-advantageous pricing of these six-month contracts and their high take-up rates in the data, as explained in Section 3.4.

Figure A5 provides a similar figure for an estimated model without random maturity choice shocks. In this alternative model, the take-up rate for six-month contracts is close to zero (about 3% in Panel C). Thus, random maturity shocks allow us to get much closer to actual take-up rates. They are, however, not sufficient to perfectly match maturity choices: increasing $\sigma_{\omega 6 \text{ months}}$ further would increase six-months take-up rates, but would also reduce the amount of endogenous selection into maturity and thus worsen the fit for other moments, in particular how consumers respond to different loan terms.

Figures 5 plots the average repayment at maturity (as a fraction of what is owed) for each of the eight arms in the experiment, both overall (Panel A) and for each maturity separately (Panel B-E). Again, the model fit is excellent: simulated repayment rates fall within the confidence interval of estimated repayment rates in the data for 29 of the 32 arms-by-maturity cases. The main issues come from the Steep multiple arm, where the model underestimates repayment for three-month contracts and overestimates it for the 12-month contract. This can be interpreted through the lens of selection: the Steep arm increases the relative price of the 12-month vs. three-month contracts; random maturity shocks limit endogenous selection into maturities and thus lead to repayment rates that are only slightly lower for 12-month contracts; instead, selection seems more important in the data since the repayment rate in the Steep arm is about 85% for three-month contracts and only about 60% for 12-month contracts.

Finally, Figure 6 plots four additional sets of moments estimated separately on each experimental arm: the difference in repayment between the first and the second half of the contract (Panel A), the probability of resuming payment in week $t+1$ conditional on missing a payment in week t (Panel B), the share of customers who have not fully repaid their loans after two years (Panel C), and the average downpayment (Panel D). The model matches the downpayment distribution almost perfectly. However, it fails to precisely account for the dynamics of repayment, as default is more persistent in the model than in the data: in the model, customers are less likely to resume payments after missing a payment (Panel B), which leads to a higher share of customers that have still not fully repaid after two years (Panel C).

Table A3 completes the description of model fit by providing the exhaustive set of all moments targeted in our estimation, together with their simulated values. Similarly, Table A4 provides additional moments – both in simulated and actual data– not used in the estimation, such as the average maturity or downpayment by experimental arm, or share repaid at 1.5 × maturity.

4.3 Identification

To understand identification, we start with local comparative statics (Table A5 in the Online Appendix for risk score 1). We calculate a set of simulated moments by varying one parameter value while keeping all others fixed at their estimated values.[27] These comparative statics provide insights into the model's mechanics, which we can illustrate through a few examples.

First, persistence (ρ) mostly affects the probability of resuming payments – when income is more persistent, a borrower is more likely to miss consecutive payments. Depreciation ϕ is also a key driver of the probability of resuming payments (once a phone is broken, the consumer will stop making payments). But higher depreciation rates also lead to lower overall repayment and lower take-up, while income persistence does not affect these moments directly.

Second, Table A5 also provides some insights into the identification of device value (v_0) and long-run mean income ($\bar{y}$). While both parameters affect overall take-up and repayment similarly (higher device value or income will lead to higher take-up and repayment), they have opposite effects on maturity choice: a higher device value makes lockout more costly, which makes longer maturity contracts with lower weekly payments (and thus reduced risk of being locked) more attractive; a higher long-run mean income tilt maturity choices toward shorter contracts, as richer consumers can better afford these contracts with higher weekly payments but lower multiples.

Third, the volatility of income shocks (σ_ϵ) mostly influences the proportion of perfect repayers (volatile income makes it more likely consumers will miss at least one payment)

[27]Because of space constraint, we cannot show comparative statics for the 52 moments targeted in estimation. Instead, we summarize the model's mechanics using 13 moments that characterize take-up, downpayment and maturity choice, and repayment dynamics

and the repayment rate for short maturities. Depreciation (ϕ) mostly affects the moments in similar way to income shock volatility (σ_ϵ), with one notable exception: a higher depreciation rate leads to a lower probability of resuming payments, while a higher volatility of income shocks leads to a higher probability of resuming payments.

Finally, Table A5 reveals that consumers' discount rate (β) governs take-up rate and maturity choice (more patient customers are more likely to take-up all but the 12 month contract). It also affects repayments via selection into maturity – all else equal, more patient customers select shorter contracts (since they are cheaper), which leads to lower repayment rates since they carry higher weekly payments.

A more comprehensive look at identification for consumers in risk score 1 can be found on Table 3. This table provides Andrews et al. (2017)'s sensitivity matrix, which corresponds to a local linear approximation of the relationship mapping the targeted moments used in estimation to parameter estimates. Since all the moments we use are probabilities, all the coefficients have the same interpretation: a coefficient of one implies that a one percentage point increase in the targeted moment would have approximately led to an increase of .01 in the parameter estimate. Tables 3 allows to understand the relative importance of each moment in the estimation of a parameter. For instance, the depreciation rate (ϕ) is essentially pinned down by three intuitive moments: the share of customers who default in two years (higher depreciation leads to more default), the probability of resuming payment (higher depreciation makes it more likely default is persistent) and the repayment rate on 12 month contract at maturity (higher depreciation increases default more for long-term maturity contracts). Those moments influence the estimate for ϕ at least twice more than any other moments.

5 Quantifying Welfare Gains

To understand the welfare implications of lockout-enabled PAYGo financing, we conduct a range of counterfactual analyses. First, we introduce our measure of welfare and quantify the improvement in household welfare compared to a benchmark without financing. Second, we estimate the potential welfare gains under the counterfactual of perfect competition among lenders. Finally, we compare the welfare effects of PAYGo financing to a more traditional secured loan. Our welfare estimates vary both by risk score and treatment arm. When describing the magnitudes of our estimates, we will generally use risk score 1 under the control treatment as our "benchmark" treatment group. The effect sizes for this group are neither the largest nor the smallest in the sample. The estimates for other risk scores and treatment groups can be found in the Appendix.

5.1 PAYGo vs the No Financing Benchmark

We start by quantifying the welfare effects of lockout-enabled PAYGo financing relative to a counterfactual with no financing. The no-financing benchmark is a natural counterfactual in our setting because the population of consumers in our data are poor and only 21% have a credit card, which is the primary alternative source of smartphone financing in Mexico. In the no-financing benchmark, consumers only option is to buy the phone with cash, which is precisely households' outside option in the model.

Our welfare measure, denoted by $\mathcal{W}_i$, is the percentage increase in weekly income over a two-year period that would deliver the same utility to the consumer as they enjoy from having access to the menu of PAYGo contracts. Formally, $\mathcal{W}_i$ solves:

$$\max\{W_i(\Gamma_i^*), O_i(y_{i0})\} = \hat{O}_i(\hat{y}_{i0}) \tag{14}$$

where

$$\hat{y}_{it} = \begin{cases} (1+\mathcal{W}_i)y_{it} & t \leq 104 \\ y_{it} & \text{otherwise} \end{cases} \tag{15}$$

$\hat{O}_i(\hat{y}_{i0})$ is the value of the outside option with the higher income process $\hat{y}_{it}$. We focus on welfare over a two-year period as it is commensurate with the expected lifespan of the phone. We use $\mathcal{W}_i$ as our preferred welfare measure because it is intuitive, easy to interpret, and invariant to additive or multiplicative transformations of the utility function. Note that $\mathcal{W}_i = 0$ for consumers that do not accept a contract. Note also that maturity-choice shocks are not included in our welfare measure. Depending on the exercise of interest, we will use both the average welfare conditional on take-up, denoted by $\mathcal{W}_{taker} \equiv \mathbb{E}[\mathcal{W}_i | i \text{ accepts a contract}]$, and the unconditional average in the population, which we denote by $\mathcal{W}_{pop} \equiv \mathbb{E}[\mathcal{W}_i]$.[28] We defer details on the computation of $\mathcal{W}_i$ to Section A.3 in the Online Appendix.

Table 4 provides the welfare estimates across treatment groups and risk scores. For our benchmark treatment group, we find that $\mathcal{W}_{taker} = 11.3\%$. That is, the average taker in the benchmark treatment group is indifferent between (a) their preferred PAYGo contract, and (b) no access to financing but a 11.3% increase in income over the next two years. The take-up rate in this treatment group is 63%, which implies an unconditional welfare effect of $\mathcal{W}_{pop} = 6.7\%$. Across the different pricing arms, the welfare estimates for takers are in the range of 9-12% for risk score 1 and 3. The welfare effects are highest in risk score 2 (12-16%) and smallest for risk score 4 (5-7%). Averaging across the population of all risk scores, we

[28] Our measure is robust to the possibility that consumers might go elsewhere for a cheaper substitute, e.g., a flip phone. The value from such options can be an inherent part of the utility from consuming their income and hence captured by the no-financing benchmark.

get $\mathcal{W}_{taker} = 10.9\%$ and $\mathcal{W}_{pop} = 5.8\%$.

Figure 7 plots the welfare effects by each level of long-run mean income ($\bar{y}_i$) for risk score 1.The welfare effects are concentrated among consumers with intermediate income, where $\mathcal{W}_{taker}$ can exceed 20%. Welfare effects diminishes for higher income consumers, as many of them can afford to buy the phone with cash. For low-income consumers, the contracts are expensive and their marginal utility of consumption is high so that take-up is low and welfare gains are small. For very poor consumers, the contracts are too expensive, and the welfare effect is zero.

5.2 Competitive Pricing

Firm profit across all risk scores and treatments groups is positive and economically significant (Table 4). Across the four risk scores, the NPV per contract ranges from $27-37 in the Control multiple, Control downpayment arm (CtrlMarkupCtrlDown) with corresponding IRRs in the range of 143%-201%.[29] Firm profit is increasing in the markup and remains significantly above zero even in the lower downpayment treatment groups across all risk scores. These findings suggest there is scope for competition among lenders to reduce prices and increase household welfare. In this subsection, we quantify the potential welfare gains under the counterfactual of perfect competition among firms.

Solving for the competitive menu of prices with different maturities is a non-trivial exercise for several reasons. First, there is the question of whether a pure-strategy competitive equilibrium exists (Rothschild and Stiglitz, 1976) and if so, whether firms break even in it (Azevedo and Gottlieb, 2017; Levy and Veiga, 2020). Even if one assumes that a zero-profit condition holds, it could hold for each contract or in the aggregate, in which case there could be multiple ways of reaching zero-profit. Finally, even if one is willing take a stance on these issues, solving for the vector of prices that maximizes household welfare subject to a break-even constraint is computationally intensive.

We sidestep these issues by restricting attention to a single maturity (12 month) and solving for the welfare maximizing terms (downpayment and markup) that make the firm break even on that contract. We selected the 12 month maturity because it is the most economically sensible maturity given the distribution of wealth and borrower income.[30] In Section A.6 of the Online Appendix, we verify that the loss in potential surplus by restricting attention to a single maturity is economically insignificant.

[29]Note that our NPV calculation implies that the firm's only marginal cost is the phone price and that there are no operating fixed costs.

[30]More specifically, the longer maturity leads to smaller payments, which helps consumers to both smooth consumption and avoid getting locked. Moreover, consumers have a longer horizon to choose whether to default if the device depreciates.

In Table 5, we report the terms for the 12 month contract across all risk scores in the competitive pricing counterfactual. We include terms for the CtrlMarkupCtrlDown group for comparison. Both the markup and minimum downpayment under competitive pricing are significantly lower than in any of the treatment arms. For instance, the markup and downpayment are 2 and 25% in the CtrlMarkupCtrlDown arm, while they are 1.50 and 4.9% in the competitive pricing counterfactual.

The reduction in prices leads to a significant increase in both take-up (from 63% to 74%) and welfare $\mathcal{W}_{taker}$ (from 11.3% to 16.3%). In Figure 7, we plot the cross section of take-up rates (Panel A) and welfare effects (Panel B) for each level of long-run mean income under competitive pricing and the LowMarkupCtrlDown group. The figure shows that the increase in take-up is most pronounced for consumers in the second quartile of the income distribution and the increase in welfare is most significant for middle income consumers.

In Table 4, we also report the welfare measures for the other three risk categories under competitive prices. The increase in take-up and welfare is even larger for the intermediate risk scores. Welfare for risk score 2 (3) increases from 12% (10%) under LowMarkupCtrlDown pricing to 25% (22%) under competitive pricing. For the highest risk score, take-up increases drastically (from 26% to 77%), primarily due to the reduction in downpayment, which falls from 50% to 12%. The difference in welfare gains, however, is more moderate (from 6% to 11%).

5.3 PAYGo vs Traditional Secured Loan

In this section, we compare lockout-enabled PAYGo to a traditional secured loan. In a traditional secured loan contract, the lender repossesses the collateral if the borrower defaults. The advantage of secured lending is that the lender recovers the value of the collateral when the borrower defaults, whereas the lender does not recover any value from locking the device. The disadvantage of a secured loan is that the repossession process is costly and may ultimately fail. Moreover, because repossession is irreversible, the consequences to consumers from defaulting are more severe than the consequences from missing payments under a PAYGo contract.

Our main finding is that the PAYGo contract dominates a traditional secured loan and by a significant margin for reasonable assumptions about the repossession technology. To establish this finding, we first solve the household's problem (take-up and repayment) when facing a secured loan. Given the solution to the household's problem, we compute firm profit and competitive prices for secured loans under various assumptions about the repossession technology. We then evaluate household welfare from a secured loan and compare it to our findings in Section 5.2.

The Secured Loan Contract and Repossession Technology A traditional secured loan contract is characterized by $\Gamma \equiv (D, T, \theta, \bar{a})$, where D, T, and θ are the same as before (downpayment, maturity, and markup) and $\bar{a}$ is the threshold number of payments missed at which the lender initiates the repossession process. We characterize the repossession technology by a pair $(c_{\text{repo}}, p_{\text{repo}})$, where c_{repo} is the cost (incurred by the lender) of the repossession process and p_{repo} is the probability that the process is ultimately successful (i.e., that the collateral is successfully repossessed). If repossession is successful, the household enters autarky and the firm receives the recovered value of the device, $\kappa_{it} = \text{Initial Price} \times \frac{v_{it}}{v_{i0}}$. If repossession fails, the household retains the collateral and the firm recovers nothing. A *frictionless* repossession technology is characterized by $c_{\text{repo}} = 0$ and $p_{\text{repo}} = 1$.

The Consumer's Problem with a Secured Loan Analyzing the consumer's problem under a secured loan is similar to the analysis in Section 3.4. The state variable is now $x_{it} = (v_{it}, y_{it}, n_{it}, m_i, a_{it})$, where a_{it} denotes number of payments in arrears. Let $U_i^{\text{repo}}(x_{it}; \Gamma)$ denote the value function of household i under a secured loan contract Γ, which is henceforth suppressed. While in repayment (i.e., for $n_{it} \geq 1$, $a_{it} < \bar{a}$), the Bellman equation for the household is

$$\begin{aligned} U_i^{\text{repo}}(v_{it}, y_{it}, n_{it}, m_i, a_{it}) = \max \Big\{ & v_{it} + u(y_{it} - m_i) + \beta \mathbb{E}[U_i^{\text{repo}}(v_{it+1}, y_{it+1}, n_{it} - 1, m_i, a_{it}) | x_{it}], \\ & v_{it} + u(y_{it}) + \beta \mathbb{E}[U_i^{\text{repo}}(v_{it+1}, y_{it+1}, n_{it}, m_i, a_{it} + 1) | x_{it}] \Big\}. \end{aligned} \tag{16}$$

The household can choose to repay, in which case the number of payments remaining decrements by one, or not, in which case the number of arrears increments by one. As long as arrears are below $\bar{a}$ at the beginning of period t, the household gets to consume the value of the device in period t.

There are two boundary conditions: default and ownership. If $a_{it} = \bar{a}$ then the household is in default and the boundary condition is:

$$U_i^{\text{repo}}(v_{it}, y_{it}, n_{it}, m_i, \bar{a}) = p_{\text{repo}} \Pi_i(0, y_{it}) + (1 - p_{\text{repo}}) \Pi_i(v_{it}, y_{it}), \tag{17}$$

which holds for all $n_{it} \geq 1$. The other boundary condition is ownership (i.e., $n_{it} = 0$):

$$U_i^{\text{repo}}(v_{it}, y_{it}, 0, m_i, a_{it}) = \Pi_i(v_{it}, y_{it}), \tag{18}$$

which holds for all $a_{it} < \bar{a}$ and where $\Pi_i(v_{it}, y_{it})$ is defined as in (3).[31] Once we have solved for the household's value function, the value from an arbitrary contract and computing the household's outside option follows that same steps as in Section 3.4.

Firm Profit While the customer is in repayment, the Bellman equation for the firm's value function is:

$$\begin{aligned} V_i^{\text{repo}}(x_{it}) =& A_i^{\text{repo}}(x_{it})\big(m_i + \delta \mathbb{E}[V_i^{\text{repo}}(v_{it+1}, y_{it+1}, n_{it} - 1, m_i, a_{it})|x_{it}]\big) \\ &+ (1 - A_i^{\text{repo}}(x_{it}))\delta \mathbb{E}[V_i^{\text{repo}}(v_{it+1}, y_{it+1}, n_{it}, m_i, a_{it} + 1)|x_{it}] \end{aligned}$$

where $A_i^{\text{repo}}(x_{it})$ is the household's optimal repayment policy. The terminal boundary condition for the firm is analogous to equation (10). The default boundary condition (i.e., $n_{it} \geq 1$, $a_{it} = \bar{a}$) is:

$$V_i^{\text{repo}}(v_{it}, y_{it}, n_{it}, m_i, \bar{a}) = p_{\text{repo}}(\kappa_{it} - c_{\text{repo}}) + (1 - p_{\text{repo}})(-c_{\text{repo}}). \tag{19}$$

The firm's NPV from lending to household i is analogous to equation (11).

Welfare Comparison To facilitate our comparison to the welfare effects of PAYGo, we focus on competitive prices for the secured loan. We follow the same approach as in Section 5.2, we solve for the zero-profit welfare-maximizing contract for a secured loan with 12 month maturity. We repeat this exercise for a range of repossession technologies, i.e., pairs of $(c_{\text{repo}}, p_{\text{repo}})$, while fixing $\bar{a} = 1$. We then calculate the welfare effects under competitive prices for each technology and compare them to the welfare effects of PAYGo from Section 5.2.

Figure 10 plots the welfare gains from PAYGo lending vs. secured lending for different repossession technologies. Figures A7-A8 depict prices, take-up and repayment for the various contracts. As the repossession technology becomes more efficient (i.e., as c_{repo} decreases or p_{repo} increases), prices fall and the welfare gain from secured lending increases. While intuitive, this finding is not obvious since a more efficient repossession technology might benefit borrowers by limiting the negative effect of missing a payment, especially for low income consumers. Figure 10 also shows that PAYGo contracts generate higher welfare gains than secured lending for (virtually) any repossession technology. The only exception is for risk score 1, where the welfare gains of secured lending with a frictionless repossession technology are roughly the same as PAYGo. Finally, under reasonable assumption about

[31] The value function in states with $n_{it} = 0$ and $a_{it} = \bar{a}$ are undefined, as arrears stop accumulating once the household enters ownership so these states are never reached.

the repossession technology, PAYGo delivers much higher welfare gains than secured lending. For risk score 1, the welfare gain from PAYGo is 39% larger (12.1% vs 8.7%) than the welfare gains from a secured loan where the repossession cost is \$50 and the probability of successful repossession is 0.6. Finally, the advantage of PAYGo over secured lending is larger for riskier consumers. For risk scores 3 and 4, the PAYGo contract delivers welfare gains that are 3-4 times larger than the secured loan mentioned above.

