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

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Abstract

Pay-as-you-go (PAYGo) financing is a novel contract that has recently become a popular form of credit, especially in low- and middle-income countries (LMICs). PAYGo financing relies on lockout technology that enables the lender to 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 gains from access to PAYGo financing are equivalent to a 3.4% increase in income while remaining highly profitable for the lender. The welfare gains are larger for low-risk consumers and consumers in the middle of the income distribution. Under reasonable assumptions, PAYGo financing outperforms traditional secured loans for all but the riskiest consumers. We explore contract design and identify variations of the PAYGo contract that further improve welfare.

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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 that expand credit access 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 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 and has been used to provide financing for a wide range of consumer durables including solar electricity systems, smartphones, automobiles, and laptops, as well as follow-up cash loans and credit lines for consumers who have completed payments on their initial loan.[3]

It is instructive to compare PAYGo lending to secured lending, where the lender repossesses 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 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 a more flexible repayment schedule than a traditional

[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.

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 collateral.

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 multiples (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 multiple (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 multiples and two arms with different minimum downpayments. The experimental data reveals important stylized facts about consumer behavior that guide our modeling choices. First, there is considerable heterogeneity across risk scores. The demand of low-risk consumers is highly elastic to multiples. In contrast, high-risk consumers respond to higher multiples by opting for longer maturity contracts. Second, there is evidence of asymmetric information and moral hazard. Higher multiples 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 with a stochastic income process. They differ ex ante by their expected and current income, which is privately observed and generates adverse

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

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. 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 multiple and downpayment variations in the pricing experiment. We use four arms of the pricing experiment for estimation and use 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 score, 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 – both in and out-of-sample and across risk-scores. The model estimates imply 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. As a validation of our model and estimation procedure, we indeed uncover higher income volatility and lower phone usage value for consumers that the lender perceives to be riskier ex-ante.

We conduct several counterfactual analyses to better understand the economic consequences of PAYGo financing. First, we quantify the welfare gains for consumers from access to PAYGo financing. More specifically, we compare consumer welfare in the estimated model relative to a no-financing benchmark. To the extent that consumers may 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 sizable welfare gains, corresponding to a 3.4% increase in income on average across all individuals in the sample under the lender's baseline pricing. The welfare gains are larger for less risky consumers and those with intermediate levels of income. For example, the welfare gain for an average consumer with the lowest risk corresponds to a 4.8% increase in income. Despite large 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 consumers. 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 the prices for each risk score are set so that the lender's rate of return is 25%.

Averaging across all risk scores, the multiple and downpayment decrease by 14% and 48% respectively under competitive pricing. The multiple reduction is larger for less risky borrowers, whereas the downpayment reduction is largest for the most risky borrower. The welfare gains under competitive pricing are 79% larger than under the lender's baseline pricing (equivalent to a 6.0% increase in income). The higher welfare gains stem from both the intensive margin – takers pay lower multiples – and the extensive margin, as take-up increases among more liquidity constrained borrowers.

Our second counterfactual exercise compares consumer welfare in the estimated model with PAYGo to a counterfactual where consumers have 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 provides an alternative benchmark through which to evaluate the welfare gains from PAYGo. We first compute competitive prices for secured loans under a range of assumptions about the lender's cost of repossession. Both the multiple and minimum downpayment increase sharply with the cost of repossession. Take-up falls (due to higher prices) and repayment increases (due to the additional screening from a higher downpayment). The net result is that consumer welfare decreases with the lender's repossession cost. We then compare consumer welfare from secured lending versus PAYGo.

Under reasonable assumptions about the repossession technology, PAYGo dominates secured lending for lower risk consumers, while secured lending generates higher welfare for the riskiest consumers. This finding highlights a key trade-off between the two forms of lending: secured lending provides stronger screening and repayment incentives, which ultimately translates to better financing terms for consumers. But conditional on default, the ex-post inefficiency of repossession is larger than lockout due to both the physical cost of repossessing collateral and the opportunity cost of permanently reallocating it to its next best user. Lower risk consumers have a higher usage value. Therefore, they have a strong incentive to repay even under the PAYGo contract; the additional incentive from secured lending leads to only a small decrease in competitive prices. Further, due to their higher usage value, the dead weight loss from reallocation is larger than for high-risk consumers. Hence, the benefits of secured lending are outweighed by the costs associated with repossession for lower risk consumers. The opposite is true for the riskiest consumers.