Table 6 provides a direct measure of the welfare gains from a PAYGo contract relative to a traditional secured loan. Therein, we compute the additional income required to make consumers with access to a secured loan as well off as consumers with access to PAYGo financing. We use competitive prices for both contracts and repeat the calculation for three different repossession technologies. For our baseline repossession technology, we use a repossession cost of \$25 and a success probability of 0.8, which we view as a conservative upper bound on the actual efficiency of physical repossession in our context. The welfare gains range from 2-5.4% (column 1). They increase monotonically with risk score as the flexible repayment schedule of PAYGo is more valuable to higher risk consumers. With a moderately worse repossession technology (column 2), the welfare gains of PAYGo relative to secured lending are roughly twice as big and range from 4.1-12.6%. Even a perfect repossession technology (column 3) is inferior to PAYGo, highlighting the advantage of (temporary) lockout compared to (permanent) repossession.

6 The Role of Lockout

6.1 Decomposing the Effects of Lockout on Firm Profit

Compared to unsecured lending, using the lockout technology to secure loans increases firm profitability by reducing both moral hazard and adverse selection. In this subsection, we decompose and quantify the effect on these two underlying frictions by varying the strength of the lockout technology, as parameterized by λ, the fraction of device value that a household loses upon missing a payment. More specifically, we hold prices fixed and illustrate what happens to firm profit as we vary λ.

Conceptually, as λ decreases, the consequence to a household from missing a payment is less severe. Thus, a decrease in λ is akin to a lower collateral requirement. This affects firm profit through two channels: screening and incentives. First, the set of consumers that accept a loan offer increases. Moreover, these marginal consumers have lower and/or riskier income than inframarginal consumers. Second, inframarginal consumers have weaker incentive to repay the loan, which leads to more strategic non-repayment. We refer to the first effect as the screening channel and the second effect as the incentive channel.

Panels A and B of Figure 8 illustrate how take-up and average repayment change as λ decreases in our benchmark treatment group. In particular, the take-up rate increases from 60% to 82% and average repayment at maturity decreases from 79% to 0% as λ decreases from one to zero. In Panel C of Figure 8, we decompose the total change in firm profit into the part that is attributable to weaker screening and the part that is attributable to weaker incentives. When $\lambda = 1$, the unconditional average profit is \$22. For $\lambda = 0.5$, the profit falls by \$18 with roughly equal amounts attributed to weaker incentives and weaker screening. For $\lambda = 0.2$, profit falls by \$76: two-thirds of the decrease is due to weaker incentives and one-third due to weaker screening.

Overall, the reduction in profits from decreasing λ can be roughly equally attributed to the two economic frictions for high values of λ. However, once λ is small, almost all consumers who can afford the minimum downpayment are taking up, so there is not much more to lose from weaker screening and the effect on repayment incentives becomes the dominant force.

6.2 Welfare-Maximizing Lockout

Under the lender's standard contract, the phone is completely locked and unusable when the borrower misses a payment (i.e., $\lambda = 1$). However, a more forgiving application of the lockout technology, where only certain features or applications on the phone are locked is technologically feasible and has been explored by various PAYGo lenders. In this subsection, we conduct a normative analysis on the strength of the lockout technology. In particular, we ask whether $\lambda = 1$ is optimal in terms of maximizing social welfare.

We have seen in Section 6.1, that higher λ alleviates both moral hazard and adverse selection, which increases lender profits making lending sustainable for a greater number of consumers. However, it also destroys more surplus ex-post following missed payments, which are (at least) in part due to negative income shocks. Thus, a smaller λ provides a greater level of risk sharing at the expense of weaker screening and incentives. Whether such a contract increases or decreases social welfare is the quantitative question we address in this section.

Holding prices fixed, decreasing λ will reduce firm profits and increase household welfare, which makes it difficult to evaluate the effect on total welfare. In order to have a clean social welfare measure, we compute competitive terms for different levels of λ and evaluate household welfare from each contract. That is, for each value of λ, we compute the multiple and minimum downpayment requirement that maximize household welfare subject to the firm making zero profit. Under competitive pricing, household welfare is equivalent to total welfare. Another reason to use competitive pricing for this exercise is that it enables us to identify the total *potential* surplus for each lending technology, whereas the lender's existing pricing schemes trade-off surplus creation and firm profit.

The results are illustrated in Figure 9. Most of the qualitative patterns are consistent across risk scores. Both the markup (Panel A) and minimum downpayment (Panel B) are decreasing and convex in λ. To get a sense of the magnitudes, as λ increases from 0.2 to 1, the markup decreases from 2.5 to 1.5 and the minimum downpayment decreases from 42% to 5% for risk score 1. To highlight the convexity, notice that the markup is 1.6 at $\lambda = 0.6$ and nearly flat thereafter.

Take-up (Panel C) is hump-shaped, first increasing and then decreasing, while repayment is strictly increasing with λ (Panel D). As λ increases, there are two offsetting forces that affect take-up. Prices fall, which increases take-up, but the consequence of missing a payment is more penal (i.e., screening is stronger), which decreases take-up. The hump-shaped pattern in the take-up rate can be understood from the convexity in prices. The steep drop in prices for low levels of λ offsets the screening effect. But as prices begin to flatten, the screening effect dominates and take-up falls.

The welfare effects are where we see more notable qualitative differences across risk scores. For the lower two risk scores, welfare is monotonically increasing in λ as the benefit from lower financing costs outweighs the reduction in risk-sharing. However, for the higher two risk scores, welfare is hump-shaped. The maximal welfare effect is for $\lambda = 0.50$ for risk score 3 and $\lambda = 0.75$ for risk score 4. Thus, for riskier consumers, the benefits of increased risk-sharing from a more forgiving application of lockout outweigh the costs of weaker incentives and screening.

7 Conclusion

Pay-as-you-go (PAYGo) financing is a novel financial contract that has recently become a popular form of credit especially in low-and-middle-income countries (LMICs). PAYGo financing crucially relies on technology that enables the lender to cheaply and remotely disable the flow benefits of the collateral when the borrower misses payments. In this paper, we combine data from a large-scale pricing experiment by a FinTech lender with a structural model to quantify the welfare implications of PAYGo financing.

Our results suggest that PAYGo financing generates large and significant welfare gains. Relative to a benchmark with no financing, access to PAYGo contracts at the terms used in our data is equivalent to a 5.8% increase in income for two years. Because these terms lead to significant lender profit, this number underestimates the potential welfare gains that PAYGo contracts can generate. In a counterfactual with competitive terms, PAYGo yields welfare gains of about 17.4% relative to a benchmark with no financing and 4.0% relative to a reasonably calibrated secured loan.

While PAYGo financing typically relies on a strong lock technology – the phone is completely unusable when the borrower misses a payment – we show that a strong lock is not necessarily optimal from a welfare standpoint. For high-risk consumers, our quantitative analysis suggests that weaker locks may results in higher overall welfare: the benefits of increased risk-sharing from a more forgiving application of lockout can outweigh the costs of weaker incentives and screening. These results call for a better understanding of the optimal use of the lockout technology in financial contracting, an endeavor we leave for future research.

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A Tables and Figures

Table 1: Pricing Experiment

Panel A: Pricing Arms

	Ctrl	Medium	High	Steep
3 month	1.36	1.4	1.55	1.4
6 month	1.54	1.63	1.8	1.7
9 month	1.64	1.8	2	1.95
12 month	2	2.2	2.4	2.5

Panel B: Downpayment Arms

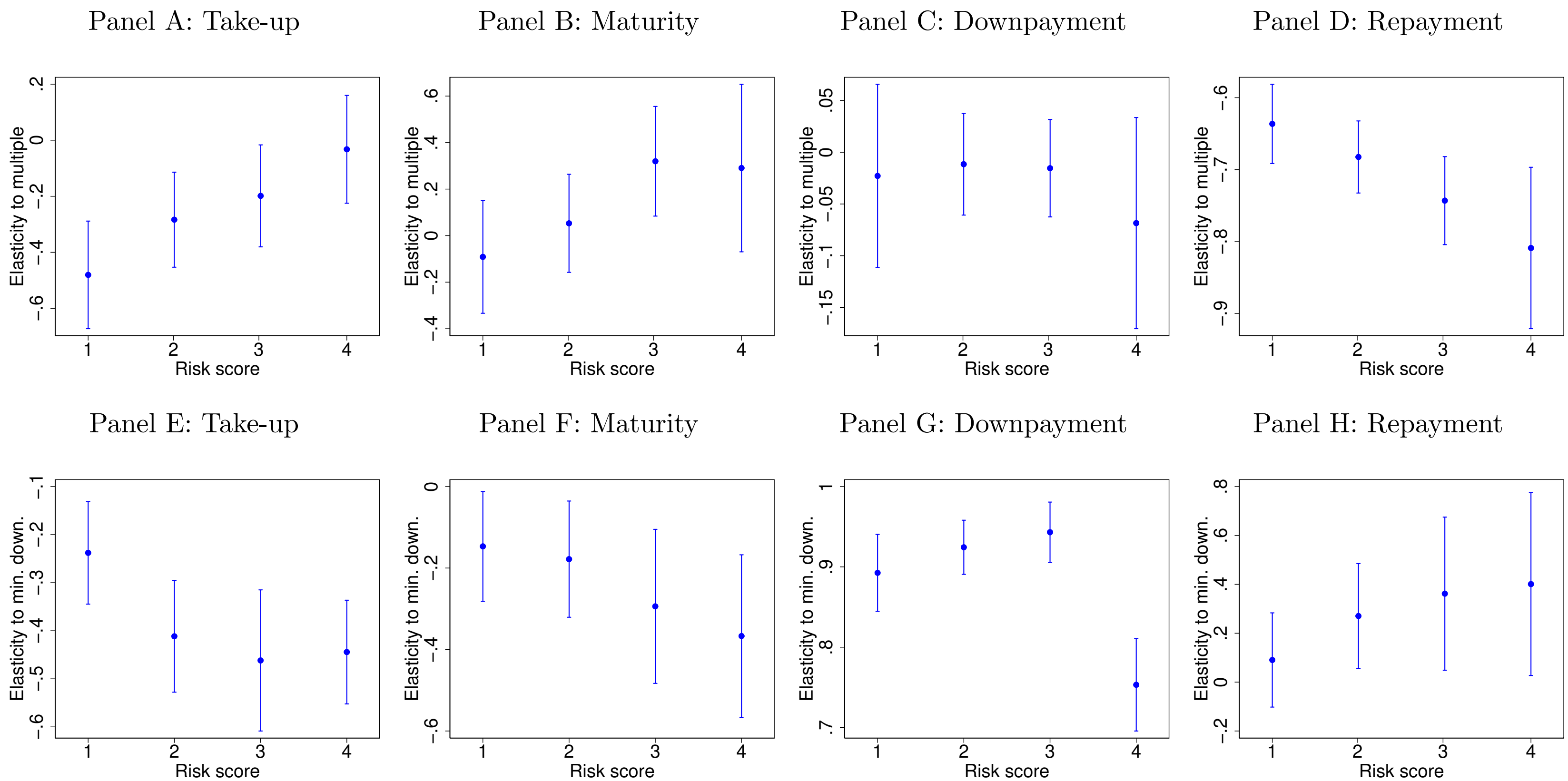
	Ctrl	Lower
Risk score 1	25%	20%
Risk score 2	30%	25%
Risk score 3	35%	30%
Risk score 4	50%	40%

Panel C: Assignment of individuals into treatment groups

Downpayment Treatment	Markup Treatment	# of Customers in This Arm	Percentage
Ctrl	0 Ctrl	4,357	15.1%
Ctrl	1 Medium	4,402	15.3%
Ctrl	2 High	4,336	15.1%
Ctrl	3 Steep	4,322	15.0%
Lower	0 Ctrl	2,851	9.9%
Lower	1 Medium	2,956	10.3%
Lower	2 High	2,818	9.8%
Lower	3 Steep	2,744	9.5%
N		28,786	

Note: This table provides details on the parameters of the different arms of the experiment. Panel A corresponds to the pricing arms. The multiple is a measure of the loan cost for borrowers – their weekly payment is given by $\frac{\text{Multiple}\times(\text{Phone Price}-\text{Downpayment})}{\text{Maturity}}$. Multiples are the same across risk scores. Panel B corresponds to the two downpayment arms as they depend on the risk score. Panel C reports the number of customers in each treatment arm of the pricing experiemnt.

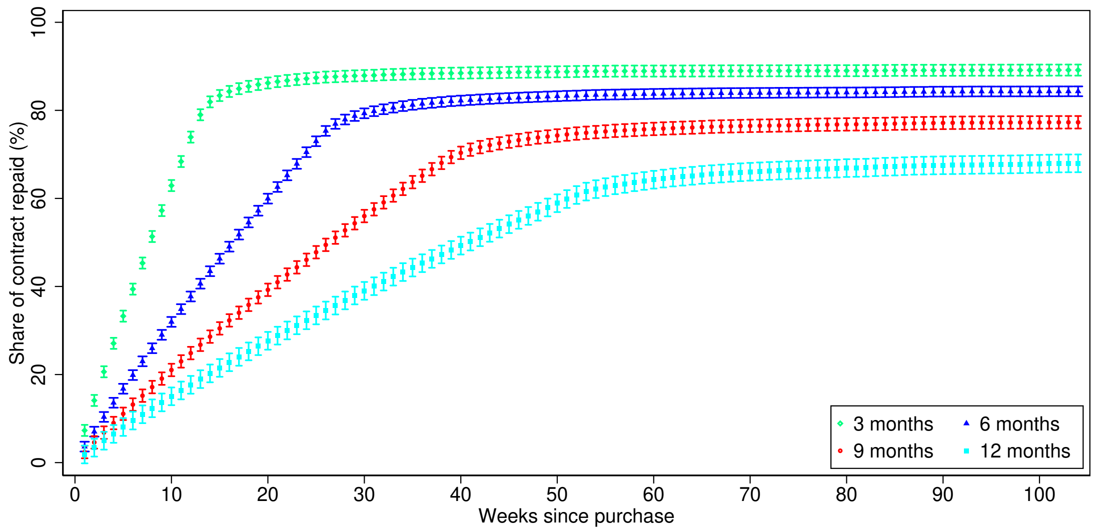
Figure 1: Elasticity to Average Multiple and Downpayment Requirement Across Risk Scores



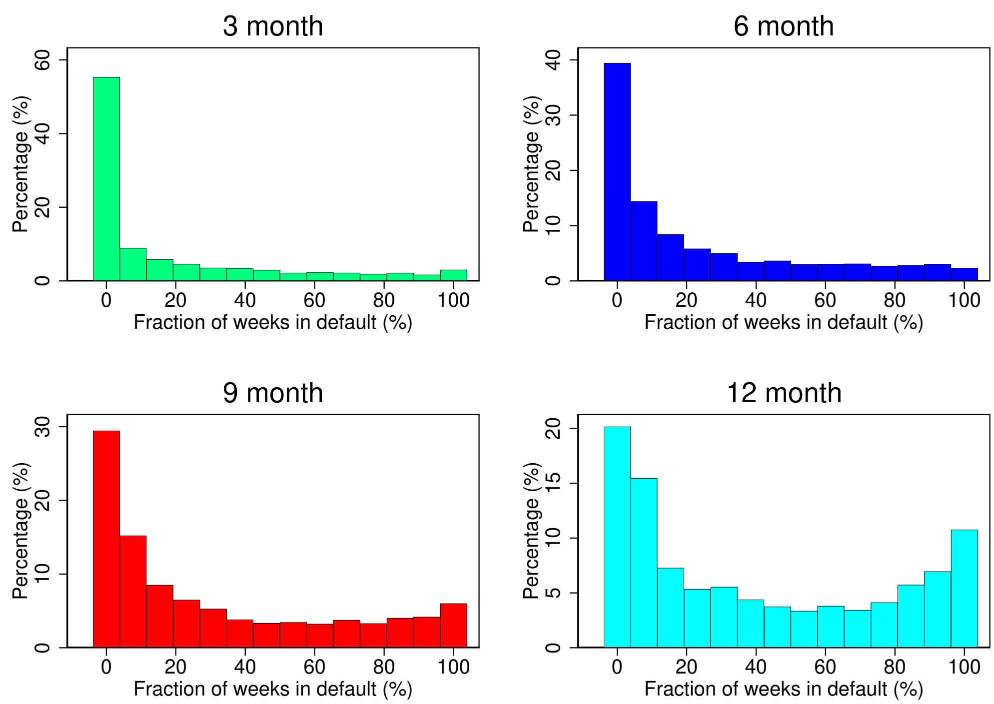
Note: In Panels A-D, for the Control, Medium and High pricing arms, we first construct the average multiple across maturity. For each risk score, we then regress a loan outcome on the log of the average multiple, controlling for the loan's downpayment arm. In Panels E-H, for each risk score, we regress a loan outcome on the log of the minimum required downpayment, controlling for the loan's pricing arm. The figure reports the resulting elasticities, estimated separately for the four different risk scores, together with 95% confidence intervals. The dependent variables are a dummy equal to one if the customer takes-up the loan (Panels A and E), the log of the loan maturity (Panel B and F), the downpayment (Panel C and G) and the share of the total amount owed to the lender repaid at maturity (Panel D and H).

Figure 2: Repayment by Maturity

Panel A: Dynamics of the fraction repaid



Panel B: Distribution of the fraction of weeks in default



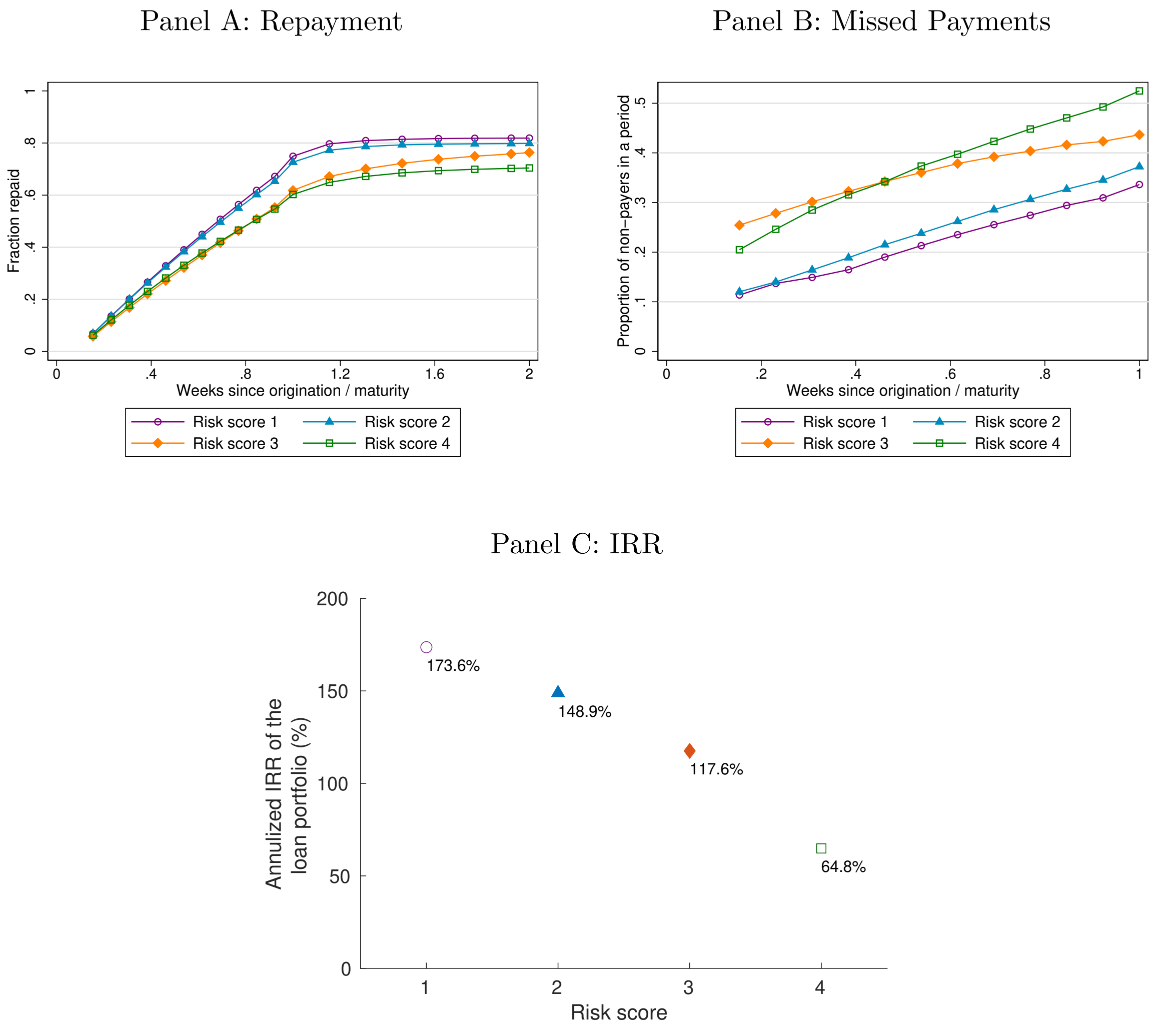
Note: Panel A shows the share of contract repaid at each point in time. Panel B shows the distribution of the fraction of weeks in default (i.e., locked) from loan initiation to maturity. Within each maturity, we average the repayment across all the risk scores and treatment groups.

TABLE 2: Parameter Estimates

	(1) Risk score 1	(2) Risk score 4
Income process parameters:		
$\bar{y}$ (average long-run mean income)	35.02	28.32
	(1.53)	(2.12)
$\sigma_{\bar{y}}$ (dispersion of long-run mean income)	1.18	0.90
	(0.03)	(0.11)
σ_ϵ (size of income shock)	0.36	0.43
	(0.02)	(0.03)
ρ (mean-reversion coef.)	0.11	0.81
	(0.07)	(0.05)
$\bar{L}$ (average initial liquidity)	152.58	75.19
	(42.14)	(4.18)
σ_L (dispersion of initial liquidity)	0.64	0.42
	(0.15)	(0.08)
Device value parameters:		
v_0 (initial device value)	27.17	29.75
	(3.00)	(3.77)
ϕ (prob. of depreciation, weekly)	0.0106	0.0161
	(0.0004)	(0.0008)
Other customer preference parameters:		
β (weekly discount rate)	0.988	0.990
	(0.001)	(0.003)
μ (value of savings)	3.92	3.83
	(0.53)	(0.48)
$\sigma_{\omega,3}$ (size of random utility shock for 3 month)	385.41	353.97
	(30.33)	(36.38)
$\sigma_{\omega,6}$ (size of random utility shock for 6 month)	372.25	298.35
	(35.84)	(33.51)
$\sigma_{\omega,9}$ (size of random utility shock for 9 month)	52.78	21.72
	(14.96)	(8.30)

Note: This table reports the model's parameter estimates. v_0, μ, $\sigma_{\omega,3}$, $\sigma_{\omega,6}$, $\sigma_{\omega,9}$, and $\sigma_{\omega,12}$ are scaled by the marginal utility evaluated at the average long-run mean income (i.e., $u'(\bar{y})$). For instance, the true value for v_0 in risk score 1 is $27.17 \times u'(35.02)$. Standard errors are in the parentheses.

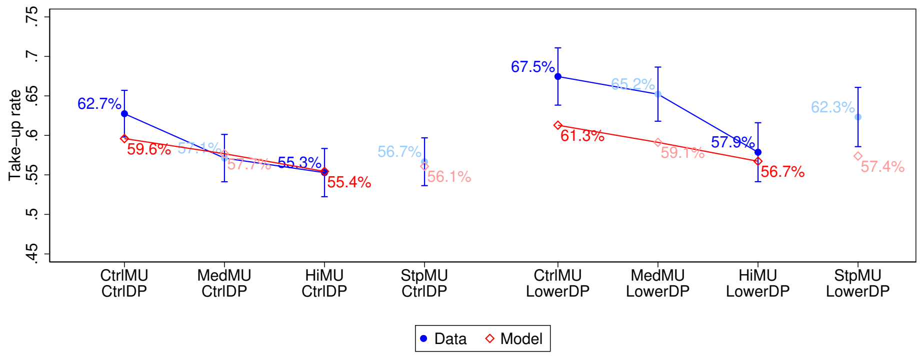
Figure 3: Comparison Across Risk Scores, Holding Treatment Constant



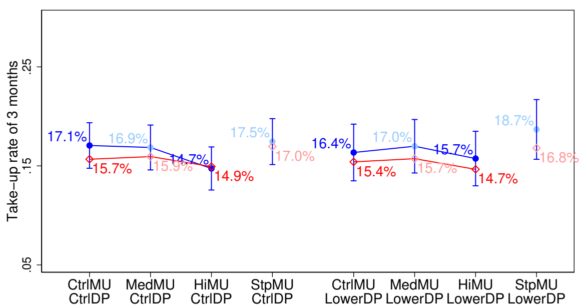
Note: we fix contract terms to those offered in the control multiple arm and the control downpayment arm. We simulate the behavior of customers with different risk scores using the parameter estimates obtained in our SMM estimation. Panel A shows the simulated average fraction repaid over time for each risk score. Panel B reports the share of non-payers over time for each risk score. Panel C plots the IRRs of the simulated loan portfolios for each risk score.

Figure 4: Model Fit - Take-Up Rates (Risk Score 1)

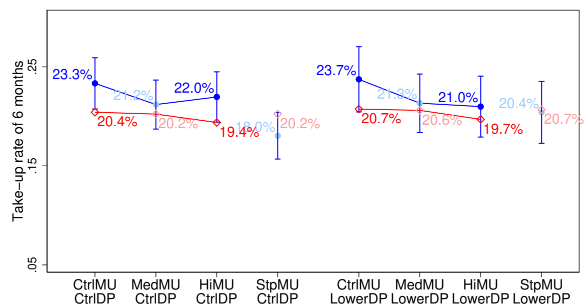
Panel A: Overall



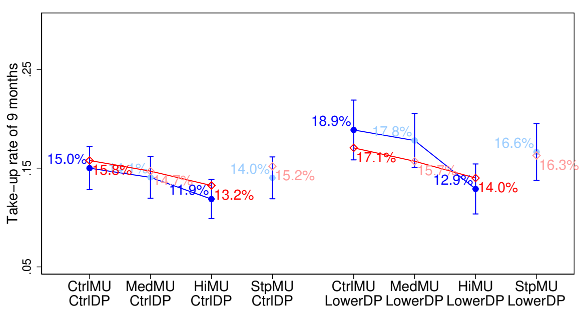
Panel B: 3 month



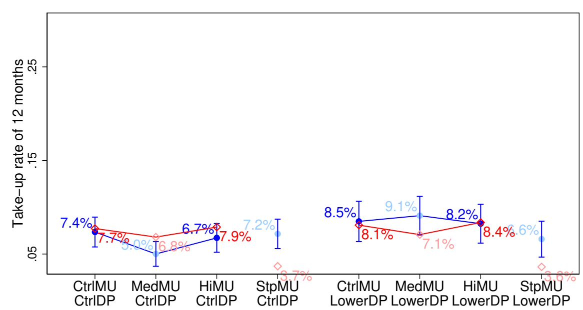
Panel C: 6 month



Panel D: 9 month



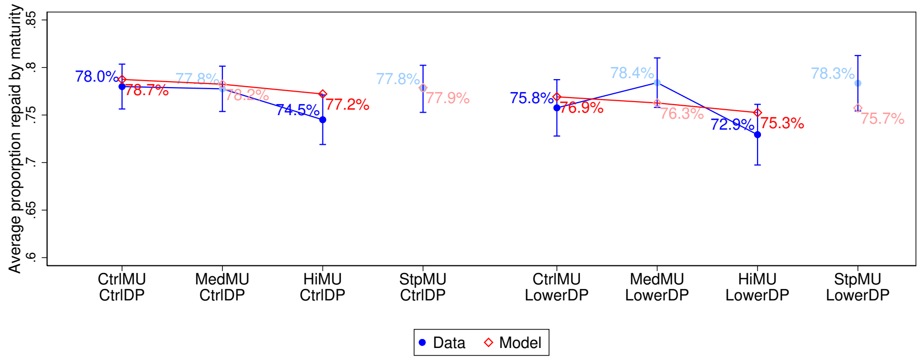
Panel E: 12 month



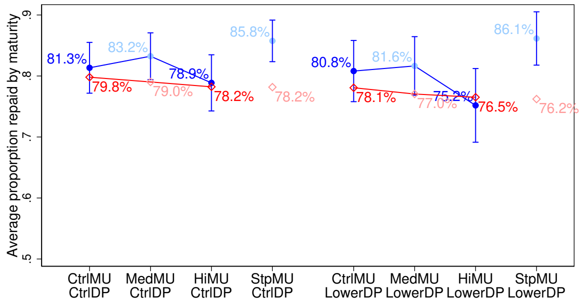
Note: This figure shows take-up rates in both actual data (in blue) and simulated data (in red) for risk score 1. Panel A reports the average take-up rate across maturity. Panel B, C, D, and E report take-up rates for the 3, 6, 9, and 12 month contracts respectively. The x-axis corresponds to the 8 experimental arms. CtrlMU (resp. MedMU, HiMU and StpMU) is the control multiple arm (resp. Medium, High and Steep). CtrlDP (resp. LowerDP) is the control downpayment arm (resp. lower downpayment arm). The four treatment groups used in the SMM estimation are in solid color while the other four appear in transparent font. The vertical bars correspond to 95% confidence intervals.

FIGURE 5: Model Fit - Repayment Rates (Risk Score 1)

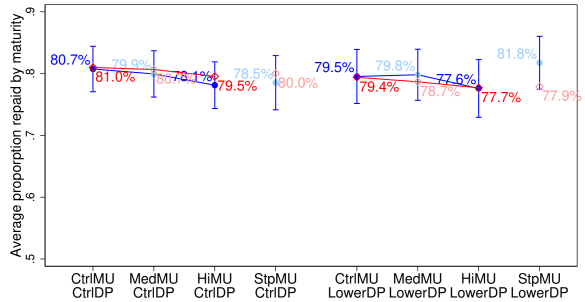
Panel A: Overall



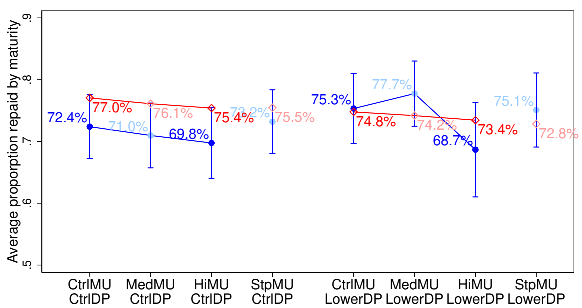
Panel B: 3 month



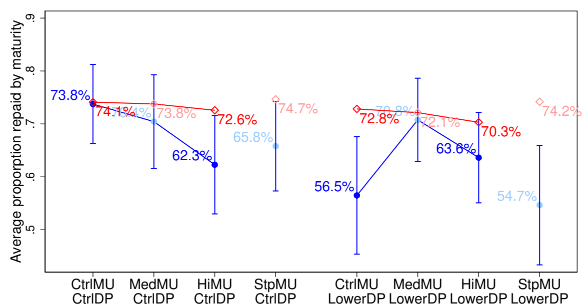
Panel C: 6 month



Panel D: 9 month



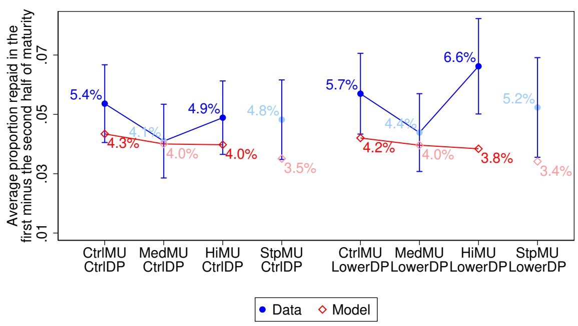
Panel E: 12 month



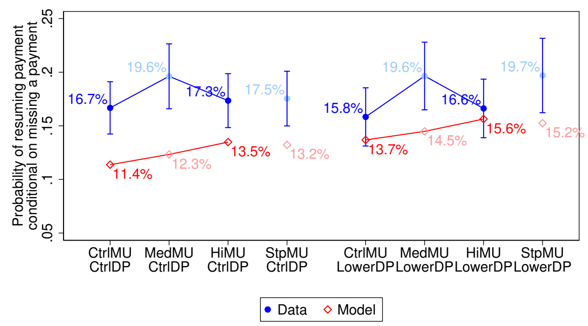
Note: This figure shows the average fraction repaid at maturity in both actual data (in blue) and simulated data (in red) for risk score 1. Panel A reports the same moment across maturity. Panel B, C, D, and E report take-up rates for the 3, 6, 9, and 12 month contracts respectively. The x-axis corresponds to the 8 experimental arms. CtrlMU (resp. MedMU, HiMU and StpMU) is the control multiple arm (resp. Medium, High and Steep). CtrlDP (resp. LowerDP) is the control downpayment arm (resp. lower downpayment arm). The four treatment groups used in the SMM estimation are in solid color while the other four appear in transparent font. The vertical bars correspond to 95% confidence intervals.

FIGURE 6: Model Fit - Other Moments (Risk Score 1)

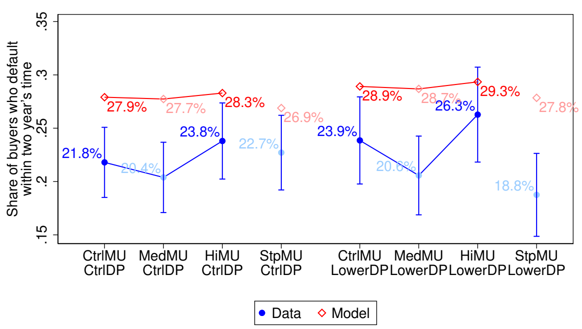
Panel A: Average difference in repayment of the first minus the second half during maturity



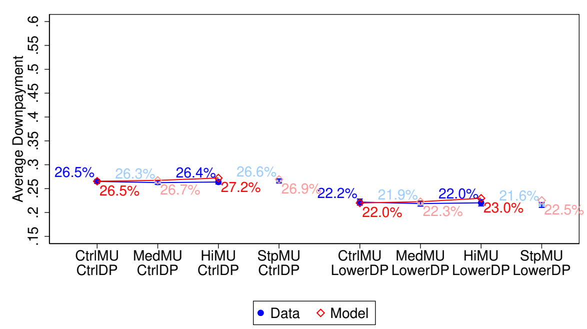
Panel B: Conditional prob. of resuming payment



Panel C: Fraction of customers who did not fully repay in two years



Panel D: Average fraction put as down payment



Note: This figure plots additional moments from actual data (in blue) and simulated data (in red) for risk score 1. Panel A shows the average difference in the share of the amount due repaid in the first half of the contract minus the share repaid in the second half. Panel B reports the probability of resuming payment in week t conditional on missing payment in week t-1. Panel C shows the fraction of customers who did not fully repay in two years. Panel D shows the average downpayment as a share of the loan amount. The x-axis corresponds to the 8 experimental arms. CtrlMU (resp. MedMU, HiMU and StpMU) is the control multiple arm (resp. Medium, High and Steep). CtrlDP (resp. LowerDP) is the control downpayment arm (resp. lower downpayment arm). The four treatment groups used in the SMM estimation are in solid color while the other four appear in transparent font. The vertical bars correspond to 95% confidence intervals.

TABLE 3: Sensitivity matrix ($\Lambda = (J'WJ)^{-1}J'W$), Risk Score 1

	$\bar{y}$	$\sigma_{\bar{y}}$	σ_{ϵ}	v_0	ϕ	ρ	β	μ	$\bar{L}$	σ_L	$\sigma_{\omega,3}$	$\sigma_{\omega,6}$	$\sigma_{\omega,9}$
Take-up of 3 months	10.4	-0.28	-0.12	-4.8	0.003	-0.74	0.000	-0.7	821.8	-1.52	844.3	-50.6	-38.5
Take-up of 6 months	-2.2	-0.37	-0.23	-29.4	0.001	-0.45	-0.009	-5.1	952.5	-5.82	57.0	1125.4	-124.5
Take-up of 9 months	-15.9	0.20	-0.00	25.1	-0.002	1.26	-0.033	-3.7	258.6	-9.28	-442.0	-1017.8	-483.9
Take-up of 12 months	25.4	-0.14	-0.10	-26.3	-0.002	0.24	0.033	3.2	1185.2	0.12	-380.8	-265.4	780.7
Repayment of 3 months at maturity	-19.6	-1.54	-0.09	-48.9	0.003	-2.15	-0.040	-14.9	-2230.3	1.02	-1473.1	-1332.5	-388.5
Repayment of 6 months at maturity	2.3	-0.23	-0.03	-14.3	-0.001	-0.65	-0.016	-5.8	-6499.6	-16.77	-363.6	-366.8	-95.9
Repayment of 9 months at maturity	-18.3	-1.49	-0.26	-78.2	-0.000	-1.42	0.005	-5.6	1122.2	7.22	-963.3	-803.3	118.1
Repayment of 12 months at maturity	-5.3	-0.16	0.04	5.1	-0.006	1.76	0.018	7.0	8093.2	24.58	2.8	23.2	146.1
Avg. repayment of first minus second half	2.2	-0.09	-0.06	-12.2	0.002	-0.74	0.011	1.1	1108.8	2.76	-209.3	-100.7	82.8
Prop. of perfect repayer	30.3	0.72	0.31	86.6	-0.002	0.71	0.014	8.9	-6567.8	-5.48	845.2	725.4	153.9
Prob. of resuming payment	6.5	1.18	0.41	87.2	-0.005	-0.12	-0.021	4.4	-1402.0	-5.12	923.1	743.0	-133.7
Fraction of customers default in two years	0.4	-1.18	-0.45	-107.8	0.011	-3.75	0.034	-4.2	3434.8	7.87	-1119.1	-816.2	237.1
Prop. of putting min. down	-65.2	0.65	-0.02	79.7	-0.002	1.30	0.005	15.1	59.0	-2.34	1928.7	1400.4	-126.1

Note: W is the weighting matrix used in our SMM estimation, which is the identity matrix. J is the Jacobian matrix.