The findings motivate a more general investigation of contract design. In particular, when repossession is infeasible, is it possible to improve on the standard PAYGo contract by locking the device using a harsher or more lenient policy?

We first investigate a contract where consumers are allowed to miss a certain number payments before the lock is initiated. This leniency policy improves insurance, but reduces both screening and incentives for repayment, which leads to higher competitive prices. Overall, our quantitative exploration shows that the welfare gains generated by such contracts is hump-shaped in the degree of leniency. At low level of leniency, more lenient contracts increase take-up rates since consumers benefit from the increased insurance while prices remain moderate. As leniency increases, this effect is reversed and more leniency leads to decreased take-up rates as prices become exceedingly high. For consumers with the lowest risk, the optimal leniency corresponds 10 missed payments before being locked. The welfare gains for this contract are about 10-15% higher than what the standard PAYGo contract delivers.

Next, we consider another form of increased insurance. In our empirical setting, the phone is effectively unusable when locked, i.e., the locking technology is strong. However, a more forgiving use of the lockout technology (e.g., where only certain features or apps on the phone are disabled or where the phone is locked only for a fraction of the week) is technologically feasible. We therefore consider contracts that use various degrees of lock "strength". A weaker lock implies weaker incentives, but improves risk-sharing. Empirically, we find that the former dominates. For each risk score, the welfare gains with a weak-lock contract are lower than with the PAYGo contract.

We entertain two deviations from the PAYGo contract that provide consumers with stronger incentives for repayment. The first type of contract locks consumers for multiple periods after each missed payments. Another variation requires consumers to pay a fee following a missed payment. Quantitatively, we find that for all risk scores, these harsher punishments do not improve on PAYGo contracts.

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 methods (e.g., Karlan and Zinman 2009, Agarwal et al. 2010, Dobbie and Skiba 2013, Stroebel 2016, Hertzberg et al. 2018, Gupta and Hansman 2022, 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, Cuesta and Sepulveda 2021, DeFusco et al. 2022, Xin 2023). 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 downpayment, maturity, and repayment, and our estimation relies on a large-scale, multi-arm experiment.

Our analysis of PAYGo financing complements Gertler et al. (2024), who show that, compared to an unsecured loan, PAYGo loans reduce both moral hazard and adverse selection and increase lender profitability. While their findings suggest that PAYGo financing improves 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 consumer 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 consumer 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., 2020) 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 used in financial contracting. While we focus on the smartphone market, increasing credit supply for smartphones is likely to generate positive externalities as they allow access to mobile money, platform-based business models, mobile investing, online learning, etc.

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, one can use 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 four pricing arms and two minimum required downpayment arms interacted. We exploit four 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.

[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 (Buchak et al., 2018; Fuster et al., 2019; Di Maggio and Yao, 2021; Agarwal et al., 2023).

[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.

2 Reduced-Form Evidence

2.1 Institutional Background

Smartphones have become a critical tool for economic development (Suri and Jack, 2016). However, most mass-market smartphones remain expensive for consumers in developing countries. Our partner in this study is a FinTech lender that offers PAYGo financing to consumers looking to purchase a smartphone, with a specific focus on the underbanked population that lacks access to traditional forms of financing. To do so, the lender installs a digital lock on the phones it finances. When consumers 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, and (3) a multiple θ. If a consumer makes a downpayment of $d_i \geq D$, and the phone price is p, she finances an amount $p - d_i$, and she has to pay back T weekly installments of $\theta(p - d_i)/T$ 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 consumer makes T payments, she owns the phone and the locking system is disabled. Consumers interested in financing a smartphone are offered a menu of contracts (T, D, θ), which consists of four possible maturities: 13, 26, 39, or 52 weeks. The multiples are the same for all consumers, 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, and financial conditions). A risk score of 1 corresponds to the least risky consumers while a risk score of 4 corresponds to the most risky.

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.

2.2 Experimental Design and Data

The pricing experiment we analyze was conducted from November 2018 to June 2019. Consumers expressing interest were randomly assigned to one of 4×2 treatment groups: 4 arms with different multiples θ interacted with 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, which features the lowest multiples. 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 Lower downpayment arm reduces the minimum downpayment across risk scores, by five percentage points for risk scores 1, 2 and 3, and by 10 percentage points for risk score 4. The allocation of consumers across pricing arms was uniform. Consumers had a 60% chance of being assigned to the Control downpayment arm, and a 40% chance of being assigned to the Lower downpayment arm.