Table 4: Welfare and Profitability Under Each Treatment Group and Under Competitive Pricing

Treatment group	(1) Take-up	(2) $\mathcal{W}_{taker}$	(3) $\mathcal{W}_{pop}$	(4) NPV	(5) IRR
Risk score 1					
LowMarkupCtrlDown	62.8%	11.3%	6.7%	37.3	201%
HighMarkupCtrlDown	55.3%	10.0%	5.5%	64.5	444%
LowMarkupLowerDown	67.5%	11.7%	7.2%	36.3	176%
Competitive Pricing	74.2%	16.3%	12.1%	0.0	25%
Risk score 2					
LowMarkupCtrlDown	61.3%	13.0%	7.8%	34.8	181%
HighMarkupCtrlDown	55.8%	12.2%	7.1%	59.7	391%
LowMarkupLowerDown	68.4%	15.5%	10.3%	35.5	164%
Competitive Pricing	94.4%	24.6%	23.2%	0.0	25%
Risk score 3					
LowMarkupCtrlDown	50.9%	9.9%	5.7%	26.8	143%
HighMarkupCtrlDown	48.9%	9.1%	4.5%	53.7	326%
LowMarkupLowerDown	59.7%	10.6%	7.0%	22.8	109%
Competitive Pricing	99.7%	22.2%	22.1%	0.0	25%
Risk score 4					
LowMarkupCtrlDown	26.2%	6.1%	1.8%	28.3	196%
HighMarkupCtrlDown	26.0%	5.1%	1.5%	37.0	239%
LowMarkupLowerDown	38.2%	7.1%	3.2%	14.4	82%
Competitive Pricing	76.8%	11.3%	8.7%	0.0	25%

Note: this table reports welfare gains and profitability of contracts for each experimental arm, as well as under the assumption of competitive pricing. Column (1) reports the take-up rate, Column (2) reports $\mathcal{W}_{taker}$, our measure of welfare gains conditional on buying a smartphone, Column (3) reports $\mathcal{W}_{pop}$, our unconditional welfare gain measure, Column (4) reports the NPV per contract over a two-year period and column (5) reports the annualized IRR for a portfolio of all loan contracts in each experimental arm over a two-year period.

Table 5: Competitive Prices

Treatment group	(1) Markup for 12 month	(2) Minimum downpayment
Risk score 1		
CtrlMarkupCtrlDown	2.00	25.0%
Competitive Pricing	1.50	4.9%
Risk score 2		
CtrlMarkupCtrlDown	2.00	30.0%
Competitive Pricing	1.55	4.0%
Risk score 3		
CtrlMarkupCtrlDown	2.00	35.0%
Competitive Pricing	1.60	0.0%
Risk score 4		
CtrlMarkupCtrlDown	2.00	50.0%
Competitive Pricing	1.85	11.8%

Note: This table reports, for each risk score, the multiple and minimum downpayment for 12 months contracts under the assumption of competitive pricing. It also reports the actual multiple and minimum downpayment in the control multiple / control downpayment arm of the experiment.

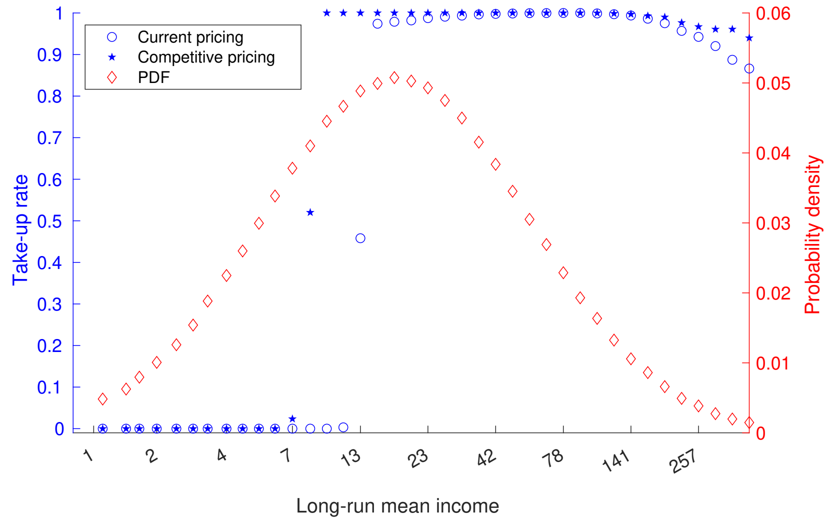
Table 6: Welfare of PAYGo Relative to Traditional Repossession

	(1) Baseline Technology $c_{\text{repo}} = \$25$, $p_{\text{repo}} = 0.8$	(2) Worse Technology $c_{\text{repo}} = \$50$, $p_{\text{repo}} = 0.6$	(3) Better Technology $c_{\text{repo}} = \$0$, $p_{\text{repo}} = 1$
Risk score 1	2.0%	4.1%	1.0%
Risk score 2	4.0%	6.3%	2.8%
Risk score 3	4.8%	12.6%	2.8%
Risk score 4	5.4%	8.8%	3.1%

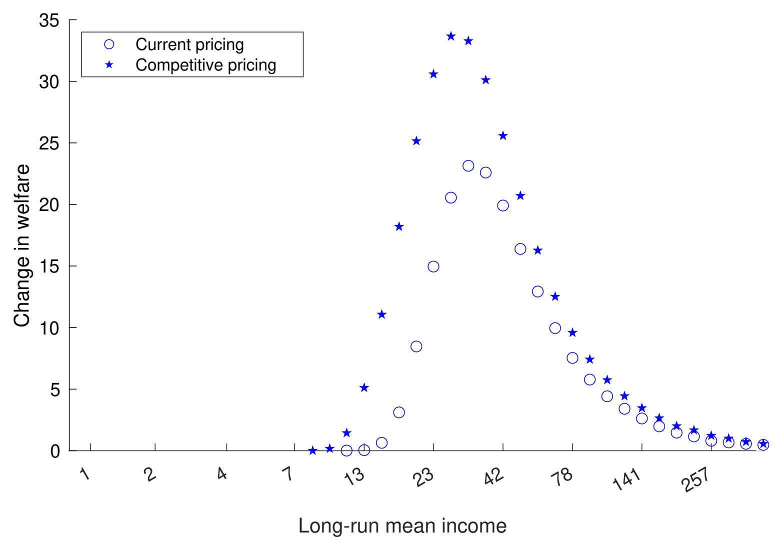
Note: This table reports the percentage increase in weekly income over a two-year period for a consumer under the traditional repossession contract that would deliver the same utility as they gain from having access to the PAYGo contract for three different repossession technologies. We use competitive prices for all technologies.

FIGURE 7: Take-up and Welfare by Income, Risk Score 1

Panel A: Take-up rates

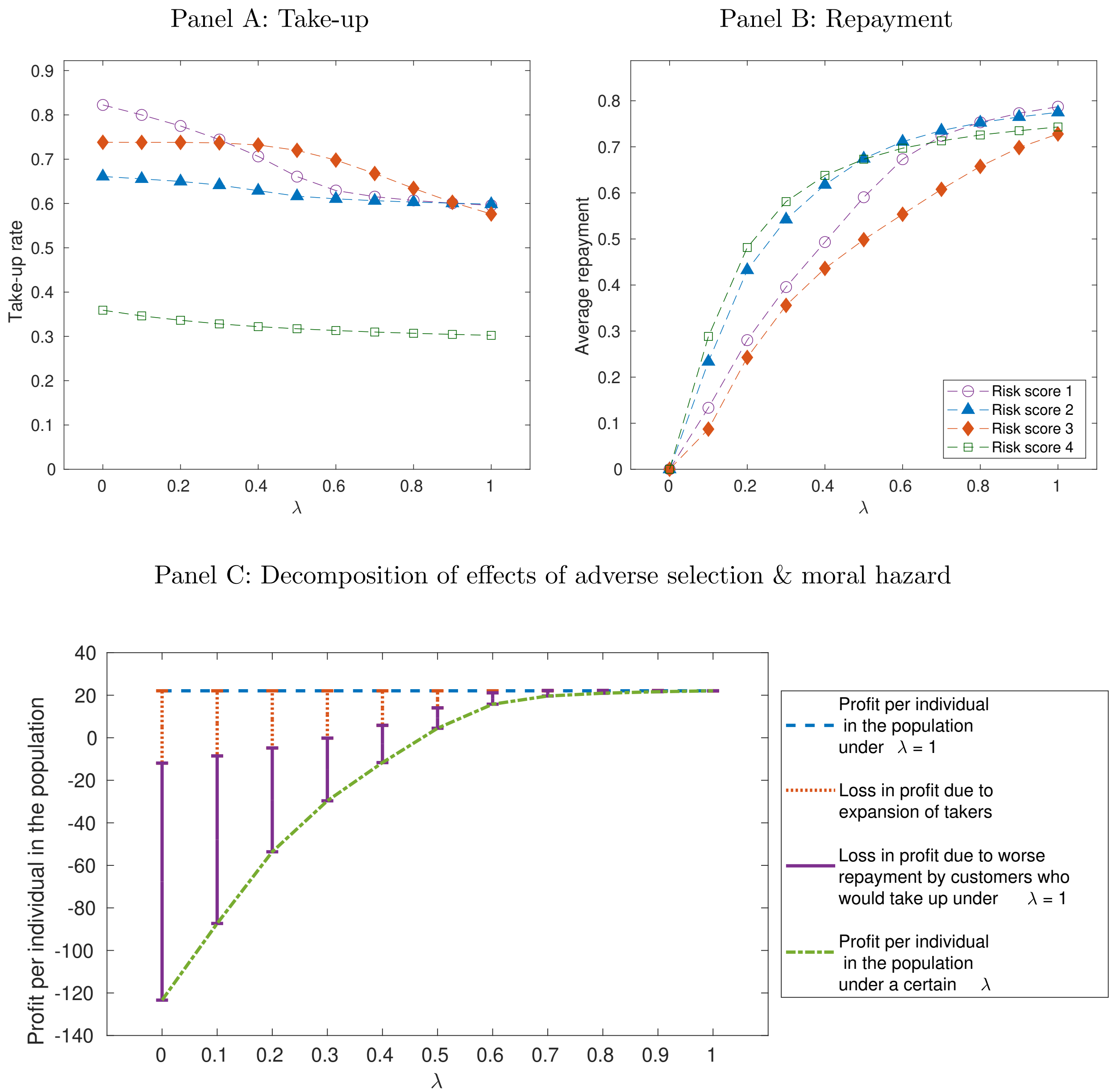


Panel B: Welfare gain $\mathcal{W}_{taker}$



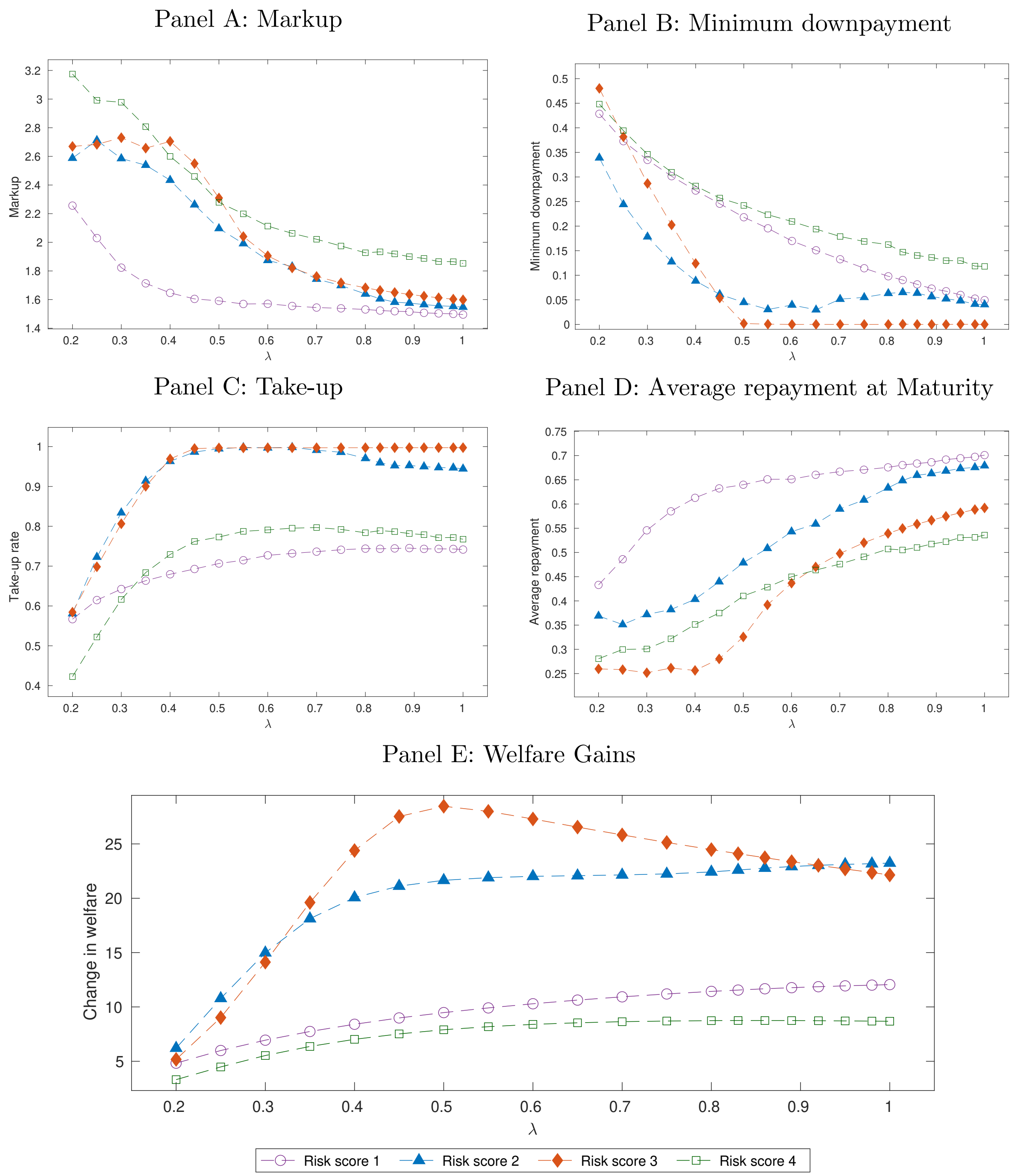
Note: We simulate the model assuming consumers face (1) the menu of contract offered in the control multiple / control downpayment arm (2) competitive prices. Panel A reports the average take-up rate by level of long-run mean income for both pricing (blue star for competitive pricing, blue circles for actual prices), together with the probability density of long-run mean income (red diamonds). Panel B reports our measure of welfare gains conditional on take-up $\mathcal{W}_{taker}$ for each level of long-run mean income $\bar{y}_i$ for both pricing.

Figure 8: Decomposition of Effects of λ into Moral Hazard and Adverse Selection



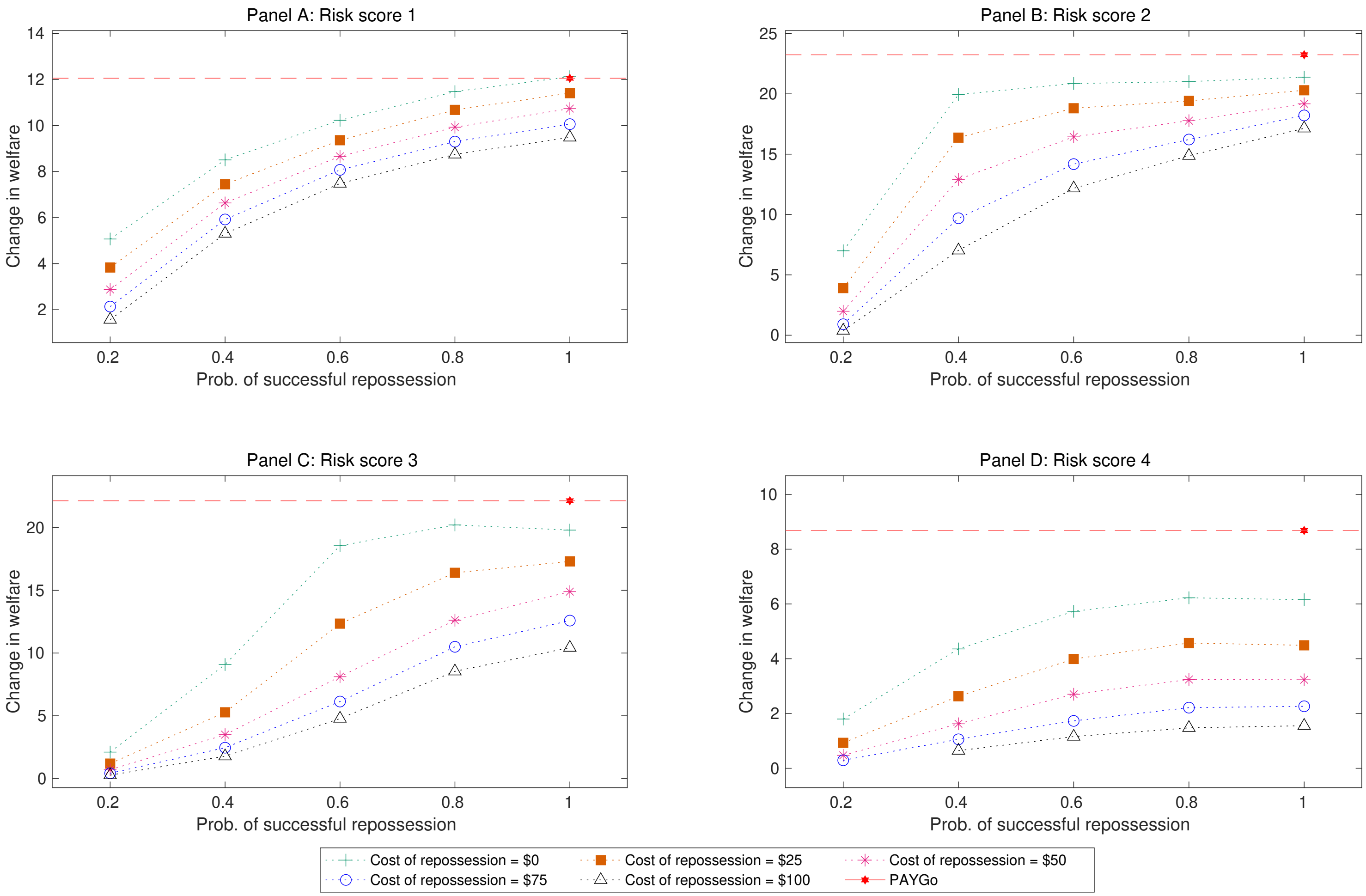
Note: we simulate the model assuming consumers face the menu of contracts offered in the control multiple / control downpayment arm and varying the efficiency of the lockout technology, λ, from 0 (no lockout) to 1 (full lockout, as in the baseline estimation). Panel A shows the average take-up rates for each value of λ. Panel B shows the average repayment at maturity. In Panel C, we decompose the loss in overall profit due to reducing λ into (a) weaker screening (the difference between actual profits and profits if the population of takers was the same as when $\lambda = 1$) and (b) weaker incentive (profit loss due to worse repayment by consumers who would take up under $\lambda = 1$). Panel C provides the decomposition for risk score 1, and the decomposition for risk score 2, 3, and 4 can be found in Figure A6 in the Appendix.

FIGURE 9: Welfare-Maximizing Lockout



Note: for each risk score, we find the competitive prices in a market where only the 12-months maturity contract is offered. This calculation is done using the baseline parameter estimates and assuming various values for λ, the efficiency of the lockout technology. For each value of λ, we then simulate a sample of consumers facing these competitive prices. Panel A reports the competitive multiple across risk scores and values of λ. Panel B reports the competitive downpayment, Panel C the average take-up rate, Panel D the average repayment at maturity, and Panel E the welfare gains conditional on take-up, $\mathcal{W}_{taker}$.

Figure 10: Welfare Gains from PAYGo versus Secured Lending under Competitive Pricing



Note: This figure compares our measure of welfare gains from PAYGo, $\mathcal{W}_{pop}$, to traditional secured lending for a range of repossession technologies. We consider traditional secured lending with $c_{\text{repo}} = \{\$0, \$25, \$50, \$75, \$100\}$ and $p_{\text{repo}} = \{0.2, 0.4, 0.6, 0.8, 1\}$. Welfare gains with the repossession technology is calculated assuming a 12-months maturity contract that is competitively priced. If zero-profit cannot be achieved for a certain repossession technology, the corresponding point is omitted.

Online Appendix

A Computation

A.1 Model Solution

The consumer's problem features two stages: take-up and repayment. In the take-up stage, the consumer chooses whether to accept the PAYGo contract, as well as the maturity and the downpayment. In the repayment stage, the consumer makes a decision whether to pay her weekly due every week. We describe our solution method starting from the repayment stage.

Discretization. To obtain the numerical solution to our model, we solve it on discretized grids. We use a grid of $\bar{y}_i$ with $GridSizeYLRM = 16$ points, a grid of L_i with $GridSizeLiq = 16$ points, and a grid of $y_{it}/\bar{y}_i$ with $GridSizeYtoYLRM = 15$ points. For the grid of $\bar{y}_i$, the two end points are $\bar{y}e^{-\frac{\sigma_{\bar{y}}^2}{2}-3\times\sigma_{\bar{y}}}$ and $\bar{y}e^{-\frac{\sigma_{\bar{y}}^2}{2}+3\times\sigma_{\bar{y}}}$. Similarly, the two end points for the grid of $\bar{L}$ are $\bar{L}e^{-\frac{\sigma_{\bar{y}}^2}{2}-3\times\sigma_{\bar{y}}}$ and $\bar{L}e^{-\frac{\sigma_{\bar{y}}^2}{2}+3\times\sigma_{\bar{y}}}$. For the grid of $y_{it}/\bar{y}_i$, we set the two end points to be the exponential of the mean of the steady-state distribution of $log(y_{it}/\bar{y}_i)$ plus/minus three times of its steady-state standard deviation. The interim points are spaced evenly.

In the take-up stage, we use a grid of downpayment of size GridSizeD = 10, which ranges from the minimum downpayment to 100% with equal space. We also use a grid that measures the share of wealth to be consumed at date 0 after putting the downpayment. That linearly spaced grid ranges from 0 to 100% and has size $GridSizeCsm = 100$. Finally, we construct four grids for each of the four maturity-choice shocks, each of size $GridSizeUShock = 9$. For the repayment stage, we use a grid for the current device value of size $GridSizeVtoV0 = 2$, i.e., the device is worth either its initial value or 0 to the consumer.

Repayment Stage. We first solve for ownership value $\Pi_i(v, y)$, where v is device value and y is current income. The flow value of ownership is $f_{\text{o}} = v + u(y)$. Starting from an initial guess $\Pi_i^0(v, y) = 0$, we use value function iteration (VFI) on the (v,y) grid to find $\Pi_i(v, y)$ as the unique limit of $\Pi_i^k(v, y) = f_{\text{o}} + \beta\mathbb{E}\left[\Pi_i^{k-1}(v', y')|v, y\right]$. We use an i subscript to denote the fact that this value depends on the consumer's long-run mean income $\bar{y}_i$ (as it affects the expected dynamics of income). It is thus solved separately for each point on the long-run mean income grid.

Next, we solve for consumers' value function in the repayment stage again via VFI. The flow utility if the consumer repays is $f_{\text{p}} = v + u(y - m)$ and $f_{\text{np}} = (1 - \lambda)v + u(y)$ if she does not. Starting from an initial guess $U_i^0(x)$, where x corresponds to the state variables (device value, current income, number of remaining payments on the contract), we find consumers' value function as the limit of

$$\begin{aligned} U_i^k(v, y, n) = \max\Big\{ & f_{\text{p}} + \beta\mathbb{E}\left[U_i^{k-1}(v', y', n-1)|v, y\right], \\ & f_{\text{np}} + \beta\mathbb{E}\left[U_i^{k-1}(v', y', n|v, y\right]\Big\}, \end{aligned}$$

with $U_i^k(v, y, 0) = \Pi_i(v, y)$ for all k. As this repayment problem differs for each level of downpayment choice (as the size of the periodic repayment m differs), for each maturity choice, and for each value of long-run mean income on the grid, it is solved for $GridSizeD \times 4 \times GridSizeYLRM$ times.

Outside Option. Before moving to the contract choice stage, we solve for the outside option. We solve for the value of the real option $F(v, y)$ via VFI. We start by obtaining the terminal value if the customer chooses to buy

$$G_i(y) = \max_{c,w} v_0 + u(c) - \mu(L_i - w) + \beta \mathbb{E}[\Pi(v^{'}, y^{'})|v = v_0, fy],$$

where w is the amount the consumer saves, L_i her liquidity and the budget constraint is: $c+w+p = y+L_i$. We impose $G_i(y) = -\infty$ whenever $w > L_i$. This problem is solved separately for each point on the liquidity grid and the long-run mean income grid (hence the i subscript).

Finally, we calculate $F_i(y)$ as the solution of the following VFI: $F_i^k(y) = \max \left\{ u(y) + \beta \mathbb{E}[F_i^{k-1}(y^{'})|y], G_i(y) \right\}$ and obtain the initial outside option as $O_i(y_0) = \mu L_i + F_i(y_0)$. Again, these two steps are done for each point on the grids for liquidity L_i and long run mean income.

Take-Up Stage. For each contract j, we first calculate the value of buying a PAYGo-financed phone given each possible level of downpayment, initial consumption of the remaining liquidity (w_i in Section 3), and each possible value of the maturity-choice shock on its grid. This value is set $-\infty$ for combinations of $y_{0i}/\bar{y}_i$, $\bar{y}_i$, and L_i such that the consumer cannot put the minimum required downpayment. We then select the optimal downpayment (and initial consumption w_i), which also delivers the value of choosing contract j, $W_i(x;\Gamma_j) + \omega_j$. By comparing all contracts in the menu offered to the consumer and her outside option, we obtain the optimal take-up and maturity choice.

Firm Profit. Expected discounted aggregate firm profit during repayment period is solved using VFI as the solution of:

$$V_k(v, y, n, \Gamma) = A^*(v, y, n)\big(m + \delta \mathbb{E}[V_{k-1}(v^{'}, y^{'}, n-1, \Gamma)|v, y] + (1 - A^*(v, y, n))\delta \mathbb{E}[V_{k-1}(v^{'}, y^{'}, n, \Gamma)|v, y],$$

where $A^*(v, y, n)$ is a consumer's optimal repayment decision. We plug $V_k(v, y, n, \Gamma)$ into Equation (11) and obtain the firm's NPV.

A.2 Simulation

We simulate a sample of 10^6 customers and their dynamics from $t = 0$ to $t = 104$ weeks. We always fix random seed in the simulation (except for when we compute parameter standard error due to simulation noise in Section A.5). We draw the time-invariant characteristics $\bar{y}_i$ and L_i and the date-0 shocks ω_{ij} based on their distribution in the cross-section. We also draw the date 0 income shock $y_{i0}/\bar{y}_i$ based on its steady state distribution, along with the income shocks ϵ_{it} for the next 104 weeks, so the cross-sectional distribution of $y_{it}/\bar{y}_i$ is constant over time.

For each consumer in the simulated sample, we first calculate the date-0 outside option by linearly interpolating the outside option O_i calculated on a grid for $y_0/\bar{y} \times \bar{y} \times L$. We also calculate the value of taking up each contract Γ_j in the menu offered to the consumer by linearly interpolating the value function $W_i(\Gamma_j)$ calculated on a grid for $y_0/\bar{y} \times \bar{y} \times L$. By comparing the highest $W_i(\Gamma_j)$ to O_i, we obtain the consumer's take-up decision. In case the consumer decides to take-up, her decision is driven by the comparison of the value of taking up contract Γ_j, $W_i(\Gamma_j)$ plus the random maturity-choice shock drawn by the consumer, ω.

Next, we simulate downpayment choices by linearly interpolating the policy function for downpayment choice from the grids of $y_0/\bar{y} \times \bar{y} \times L$ to the simulated sample.

To simulate the repayment dynamics, we first draw a sequence of device value v_{it}/v_{i0} for takers. Then, we simply linearly interpolate the policy function of repayment choice A calculated on the grids of $y_0/\bar{y} \times v_t/v_0 \times \bar{y} \times d \times n$ to the simulated customer dynamics using the "nearest" method. This simulation is done sequentially from $t = 1$ to $t = 104$.

A.3 Welfare Calculation

Our goal is to find the proportional increase in consumer income that is equivalent to having access to a PAYGo-enabled contract, i.e., solving for: $\max\{W(\Gamma^*), O(y_0)\} = \hat{O}(\hat{y}_0)$ where $\hat{y}_t = (1+\mathcal{W})y_t$ if $t \leq 104$ and y_t otherwise.

$\hat{O}(\hat{y}_0)$ is the value of the outside option with the higher income process $\hat{y}_{it}$. As $\hat{O}(\hat{y}_0)$ entails the solution of a dynamic programming problem where the customer chooses whether to buy with cash optimally in each period, it cannot be represented as an analytical function of $\mathcal{W}$. Hence, no closed-formed solution exists for our welfare measure. Instead, we solve for it numerically for each customer type (defined by its date-0 income y_{i0}, its long-run mean income $\bar{y}_i$, and its initial liquidity L_i). Given the large size of possible customer types, we minimize computing time by solving on a discrete grid: we define an extra grid for the proportional increase in income of size $\mathit{GridSizeExtraInc} = 200$ that ranges from 0% and 100%, and calculate the value of a customer who enjoys an increase in income over a period of two years ($0 \leq t \leq 104$) for every level on this grid. $\mathcal{W}$ corresponds to the increase such that $\hat{O}(\hat{y}_0)$ is the closest to $\max\{W(\Gamma), O(y_0)\}$. Using a grid size of 200 allows us to minimize computational error.

Computing $\hat{O}(\hat{y}_0)$ is different than computing the outside option since the proportional increase in income affects customers for a finite horizon of two years. We first define the option value as $\hat{F}(\hat{y}_t, t)$. As the proportional increase in income exists for a finite period, this option value depends on the time t. For $t > 104, \hat{F}(\hat{y}_t, t) = F(y_t)$. To obtain the option value for $t = 104$ and before, we use backward induction, starting from $t = 104$, and obtain the option value one period ahead as

$$\hat{F}(\hat{y}_t, t) = \max\Big\{u(\hat{y}_t) + \beta\mathbb{E}[\hat{F}(\hat{y}_{t+1}, t+1)|\hat{y}_t], \hat{G}(\hat{y}_t, t)\Big\}.$$

Here $\hat{G}(\hat{y}_t, t)$ is the value if the customer buys with cash, which equals

$$\begin{aligned}\hat{G}(\hat{y}_t, t) = &\max_{c_t, w} v_0 + u(c_t) - \mu(L - w) + \beta\mathbb{E}[\hat{\Pi}(v_{t+1}, \hat{y}_{t+1}, t+1)|v_t = v_0, \hat{y}_t]\\ &\text{s.t. } c_t + w + p \leq \hat{y}_t + L, \quad w \leq L \text{ and } c_t, w \geq 0.\end{aligned}$$

We solve this program numerically as we do for the outside option in the main simulation, with one difference: $\hat{\Pi}(v_{t+1}, \hat{y}_{t+1}, t+1)$ is the value of owning the device while consuming $\hat{y}_t$ from time $t+1$ on; it depends on time t as the increase in income $\mathcal{W}$ in received only for two years. $\hat{\Pi}(v_{t+1}, \hat{y}_{t+1}, t+1)$ is also calculated via backward induction. The value of the outside option with proportional increase in income is $\hat{O}(y_0) = \mu L + \hat{F}(\hat{y}_0, 0)$. This delivers $\mathcal{W}$ on the grid for customer types, and allows to get $\mathcal{W}$ for every customers in our simulations through linear interpolation.

A.4 The Tik-Tak algorithm

Our SMM uses the Tik-Tak algorithm, which has been shown to have superior performance for numerical optimization problems with large parameter space (Guvenen, 2011; Arnoud et al., 2019). We first initialize the algorithm by choosing the bounds for all the parameters to be estimated. We then generate a quasi-random sequence of $N_{\text{Sobel}} = 50,000$ Sobel's points. We evaluate the SMM error $(m(\Theta) - m)'W(m(\Theta) - m)$ at each of the N_{Sobel} Sobel's points and pick the resulting $N^* = 100$ lowest SMM error. Let $\mathbf{s} = s_1, ..., s_{N^*}$. We then run N^* local search using the Nelder-Mead algorithm at starting points $s_i^{\text{starting point}}$ where $s_i^{\text{starting point}} = \theta_i p_{i-1}^{\text{low}} + (1 - \theta_i)s_i$, with p_{i-1} being the best parameter estimate at the beginning of the i$^{\text{th}}$ minimization (and $p_1 = s_1$). We use weights $\theta_i = \min[\max[0.1, (i/N^*)^{1/2}], 0.995]$. To obtain our parameter estimates, we run one last minimization starting at p_{N^*}.

A.5 Standard Errors

The variance-covariance matrix of parameter estimates is $(J' K_{\mathbf{mm}}^{-1} J)^{-1}$, where J is the Jacobian matrix evaluated at the estimates and $K_{\mathbf{mm}}$ is the the variance-covariance matrix of data moments. We obtain $K_{\mathbf{mm}}$ via bootstrapping using the actual sample. Standard errors correspond to the square roots of the diagonal terms of this variance-covariance matrix.

A.6 Competitive Terms

Competitive terms corresponds to multiples and minimum downpayment requirements that maximize welfare per individual, $\mathcal{W}_{pop}$, while leaving zero profit for the firm. To solve for these competitive prices, we use a penalty method with multiple starts. We define an objective function with penalty coefficient η $\Lambda(M|\eta) = \mathcal{W}_{pop}(M) - \eta \times \mathbb{E}[\text{NPV}_i|M]^2$, where M corresponds to the contract terms (multiple, minimum required downpayment). We start with $N = 1,000$ random sets of contract terms sampled as Sobel sequences and evaluate the objective function using $\eta = 0.1$. We pick out the $N_\star = 20$ sets of contracts with highest value. We also fix a sequence of penalty coefficient $\boldsymbol{\eta} = \{\eta_1, ..., \eta_{N_\eta}\} = \{0.1, 1, 10, 100\}$. Then, starting from one of these $N_\star$ contracts, we run a local optimization for $\Lambda(M|\eta_1)$, then use the resulting contract as a starting point to maximize $\Lambda(M|\eta_2)$, and repeat until η_{100}. This delivers a set of 20 optimal contracts (corresponding to each of the initial 20 contracts) and the zero-profit welfare-maximizing contract corresponds to the best of these 20 contracts.

We verify this solution with a brute force method. For each level of downpayment from 0 to 1 on a grid of size 200, we solve for the markup that yields zero profit. As markup and downpayment are complements in profit, the zero-profit-line in a 2-D plane of multiple and downpayment is downward sloping. We then calculate $\mathbb{E}[\mathcal{W}_i]$ for each point on this zero-profit line. The competitive prices correspond to the point that delivers the highest welfare. This brute-force method yields identical contracts than our optimization algorithm, but is much more computationally intensive.

A.7 Parallelization

When solving the model (for a given set of structural parameters), we need to obtain the value and policy functions for 4 maturities in each treatment arm. We use 4 treatment arms. We estimate the model separately for each of the 4 risk score. Hence, we face 64 similar yet independent problems. We solve them in parallel. In our simulations, we also generate samples under 4 treatment arms and for 4 risk scores, which also do using parallelization. Due to the large dimensionality, we always let each process in the parallel pool employ a separate GPU. These parallelization greatly reduces the total computation time.