Our dataset contains information about consumers 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 consumers are subjects in the pricing experiment (Table 1). The typical consumer 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.

In the experiment, 52% of the consumers 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 3-month contract, 38% for a 6-month contract, 22% for a 9-month contract and 11% for a 12-month contract. The minimum downpayment requirement appears binding for most consumers: 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 $143. 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. The average taker repays 74% of the total amount owed to the lender at maturity. Only 32% of borrowers have fully repaid the amount owed at maturity. 74% of takers repay their loan in full within two years of origination, and it takes them on average 114% of the contract's maturity to reach full repayment. Panel B of Figure 1 shows a histogram of the share of promised payments missed across maturity. The figure highlight borrowers' inconsistent repayment behavior. 22% of borrowers have missed 50% or more of the promised payments at contract maturity. This number rises to almost 40% for borrowers in the 12-month contract. Both panels clearly demonstrates that repayment

[9] Table A1 documents some heterogeneity in the price of smartphones purchased: the standard deviation of smartphone prices among takers is $78. 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.

is worse for longer maturity contracts.

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 6-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 6-month contract, pays a *bi-weekly* interest rate of 3.49%, which corresponds to an APR of 91%.

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 pricing 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 consumer i in her assigned pricing arm. $\mathbb{1}_{i \in \text{low min down}}$ is a dummy equal to one if consumer i is assigned to the lower 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) 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 ($t = -5.1$). Across borrowers, low risk scores are the most elastic, while the take-up elasticity of borrowers with a risk score of 4 is small and insignificant (Panel A, Figure 2). A possible interpretation is that low risk score borrowers have better outside options for credit than high risk score (e.g., they can use cash to finance their phones when financing costs increase). Conditional on take-up, higher-risk borrowers (risk scores 3 and 4) respond to increased loan cost by shifting to longer maturity loans (Panel B), which are more expensive (higher multiples) but carry lower weekly payments.[10] In contrast, downpayment choices do not respond to increased multiples (Panel C). Finally, the experiment provides clear evidence of adverse selection/moral hazards in repayment: conditional on take-up, a 1% increase in the average multiple reduces the share of the loan repaid at maturity by -0.38% ($t = -3.8$, Panel D). This elasticity is constant across risk scores. For high-risk borrowers, this negative repayment elasticity cannot be driven by adverse selection since their take-up decision does not respond to multiples (Panel A) and thus likely results from higher weekly payments. For low-risk borrowers, this negative repayment elasticity can also be driven by adverse selection given their high take-up elasticity.

While we find evidence of adverse selection/moral hazard in repayment, their scope appears more limited than what has been measured in other contexts. For instance, exploiting a pricing experiment ran by a Chinese fintech firm, DeFusco et al. (2022) find that, in response to a one percent increase in APR, the share of promised payments missed at maturity increase by 0.096. In a similar, unreported, regression, we find instead a semi-elasticity of 0.039. This finding is consistent with the interpretation that, compared to unsecured loans, PAYGo contracts mitigate information asymmetries, a result that echoes Gertler et al. (2024).

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

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

where $\mathbb{1}_{i \in \text{price arm } l}$ is a dummy equal to one if consumer 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 2). 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 consumers who are more likely to be liquidity constrained. On average, consumers facing higher downpayments shift to significantly shorter maturity contracts (Panel F): higher downpayments increase the financed amount, which decreases weekly payments; as a result, borrowers—especially risky ones who borrow with longer terms—can afford shorter maturity, which have higher weekly payments but lower multiples.[11]. Since higher minimum downpayments potentially induce positive selection and

[10] 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 ($t = 9.9$).

[11] Overall, higher downpayments lead to a reduction in weekly payments despite the shift to shorter maturity: across risk scores, the elasticity of weekly payments to minimum downpayment is -0.40 ($t = -25.6$).

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 1 shows how the share repaid varies 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 1 shows the distribution of the fraction of weeks in default. Together with the evidence of Panel B in Figure 2, Figure 1 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. A consumer 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, the consumer decide whether to make the payment in that period after privately observing her 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 income at date t, which is denoted by y_{it}, which follows a Markov process. In addition to her date 0 income, consumer i can withdraw liquidity L_i at a unit cost μ_i, which can be used for the downpayment or date 0 consumption.[12] Consumers do not have

[12] Withdrawal of liquidity 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

access to an external borrowing or savings technology.