B Additional Tables and Figures

Table A1: Summary Statistics

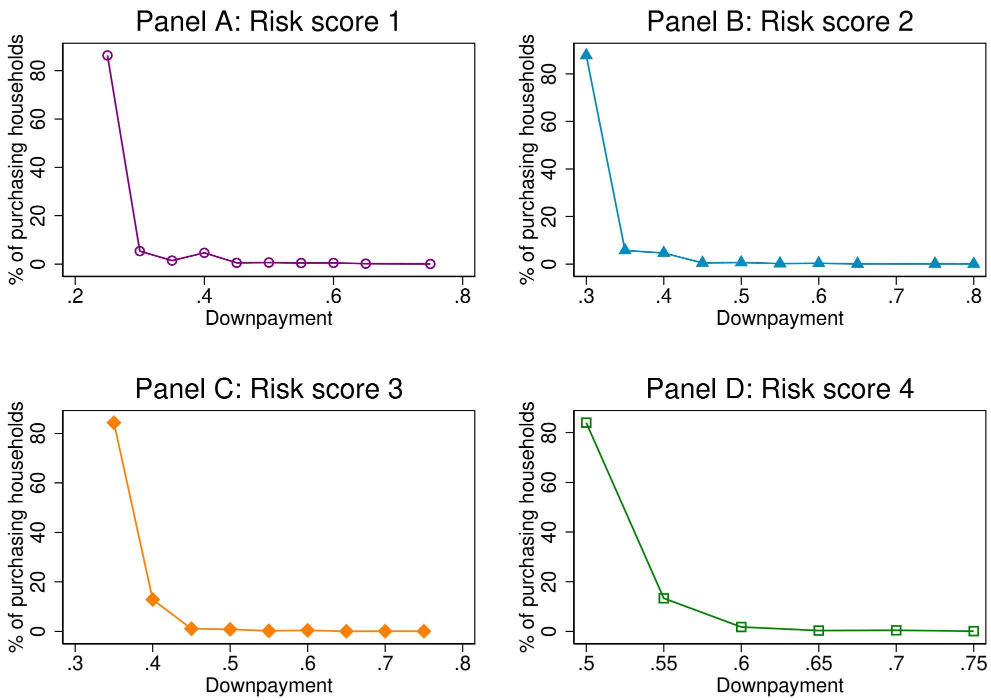
	Mean	SD	Median	5% Percentile	95% Percentile	Risk score 1	Risk score 2	Risk score 3	Risk score 4
Customer Characteristics									
Age	32.4	9.6	31.0	20.0	50.0	36.0	33.0	31.0	29.1
Gender available	0.85					0.89	0.86	0.83	0.82
Is male	0.43					0.46	0.42	0.42	0.45
Has bank account	0.57					0.56	0.56	0.57	0.58
Has credit card	0.21					0.25	0.20	0.20	0.19
Occupation									
- Private sector worker	0.53					0.52	0.52	0.54	0.54
- Public sector worker	0.24					0.25	0.24	0.24	0.23
- Independent entreprenuer	0.16					0.16	0.17	0.15	0.16
- Other (informal economy)	0.07					0.06	0.07	0.07	0.07
- Retired	0.00					0.01	0.01	0.00	0.00
Risk score									
- 1	0.24								
- 2	0.30								
- 3	0.27								
- 4	0.20								
Continuous risk score	0.25	0.10	0.24	0.10	0.42	0.15	0.22	0.27	0.35
Is buyer	0.52					0.60	0.61	0.52	0.30
Buyer Characteristics									
Age	33.0	9.7	31.0	20.0	51.0	36.1	33.3	31.1	29.4
Gender available	0.80					0.86	0.82	0.77	0.66
Is male	0.40					0.44	0.40	0.39	0.35
Has bank account	0.57					0.55	0.56	0.58	0.58
Has credit card	0.20					0.23	0.20	0.20	0.16
Occupation									
- Private sector worker	0.53					0.52	0.52	0.54	0.54
- Public sector worker	0.24					0.25	0.24	0.24	0.23
- Independent entreprenuer	0.16					0.16	0.17	0.15	0.16
- Other (informal economy)	0.07					0.06	0.07	0.07	0.07
- Retired	0.01					0.01	0.01	0.00	0.00
Risk score									
- 1	0.27								
- 2	0.35								
- 3	0.27								
- 4	0.12								
Continuous risk score	0.23	0.09	0.22	0.11	0.39	0.16	0.22	0.27	0.35

Table A1: Summary Statistics (continued)

	Mean	SD	Median	5% Percentile	95% Percentile	Risk score 1	Risk score 2	Risk score 3	Risk score 4
Phone Characteristics									
Brand									
- Samsung	0.94					0.96	0.95	0.94	0.84
- Motorola	0.05					0.03	0.03	0.05	0.13
- LGE	0.02					0.01	0.01	0.02	0.02
List price	206.1	77.9	193.2	115.9	345.1	210.1	208.8	207.8	184.6
Transaction Characteristics									
Minimum downpayment ratio	0.30	0.07	0.30	0.20	0.50	0.23	0.28	0.33	0.45
Minimum downpayment amount	61.8	26.0	57.2	29.0	110.1	49.0	59.0	68.8	83.4
Actual downpayment ratio	0.31	0.08	0.30	0.20	0.50	0.25	0.29	0.34	0.45
Actual downpayment amount	63.3	29.0	58.0	29.0	113.3	51.6	60.3	69.6	84.9
Financed amount	142.8	57.9	129.8	77.0	252.4	158.5	148.5	138.1	99.7
Multiple	1.70	0.28	1.64	1.37	2.40	1.71	1.71	1.70	1.66
Term Length									
- 3 Months	0.29					0.28	0.28	0.29	0.39
- 6 Months	0.38					0.36	0.38	0.39	0.38
- 9 Months	0.22					0.25	0.24	0.22	0.15
- 12 Months	0.11					0.12	0.11	0.10	0.08
Weekly payment obligation	9.8	4.9	9.0	4.3	19.5	10.7	10.1	9.6	7.7
Loan outcomes (Samsung only)									
Total amount paid	200.6	125.3	180.8	12.4	427.9	229.1	210.5	186.4	128.7
Total amount paid / Amount due	0.82	0.33	1.00	0.06	1.00	0.85	0.83	0.79	0.79
If fully repaid	0.74					0.78	0.75	0.70	0.71

Note: In this table we report the summary statistics of our sample. We report statistics based on all risk scores in columns (1)-(5), and the sample mean within each risk score in columns (6)-(9). The characteristics of buyers, phones, and transactions are conditional on being a purchasing household, and the loan outcomes are conditional on the contract being a Samsung phone. The list price, minimum downpayment amount, actual downpayment amount, financed amount, weekly payment obligation, and total amount paid are in US dollars converted based on the exchange rate during our sample period.

Figure A1: Histogram of Downpayments by Risk Score



Note: The figure reports the histogram of selected downpayment in the control arm (i.e., Control pricing and Control minimum required downpayment) of the experiment, for each risk score. The minimum required downpayments are 25%, 30%, 35% and 50% for risk scores of 1, 2, 3 and 4 respectively.

Table A2: Parameter Estimates for the Middle Two Risk Scores

	(1) Risk score 2	(2) Risk score 3
Income process parameters:		
$\bar{y}$ (average long-run mean income)	33.39	28.30
	(1.43)	(1.22)
$\sigma_{\bar{y}}$ (dispersion of long-run mean income)	0.81	0.19
	(0.04)	(0.06)
σ_{ϵ} (size of income shock)	0.40	0.28
	(0.02)	(0.01)
ρ (mean-reversion coef.)	0.04	0.95
	(0.06)	(0.00)
$\bar{L}$ (average initial liquidity)	131.21	167.56
	(28.23)	(28.43)
σ_L (dispersion of initial liquidity)	1.32	1.10
	(0.10)	(0.12)
Device value parameters:		
v_0 (initial device value)	28.61	23.47
	(2.74)	(2.02)
ϕ (prob. of depreciation, weekly)	0.0120	0.0091
	(0.0004)	(0.0004)
Other customer preference parameters:		
β (weekly discount rate)	0.997	0.980
	(0.001)	(0.002)
μ (value of savings)	4.86	4.79
	(0.21)	(0.65)
$\sigma_{\omega,3}$ (size of random utility shock for 3 month)	364.70	306.55
	(20.34)	(26.82)
$\sigma_{\omega,6}$ (size of random utility shock for 6 month)	392.00	398.61
	(29.20)	(39.76)
$\sigma_{\omega,9}$ (size of random utility shock for 9 month)	73.94	20.99
	(14.52)	(5.79)

Note: This table reports the results of our SMM estimations. Parameters with † are preset and all other parameters are estimated. The values presented in this table for parameters v_0, $\sigma_{\omega,3}$, $\sigma_{\omega,6}$, $\sigma_{\omega,9}$, and $\sigma_{\omega,12}$ are scaled by the marginal utility evaluated at the average long-run mean income (i.e., $u'(\bar{y})$). This is saying that the true value of these parameters are the numbers in the table times $u'(\bar{y})$. We present the transformed values here to give better intuition over the magnitude of these parameters. Similarly, the true value of μ_i for household i is the value presented in this table times $u'(\bar{y}_i)$. Standard errors are in the parentheses.

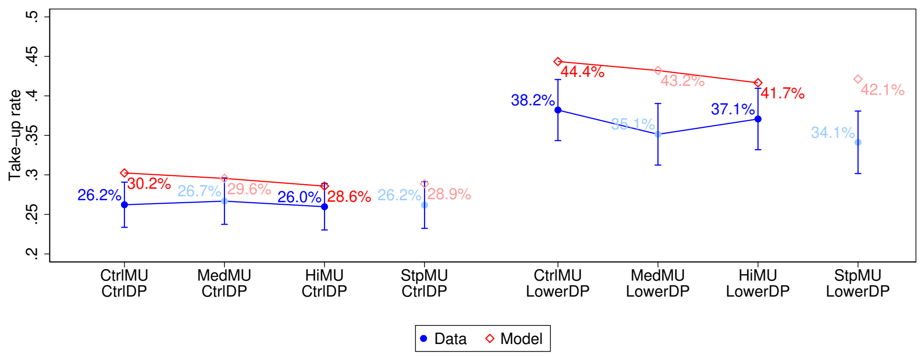
Table A3: Sample and Simulated Moments

	(1) Risk score 1	(2) Risk score 2	(3) Risk score 3	(4) Risk score 4
	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP
Take-up & Maturity choice				
3 month	17.1%/14.7%/16.4%/15.7%	17.3%/14.4%/17.1%/17.0%	15.8%/13.4%/16.5%/12.9%	12.7%/9.8%/13.0%/12.6%
	15.5%/14.8%/15.2%/14.5%	*15.9%/15.7%/16.8%/16.7%*	*13.9%/12.6%/15.4%/14.1%*	*10.0%/9.5%/13.7%/13.1%*
	(1.2/-0.2/0.7/0.8)	(1.3/-1.4/0.1/0.2)	(1.7/0.7/0.8/-1.0)	(2.7/0.3/-0.6/-0.4)
6 month	23.3%/22.0%/23.7%/21.0%	23.0%/22.3%/24.8%/23.2%	21.1%/18.8%/22.8%/21.7%	8.8%/9.6%/15.3%/15.8%
	20.4%/19.4%/20.8%/19.7%	*21.5%/21.1%/23.8%/23.4%*	*20.5%/18.1%/23.5%/20.8%*	*10.4%/9.9%/15.1%/14.5%*
	(2.3/2.1/1.9/0.8)	(1.3/1.0/0.7/-0.1)	(0.4/0.6/-0.5/0.5)	(-1.6/-0.4/0.1/0.9)
9 month	15.0%/11.9%/18.9%/12.9%	13.6%/12.0%/18.8%/15.9%	9.8%/10.6%/14.2%/12.1%	3.2%/4.4%/7.0%/5.6%
	15.9%/13.3%/17.2%/14.1%	*16.4%/14.8%/19.3%/17.3%*	*16.2%/12.2%/18.5%/14.0%*	*6.9%/6.0%/11.4%/9.6%*
	(-0.7/-1.3/1.2/-0.8)	(-2.6/-2.8/-0.3/-1.0)	(-5.8/-1.6/-3.0/-1.5)	(-4.3/-2.0/-3.4/-3.3)
12 month	7.4%/6.7%/8.5%/8.2%	7.4%/7.1%/7.7%/8.7%	4.2%/6.1%/6.2%/7.5%	1.6%/2.2%/3.0%/3.1%
	7.7%/7.9%/8.1%/8.4%	*6.2%/6.1%/6.8%/6.9%*	*7.0%/6.7%/8.2%/8.3%*	*2.9%/3.1%/4.1%/4.5%*
	(-0.4/-1.4/0.4/-0.1)	(1.9/1.5/1.0/2.1)	(-3.6/-0.9/-2.0/-0.7)	(-2.5/-1.5/-1.4/-1.8)
Overall	62.7%/55.3%/67.5%/57.9%	61.3%/55.8%/68.4%/64.8%	50.9%/48.9%/59.7%/54.1%	26.2%/26.0%/38.2%/37.1%
	59.6%/55.4%/61.3%/56.7%	*59.9%/57.7%/66.7%/64.2%*	*57.6%/49.7%/65.6%/57.1%*	*30.2%/28.6%/44.3%/41.6%*
	(2.0/-0.1/3.2/0.6)	(1.0/-1.4/1.0/0.3)	(-4.6/-0.6/-3.4/-1.7)	(-2.6/-1.7/-3.1/-2.3)
Repayment and default				
3 month, at maturity	81.3%/78.9%/80.8%/75.2%	81.2%/78.4%/77.6%/76.3%	78.5%/74.0%/70.4%/80.1%	80.7%/74.2%/74.5%/75.8%
	79.8%/78.2%/78.1%/76.5%	*79.7%/77.0%/78.1%/74.9%*	*76.4%/75.3%/71.5%/70.3%*	*78.8%/77.7%/71.5%/70.2%*
	(0.7/0.3/1.0/-0.5)	(0.9/0.7/-0.2/0.6)	(0.9/-0.4/-0.3/2.7)	(0.6/-1.0/0.9/1.5)
6 month, at maturity	80.7%/78.1%/79.5%/77.6%	78.2%/77.1%/79.9%/71.2%	73.7%/70.1%/73.0%/72.7%	75.6%/65.1%/64.5%/68.6%
	81.2%/79.6%/79.4%/77.7%	*79.6%/77.7%/78.3%/76.0%*	*74.5%/73.2%/70.8%/69.3%*	*75.9%/74.8%/71.6%/69.9%*
	(-0.1/-0.7/0.1/-0.0)	(-0.8/-0.3/0.9/-2.2)	(-0.5/-1.4/0.8/1.4)	(-0.1/-2.6/-1.9/-0.3)
9 month, at maturity	72.4%/69.8%/75.3%/68.7%	72.1%/68.5%/69.7%/70.4%	65.9%/70.0%/69.7%/58.0%	67.0%/58.0%/59.6%/67.8%
	76.8%/75.5%/74.8%/73.2%	*74.6%/73.1%/73.0%/71.1%*	*70.8%/69.0%/67.8%/65.9%*	*69.4%/68.6%/66.0%/64.5%*
	(-1.9/-2.0/0.2/-1.5)	(-1.1/-1.8/-1.4/-0.3)	(-1.6/0.2/0.6/-2.3)	(-0.4/-1.8/-1.2/0.5)
12 month, at maturity	74.6%/62.3%/56.5%/63.6%	63.4%/57.2%/62.3%/60.6%	65.8%/58.4%/58.7%/58.3%	58.7%/63.7%/65.0%/40.3%
	73.9%/72.4%/72.5%/70.4%	*72.0%/70.8%/71.2%/69.8%*	*65.5%/63.7%/62.3%/60.4%*	*65.0%/64.4%/63.3%/61.6%*
	(0.1/-2.6/-3.6/-1.5)	(-2.5/-3.8/-2.1/-2.2)	(0.0/-1.4/-0.8/-0.4)	(-0.7/-0.1/0.2/-2.5)
All loans, at maturity	78.1%/74.5%/75.8%/72.9%	75.8%/73.0%/74.5%/70.8%	72.9%/69.7%/69.9%/69.0%	76.0%/67.2%/67.2%/68.6%
	78.7%/77.2%/76.9%/75.2%	*77.5%/75.6%/76.0%/73.7%*	*72.8%/71.4%/69.1%/67.4%*	*74.3%/73.3%/69.3%/67.9%*
	(-0.5/-2.2/-0.8/-1.5)	(-1.6/-2.3/-1.2/-2.1)	(-0.0/-1.3/0.5/1.0)	(0.7/-2.7/-0.9/0.3)
Average repayment of first minus second half	5.4%/4.9%/5.7%/6.6%	4.6%/5.4%/4.6%/6.2%	4.3%/5.4%/5.8%/7.1%	3.2%/4.9%/7.0%/4.0%
	4.4%/4.0%/4.3%/3.9%	*5.2%/4.9%/5.2%/4.8%*	*5.5%/6.2%/4.9%/5.6%*	*7.0%/7.1%/6.9%/6.8%*
	(1.7/1.5/2.1/3.7)	(-1.1/1.1/-0.8/2.1)	(-1.7/-1.0/1.1/1.7)	(-3.3/-1.9/0.1/-2.3)
Proportion of buyers who repay perfectly	42.8%/38.6%/41.4%/36.2%	41.7%/40.1%/39.3%/32.3%	40.3%/33.5%/30.9%/32.5%	48.0%/34.4%/30.1%/30.1%
	40.8%/37.2%/37.6%/34.2%	*40.2%/35.2%/36.8%/31.8%*	*37.8%/35.3%/32.6%/30.0%*	*39.7%/36.8%/29.6%/26.7%*
	(0.9/0.7/1.6/0.8)	(0.8/2.7/1.2/0.3)	(1.2/-0.9/-0.7/1.1)	(2.4/-0.7/0.2/1.2)
Conditional prob. of resuming payment	16.7%/17.3%/15.8%/16.6%	18.7%/15.5%/17.6%/15.0%	14.6%/14.7%/15.2%/13.0%	14.2%/10.9%/12.3%/12.1%
	11.3%/13.5%/13.7%/15.6%	*10.4%/12.8%/12.1%/14.4%*	*6.4%/6.4%/6.7%/6.7%*	*4.0%/4.5%/5.8%/6.3%*
	(-4.0/-2.8/-1.3/-0.5)	(-6.9/-2.3/-3.8/-0.1)	(-7.4/-7.8/-7.1/-5.6)	(-4.9/-4.5/-4.2/-3.8)
Fraction of customers who did not fully repay in two years	21.8%/23.8%/23.9%/26.3%	22.6%/25.2%/21.9%/29.5%	25.8%/29.4%/31.2%/33.0%	21.6%/33.9%/37.8%/30.1%
	28.0%/28.4%/29.0%/29.4%	*30.7%/31.2%/31.6%/32.2%*	*29.0%/30.0%/30.8%/32.2%*	*36.8%/37.3%/39.2%/40.0%*
	(-3.3/-2.3/-2.2/-1.3)	(-4.7/-3.3/-4.8/-1.2)	(-1.3/0.2/0.6/0.8)	(-4.5/-0.9/-0.4/-2.8)
Down Payment				
Prop of customers at minimum down payment	96.9%/95.7%/93.0%/94.8%	97.7%/98.8%/97.1%/97.1%	97.4%/97.6%/98.7%/98.8%	97.9%/99.1%/92.6%/90.8%
	93.3%/89.2%/91.0%/86.0%	*94.4%/91.1%/93.1%/89.5%*	*94.0%/92.2%/93.2%/91.3%*	*93.2%/90.4%/92.8%/89.5%*
	(3.6/5.0/1.4/5.0)	(4.1/7.3/3.8/5.7)	(3.5/4.8/4.8/5.4)	(2.9/4.4/-0.1/0.7)
Error	0.093	0.115	0.082	0.177

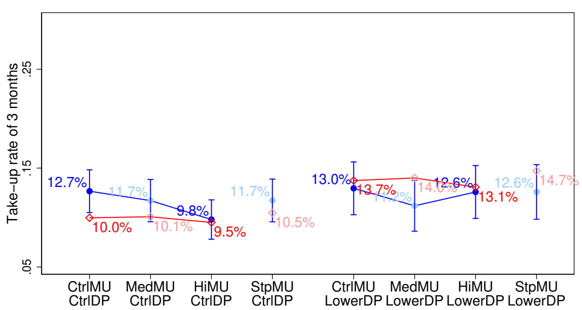
Note: This table reports the sample moments along with simulated moments for risk scores 1 and 4. Within each column, we report sample moments above and simulated moments below in *italics*. T-stats from a two-sample test of equality is reported in the parentheses.

Figure A2: Model Fit - Take-up Rates, Risk Score 4

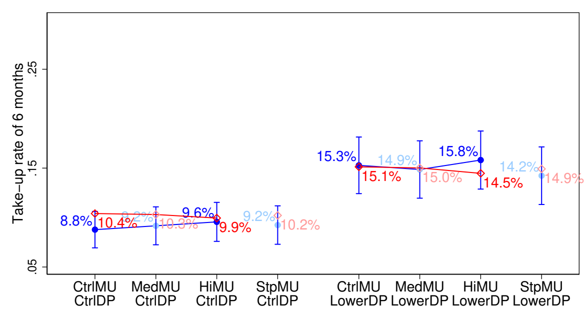
Panel A: Overall



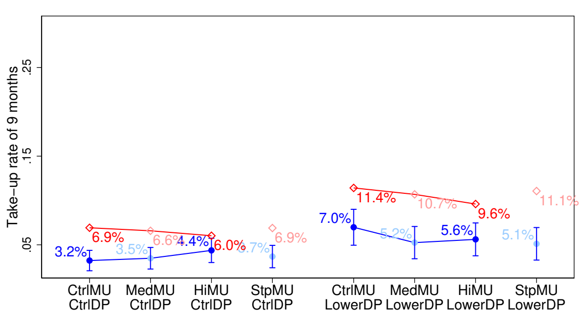
Panel B: 3 month



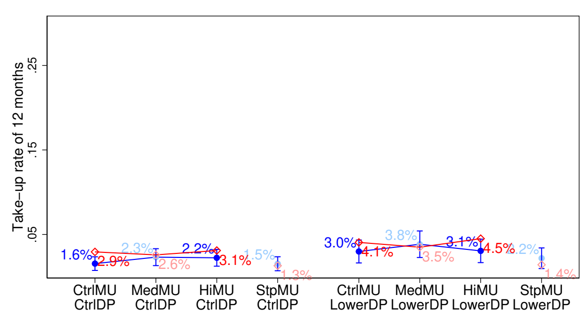
Panel C: 6 month



Panel D: 9 month

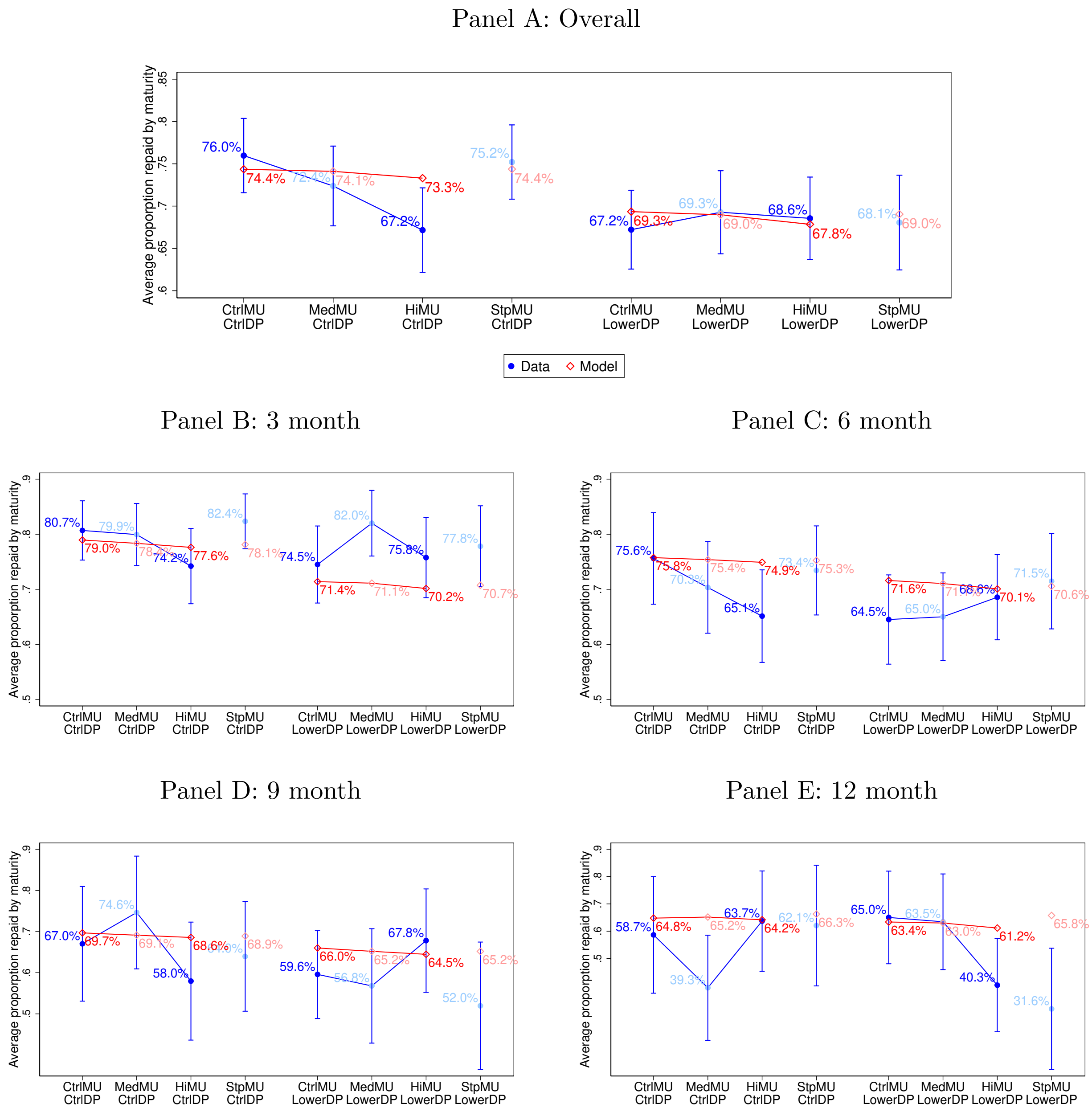


Panel E: 12 month



Note: This figure shows take-up rates in both actual data (in blue) and simulated data (in red) for risk score 4. Penal A reports the overall take-up rate. Panel B, C, D, and E report take-up rates for the 3, 6, 9, and 12 month contracts respectively. From the left to the right are moments in the Control, Medium, High, and Steep pricing arms in the Ctrl minimum downpayment arm, and these four pricing arms in the Lower minimum down payment arm. The four treatment groups used in the SMM estimation are in solid color while the rest four are transparent. 95% confidence intervals are plotted for the moments in actual data.

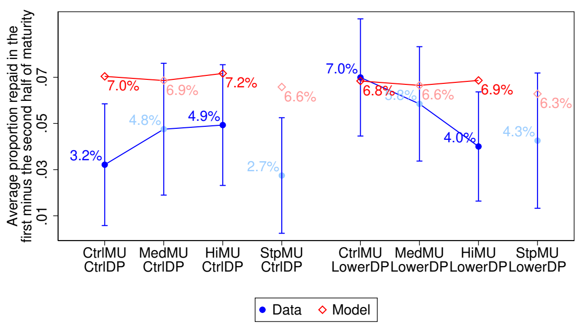
FIGURE A3: Model Fit - Repayment Rates, Risk Score 4



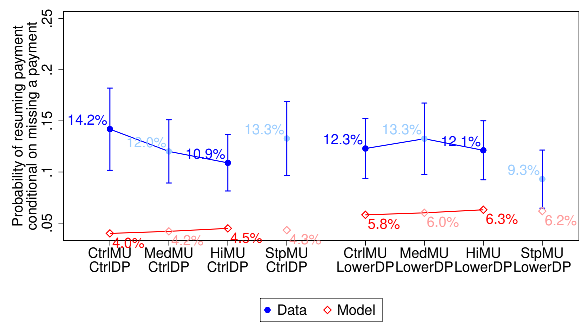
Note: This figure shows average fraction repaid at maturity in both actual data (in blue) and simulated data (in red) for risk score 4. Penal A reports the average across all maturities. Panel B, C, D, and E report average repayment for the 3, 6, 9, and 12 month contracts respectively. From the left to the right are moments in the Control, Medium, High, and Steep pricing arms in the Ctrl minimum downpayment arm, and these four pricing arms in the Lower minimum down payment arm. The four treatment groups used in the SMM estimation are in solid color while the rest four are transparent. 95% confidence intervals are plotted for the moments in actual data.

Figure A4: Model Fit - Other Moments, Risk Score 4

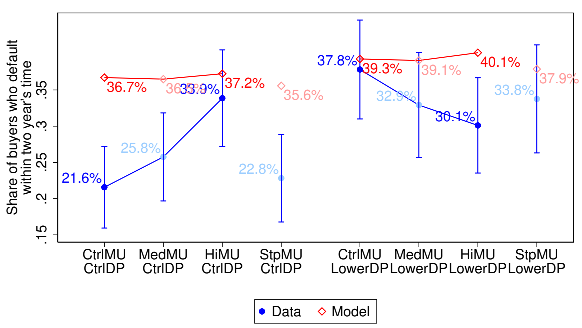
Panel A: Average difference in repayment of the first minus the second half during maturity



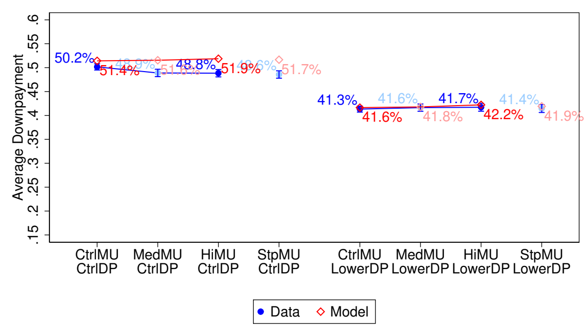
Panel B: Conditional prob. of resuming payment



Panel C: Fraction of customers who did not fully repay in two years



Panel D: Average fraction put as down payment



Note: This figure shows moments in both actual data (in blue) and simulated data (in red) for risk score 4. Panel A shows the average difference in repayment of the first minus the second half during maturity in both the actual and simulated data. Panel B shows the conditional probability of resuming payment. Panel C shows the fraction of customers who did not fully repay in two years. Panel D shows average fraction put as down payment. From the left to the right are moments in the Control, Medium, High, and Steep pricing arms in the Ctrl minimum downpayment arm, and these four pricing arms in the Lower minimum down payment arm. The four treatment groups used in the SMM estimation are in solid color while the rest four are transparent. 95% confidence intervals are plotted for the moments in actual data.

Table A4: Model Validation Using Moments Not Used in the SMM Estimation

	(1) Risk score 1	(2) Risk score 2	(3) Risk score 3	(2) Risk score 4
	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP
Take-up				
Average maturity in months	6.60/6.57/6.87/6.71	6.54/6.64/6.75/6.76	6.14/6.57/6.51/6.79	5.28/5.89/6.00/5.93
	6.80/6.77/6.89/6.86	*6.64/6.59/6.72/6.67*	*6.85/6.79/6.89/6.87*	*6.28/6.29/6.39/6.40*
	(-1.52/-1.47/-0.04/-0.94)	(-0.86/0.49/0.32/0.76)	(-5.73/-1.65/-2.76/-0.45)	(-5.32/-2.01/-2.07/-2.38)
Repayment and default				
3 month, at 1.5 × maturity	87.7%/85.5%/88.6%/82.4%	87.8%/85.3%/85.1%/84.1%	84.6%/82.6%/77.6%/85.8%	87.7%/81.1%/82.7%/82.9%
	87.8%/87.1%/86.4%/85.7%	*87.4%/85.8%/86.4%/84.3%*	*81.9%/80.8%/77.9%/76.7%*	*84.7%/83.9%/79.7%/78.7%*
	(-0.0/-0.9/0.8/-1.3)	(0.3/-0.2/-0.6/-0.1)	(1.3/0.8/-0.0/2.6)	(1.1/-0.8/0.9/1.1)
6 month, at 1.5 × maturity	85.6%/85.7%/85.7%/83.5%	84.8%/83.3%/87.1%/77.9%	80.3%/78.2%/80.0%/80.0%	82.2%/70.6%/71.2%/76.5%
	85.7%/85.2%/84.9%/84.3%	*83.7%/83.0%/83.1%/82.1%*	*80.9%/79.9%/78.4%/77.0%*	*79.5%/78.9%/77.3%/76.3%*
	(0.0/0.3/0.3/-0.3)	(0.5/0.2/1.9/-1.9)	(-0.5/-0.8/0.6/1.2)	(0.7/-2.2/-1.6/0.0)
9 month, at 1.5 × maturity	78.4%/77.1%/81.3%/75.5%	79.3%/73.3%/76.2%/77.3%	73.5%/76.7%/76.2%/63.6%	71.1%/62.3%/64.9%/70.9%
	80.2%/80.0%/79.7%/79.0%	*77.9%/77.4%/77.3%/76.4%*	*77.7%/76.4%/75.9%/74.3%*	*71.9%/71.7%/70.5%/69.7%*
	(-0.8/-0.9/0.6/-1.1)	(0.5/-1.6/-0.5/0.2)	(-1.4/0.0/0.1/-3.1)	(-0.2/-1.5/-1.0/0.2)
12 month, at 1.5 × maturity	79.4%/66.0%/60.3%/70.7%	71.3%/63.6%/69.8%/65.8%	72.4%/65.9%/66.0%/63.0%	64.0%/67.6%/71.1%/46.0%
	75.6%/75.1%/75.1%/74.3%	*73.2%/72.8%/72.7%/72.4%*	*72.9%/71.6%/70.9%/69.3%*	*66.1%/65.9%/65.4%/64.5%*
	(0.9/-2.3/-3.2/-0.8)	(-0.5/-2.5/-0.7/-1.5)	(-0.1/-1.4/-1.0/-1.3)	(-0.2/0.2/0.6/-2.0)
All loans, at 1.5 × maturity	83.6%/81.3%/82.0%/79.6%	82.6%/79.1%/81.6%/77.6%	79.5%/77.6%/76.9%/75.2%	82.4%/72.8%/74.1%/75.2%
	83.5%/83.0%/82.5%/81.9%	*82.0%/81.2%/81.2%/80.1%*	*79.3%/78.1%/76.6%/75.1%*	*78.2%/77.6%/75.2%/74.3%*
	(0.1/-1.4/-0.4/-1.6)	(0.5/-1.8/0.2/-1.8)	(0.1/-0.5/0.1/0.0)	(1.8/-2.0/-0.4/0.4)
Dispersion of fraction repaid at matuity	29.6%/31.1%/31.0%/31.6%	30.2%/32.5%/31.8%/32.5%	32.3%/32.7%/32.1%/33.0%	32.2%/35.5%/33.2%/34.1%
	28.8%/28.9%/29.3%/29.4%	*29.6%/29.7%/29.9%/30.1%*	*31.9%/32.0%/33.1%/33.2%*	*31.7%/31.7%/32.3%/32.3%*
	(1.1/1.2/1.1/1.2)	(1.0/1.2/1.1/1.2)	(1.0/1.0/0.9/1.0)	(1.0/1.3/1.1/1.1)
Time to default conditional on being a defaulter	55.3%/51.4%/52.7%/52.2%	54.8%/40.4%/39.9%/51.2%	48.2%/49.0%/46.1%/40.9%	47.1%/36.3%/67.3%/40.5%
	49.5%/50.7%/51.2%/52.4%	*49.5%/51.6%/50.9%/53.6%*	*58.7%/61.0%/61.6%/64.3%*	*47.8%/48.6%/51.3%/52.8%*
	(2.0/0.3/0.4/-0.1)	(2.0/-3.8/-3.2/-0.7)	(-2.2/-2.6/-3.0/-4.0)	(-0.2/-2.7/3.3/-2.1)
Down Payment				
average down payment	26.5%/26.4%/22.2%/22.0%	30.9%/30.7%/26.0%/26.1%	35.8%/35.7%/30.8%/30.8%	50.2%/48.8%/41.3%/41.7%
	26.5%/27.2%/22.0%/23.0%	*31.1%/31.7%/26.4%/27.0%*	*36.4%/36.9%/31.6%/32.1%*	*51.4%/51.8%/41.6%/42.2%*
	(-0.1/-2.4/0.5/-1.9)	(-1.1/-4.0/-1.4/-2.7)	(-2.1/-3.5/-2.2/-2.9)	(-3.0/-6.4/-0.5/-0.9)

Note: This table reports the sample moments along with simulated moments for risk scores 1 and 4. Within each column, we report sample moments above and simulated moments below in *italics*. T-stats from a two-sample test of equality is reported in the parentheses.

Table A5: Jacobian Matrix, Risk Score 1

Moments in the Low Markup Ctrl Down Payment treatment group	$\bar{y}$	$\sigma_{\bar{y}}$	σ_{ϵ}	v_0	ϕ	ρ	β	μ	$\bar{L}$	σ_L	$\sigma_{\omega,3}$	$\sigma_{\omega,6}$	$\sigma_{\omega,9}$
Take-up of 3 months	0.00228	-0.12	0.04	0.00012	-1.83	0.00	1.79	-0.00341	0.00002	-0.01	0.000187	-0.000093	-0.000111
Take-up of 6 months	0.00115	-0.16	-0.02	0.00254	-3.31	-0.00	3.32	-0.00753	0.00005	-0.02	-0.000109	0.000157	-0.000148
Take-up of 9 months	-0.00017	-0.13	-0.05	0.00423	-6.03	-0.00	6.16	-0.01116	0.00005	-0.02	-0.000058	-0.000054	-0.000279
Take-up of 12 months	-0.00082	-0.06	-0.06	0.00189	2.22	-0.00	-2.23	-0.00380	0.00002	-0.01	-0.000020	-0.000011	0.000538
Repayment of 3 months at maturity	0.00138	0.03	-0.52	0.00172	-2.41	-0.02	-3.10	0.00372	-0.00003	0.01	-0.000104	0.000004	0.000012
Repayment of 6 months at maturity	0.00168	0.00	-0.30	-0.00043	-7.64	-0.01	-3.08	0.01041	-0.00003	0.00	-0.000011	-0.000007	0.000005
Repayment of 9 months at maturity	0.00112	-0.01	-0.26	-0.00085	-10.35	-0.01	-4.13	0.01320	-0.00002	0.01	-0.000011	-0.000002	0.000078
Repayment of 12 months at maturity	0.00108	-0.00	-0.16	-0.00056	-17.37	0.00	-1.03	0.00740	0.00001	0.01	-0.000005	0.000002	-0.000128
Avg. repayment of first minus second half	-0.00037	-0.00	-0.04	0.00062	4.88	-0.00	-0.09	0.00067	0.00000	-0.00	-0.000034	0.000009	0.000040
Prop. of perfect repayer	0.00357	0.04	-1.00	0.00144	-6.39	-0.01	-5.29	0.01810	-0.00008	0.02	-0.000048	0.000008	0.000006
Prob. of resuming payment	-0.00188	0.00	0.46	0.00039	-14.00	-0.04	4.54	-0.01528	0.00002	-0.01	0.000038	-0.000002	-0.000045
Fraction of customers default in two years	-0.00129	-0.00	0.07	0.00109	20.88	0.00	0.76	-0.00459	0.00002	-0.00	-0.000039	0.000005	0.000132
Prop. of putting min. down	-0.00262	-0.06	-0.19	0.00102	0.26	-0.01	-0.38	0.01701	0.00001	-0.01	-0.000005	0.000003	0.000009

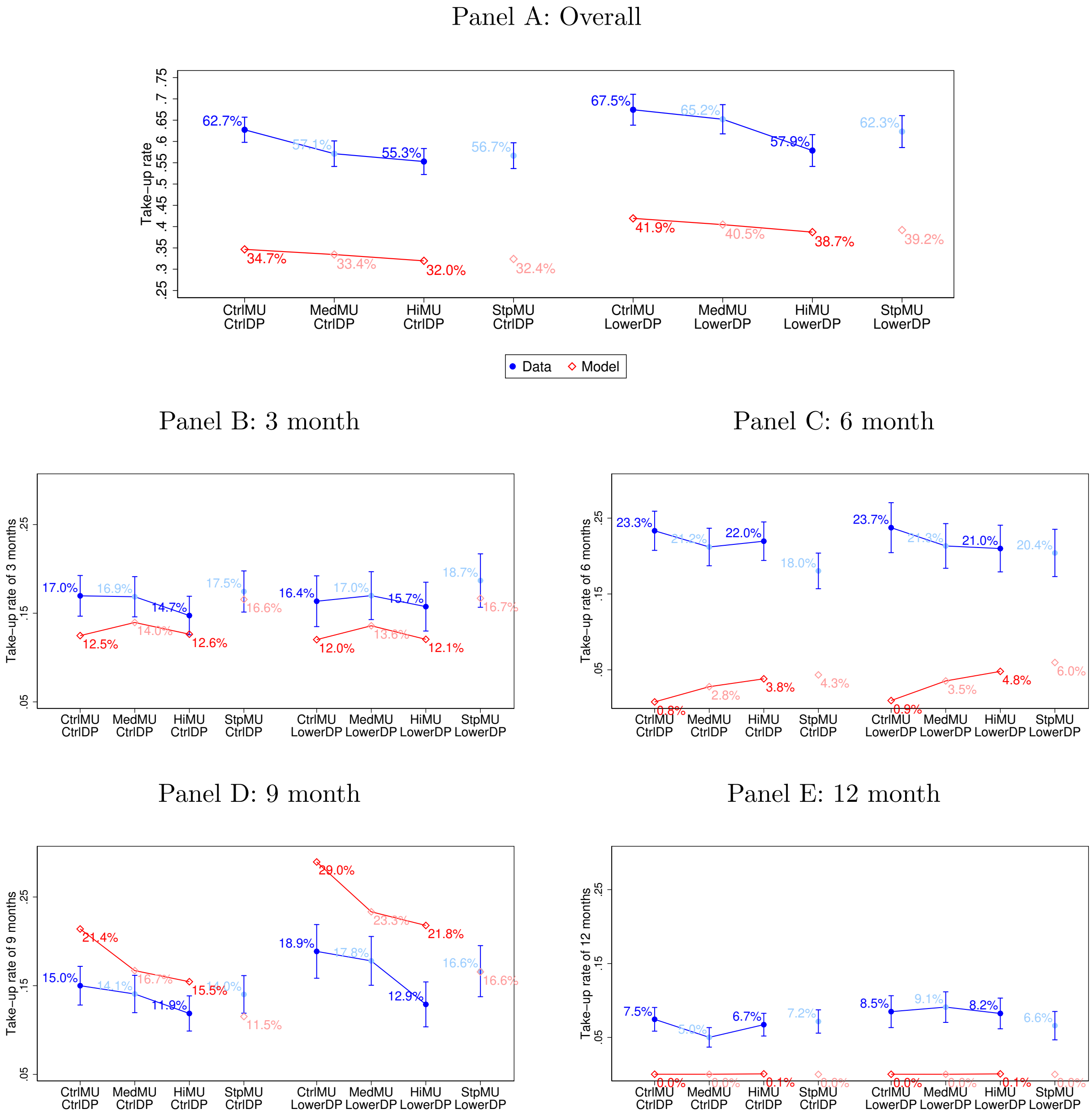
Note: This Table plots the Jacobian matrix for consumers in risk score 1 allocated to the low multiple arm and the control downpayment arms. When we vary parameters that can affect consumers' marginal utility (i.e., $\bar{y}, \gamma, \sigma_{\bar{y}}$), we also vary v_0, μ, and $\sigma_{\omega 3/6/9/12 \text{ month}}$, so that the ratios of v_0 and $\sigma_{\omega 3/6/9/12 \text{ month}}$ to $u'(\bar{y})$ or the ratio of μ to $u'(\bar{y}_i)$ are constant.

Table A6: Parameter Estimates for the Model without Maturity-Choice Shock, Risk Score 1

	(1) Risk score 1
Income process parameters:	
$\bar{y}$ (average long-run mean income)	24.03
	(0.59)
$\sigma_{\bar{y}}$ (dispersion of long-run mean income)	0.75
	(0.03)
σ_{ϵ} (size of income shock)	0.28
	(0.01)
ρ (mean-reversion coef.)	0.97
	(0.00)
$\bar{L}$ (average initial liquidity)	110.05
	(20.23)
σ_L (dispersion of initial liquidity)	1.35
	(0.08)
Device value parameters:	
v_0 (initial device value)	23.05
	(1.12)
ϕ (prob. of depreciation, weekly)	0.0063
	(0.0004)
Other customer preference parameters:	
β (weekly discount rate)	0.988
	(0.001)
μ (value of savings)	9.97
	(0.36)
$\sigma_{\omega,3}$ (size of random utility shock for 3 month)	$0.00^{\dagger}$
$\sigma_{\omega,6}$ (size of random utility shock for 6 month)	$0.00^{\dagger}$
$\sigma_{\omega,9}$ (size of random utility shock for 9 month)	$0.00^{\dagger}$

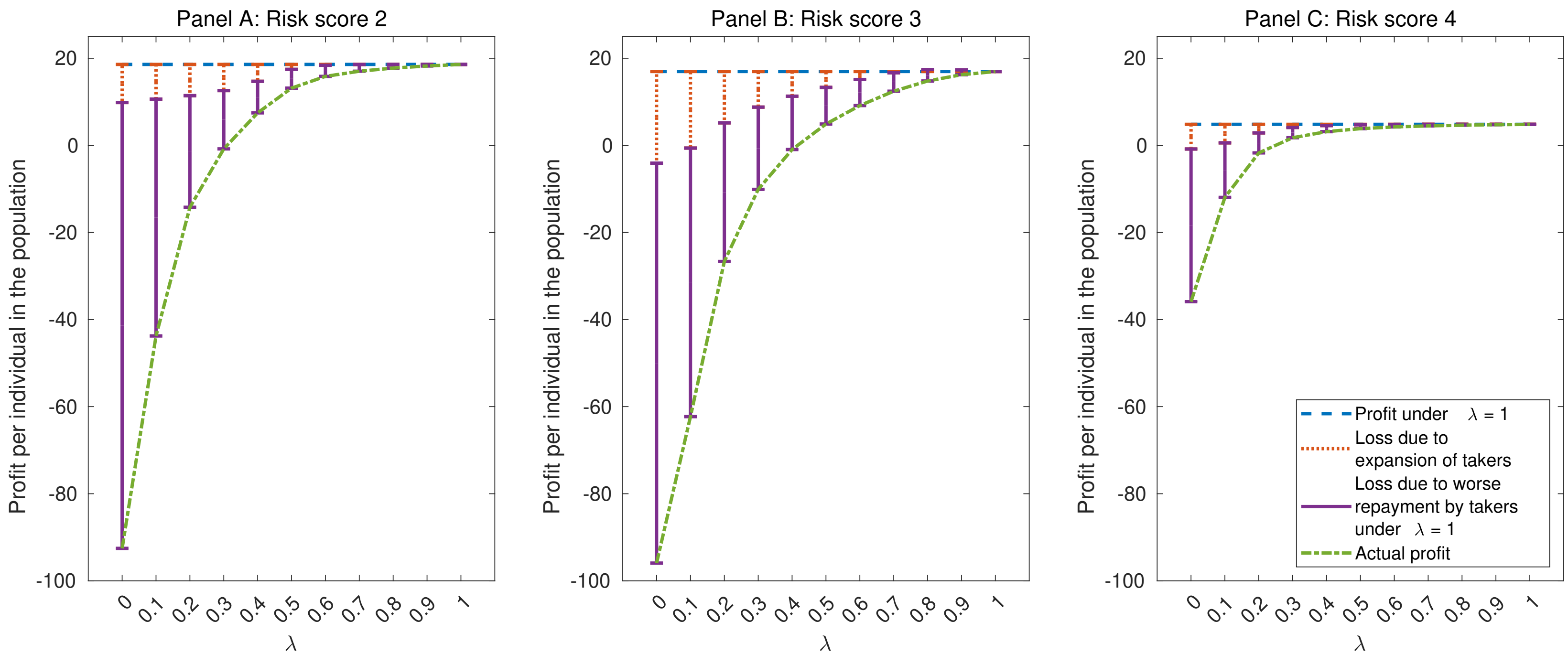
Note: This table reports the results of our SMM estimations. Parameters with † are preset and all other parameters are estimated. The values presented in this table for parameters v_0, $\sigma_{\omega,3}$, $\sigma_{\omega,6}$, $\sigma_{\omega,9}$, and $\sigma_{\omega,12}$ are scaled by the marginal utility evaluated at the average long-run mean income (i.e., $u'(\bar{y})$). This is saying that the true value of these parameters are the numbers in the table times $u'(\bar{y})$. We present the transformed values here to give better intuition over the magnitude of these parameters. Similarly, the true value of μ_i for household i is the value presented in this table times $u'(\bar{y}_i)$. Standard errors are in the parentheses.

Figure A5: Model Fit - Take-up Rates for the Model without Maturity-Choice Shock, Risk Score 1



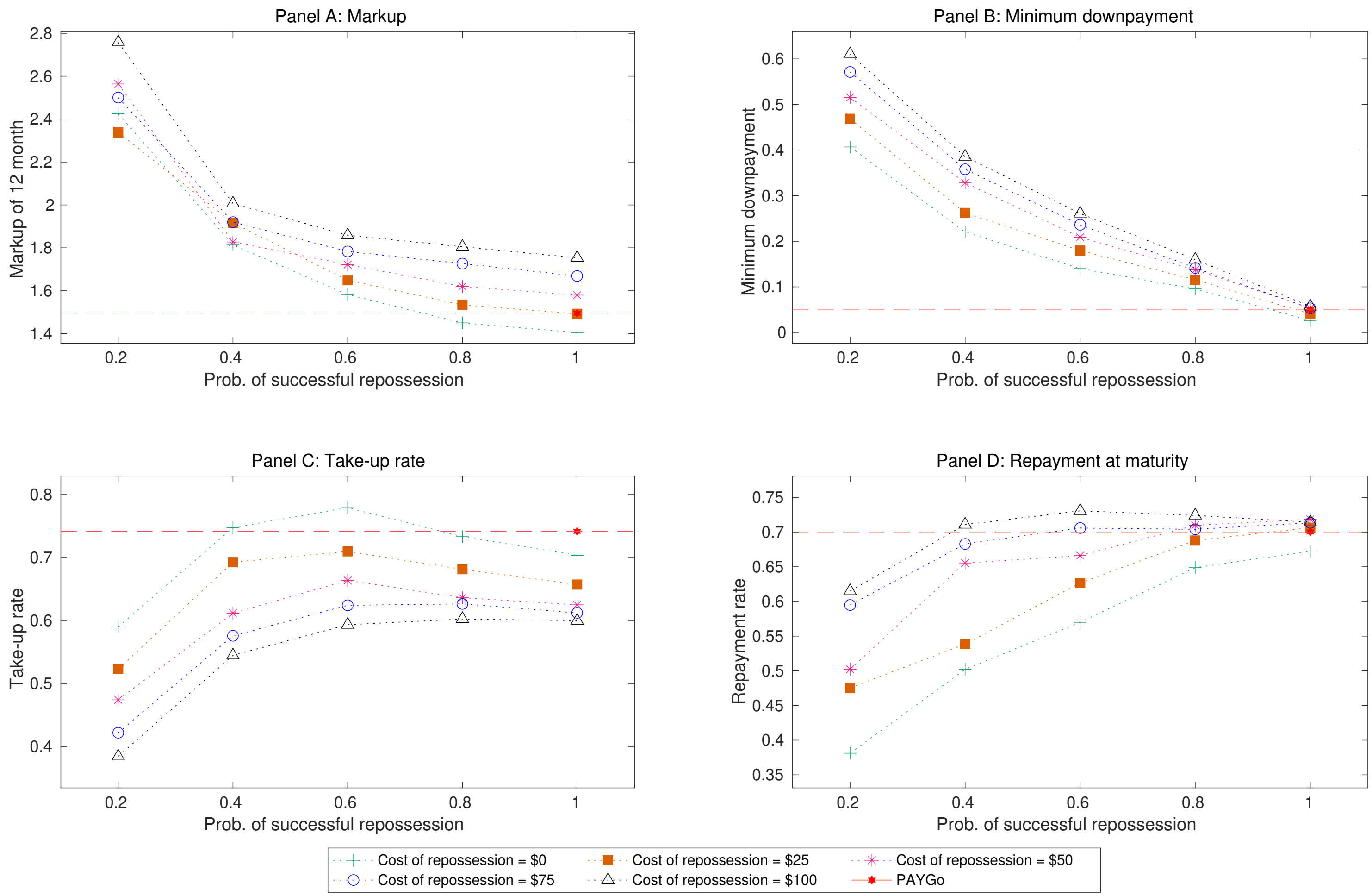
Note: This figure shows take-up rates in both actual data (in blue) and simulated data (in red) for risk score 1. Penal A reports the overall take-up rate. Panel B, C, D, and E report take-up rates for the 3, 6, 9, and 12 month contracts respectively. From the left to the right are moments in the Control, Medium, High, and Steep pricing arms in the Ctrl minimum downpayment arm, and these four pricing arms in the Lower minimum down payment arm. The four treatment groups used in the SMM estimation are in solid color while the rest four are transparent. 95% confidence intervals are plotted for the moments in actual data.

Figure A6: Decomposition of Effects of λ into Moral Hazard and Adverse Selection



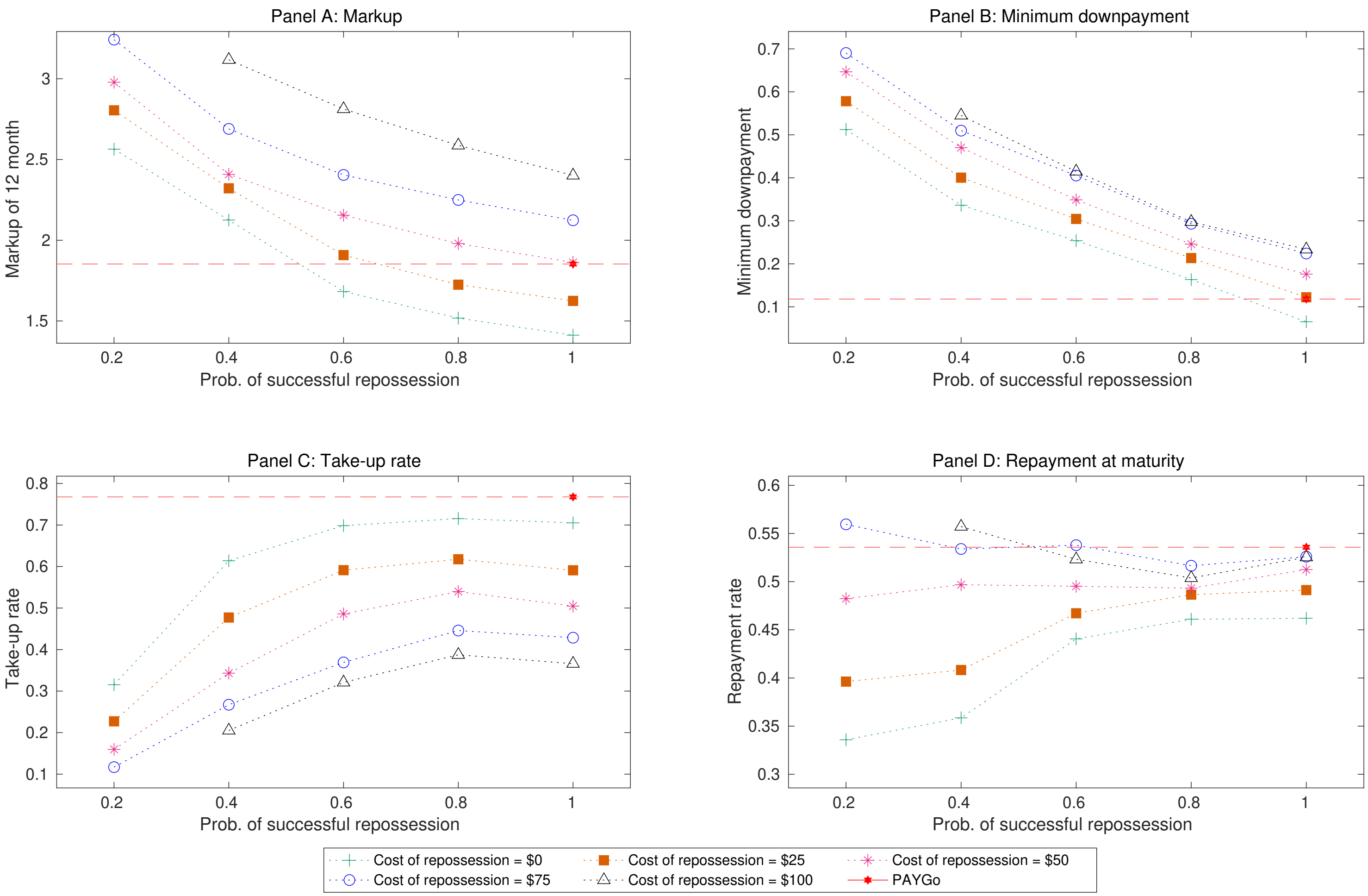
Note: This figure shows results from simulations where λ is varied while prices are fixed at the level of the CtrlMarkupCtrlDown treatment arm. We decompose the effects of a smaller λ on firm profit into the effects of weaker screening and effects of weaker incentive.

FIGURE A7: Comparison to Traditional Repossession, under Competitive Prices, Risk Score 1



Note: This figure plots the competitive markup, minimum down payment, simulated take-up rate, and simulated repayment at maturity, of PAYGo to traditional secured lending for a range of repossession technologies. We look at traditional secured lending with $c_{\text{repo}} = \{\$0, \$25, \$50, \$75, \$100\}$ and $p_{\text{repo}} = \{0.2, 0.4, 0.6, 0.8, 1\}$. For repossession technology, we solve for competitive prices of a 12 month maturity loan. Then we simulate a sample of consumers under competitive prices and obtain simulated take-up and repayment. If zero-profit cannot be achieved for a certain repossession technology, the corresponding point is omitted.

FIGURE A8: Comparison to Traditional Repossession, under Competitive Prices, Risk Score 4



Note: This figure plots the competitive markup, minimum down payment, simulated take-up rate, and simulated repayment at maturity, of PAYGo to traditional secured lending for a range of repossession technologies. We look at traditional secured lending with $c_{\text{repo}} = \{\$0, \$25, \$50, \$75, \$100\}$ and $p_{\text{repo}} = \{0.2, 0.4, 0.6, 0.8, 1\}$. For repossession technology, we solve for competitive prices of a 12 month maturity loan. Then we simulate a sample of consumers under competitive prices and obtain simulated take-up and repayment. If zero-profit cannot be achieved for a certain repossession technology, the corresponding point is omitted.