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 multiple. 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 $p - d_i$ and the per-period payment amount is $m = \theta(p - d_i)/T$. When consumer i makes the required payment in period t then the device is "unlocked" and the consumer enjoys the usage value 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 usage value $q_{it} = (1 - \lambda)v_{it}$, 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, she owns the device, and it is permanently unlocked.

All consumers have an initial usage value, $v_{i0} = \bar{v}$. 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, multiple, and minimum downpayment. Payments are made on a weekly basis.[13]

3.4 The Consumer's Problem

Consumers make several decisions in the model. First, they 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 the optimal repayment policy of the consumer. Next, we characterize the consumer's ex-ante value for a given contract.

would be too rich to match their repayment decisions.

[13]Prepaying for future weeks increases the effective interest rate and is rarely observed in the data. Hence, we do not incorporate this feature in the model.

Then, after describing the consumer's outside option, we solve for her optimal downpayment, maturity, and take-up decisions.

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).[14] 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

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

In words, the consumer optimally makes a payment if the extra usage value 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),

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

Value of a Contract Given a contract Γ, the consumer must choose how much to put down as well as how much to consume on date 0 subject to (1) their budget constraint and (2) the downpayment constraint. The solution to this problem yields consumer i's ex-ante value for contract Γ, which we denote by $W_i(\Gamma)$. Let $m(d_i) = \frac{\theta(p-d_i)}{T}$ be the weekly payment on the contract given a downpayment d_i. Then, the consumer's value for any contract Γ is

[14] 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., mean income).

given by:

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

The term $\mu_i L_i$ captures the consumer i's cost from withdrawing L_i units of liquidity, where μ_i can be interpreted as the consumer's shadow value for a unit of liquidity.[15] 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 consumers 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, consumers' outside option is a real option, which includes the option to never purchase the device. The value of this outside option 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.

$$
O_i(y_{it}) = \max \left\{ u(y_{it}) + \beta \mathbb{E}[O_i(y_{i,t+1}) | y_{it}], G_i(y_{it}) \right\}. \tag{5}
$$

Conditional on buying with cash, the consumer must choose how much liquidity to withdraw and correspondingly how much to consume. Therefore, the value from buying with cash is given by:

$$
\begin{aligned}
G_i(y_{it}) = & \max_{L_i, c_{it}} v_0 + u(c_{it}) - \mu_i L_i + \beta \mathbb{E}[\Pi(v_{i,t+1}, y_{i,t+1}) | v_{i0}, y_{it}] \\
\text{s.t.} \ & c_{it} + p \leq y_{it} + L_i, \\
& c_{it}, L_i \geq 0.
\end{aligned}
\tag{6}
$$

Maturity Choice: Contract Selection Each consumer faces a menu of contracts $\mathcal{M}_i = \{\Gamma^j\}_{j \in J}$, 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 multiple. Mirroring the classic logit demand system (Berry et al., 1995; Berry, 1994), we assume that there is a fixed effect ξ_j for each contract Γ^j, and consumers draw a

[15] 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 mean income, i.e. $\mu_i = \mu \times u'(\bar{y}_i)$.

random utility shock ω_{ij} for each $\Gamma^j \in \mathcal{M}_i$. These features are a standard modeling device for matching heterogeneity in consumer behavior when estimating demand systems.

If all contracts are worse than the outside option, i.e., $\mathcal{M}_i^* \equiv \{\Gamma^j \in \mathcal{M}_i : W_i(\Gamma^j) + \xi_j + \omega_{ij} \geq O_i(y_{i0})\}$ is an empty set, the consumer does not take up. Otherwise, the consumer selects the contract from $\mathcal{M}_i$ that delivers the highest value, which we denote by Γ_i^*, where

$$\Gamma_i^* = \arg\max_{\Gamma^j \in \mathcal{M}_i^*} W_i(\Gamma^j) + \xi_j + \omega_{ij}. \tag{7}$$

In our setting, the random utility shocks can be interpreted as capturing unmodeled heterogeneity in consumers' preferences (e.g., discount factors or usage values). We use them to match the observed maturity choice in the pricing experiment. Most notably, 37% of takers select the 6-month contract, even though its multiple is only slightly lower than the 9-month contract and hence is effectively dominated by either the 3-month (low multiple) or 9-month (low payment) contracts.[16]

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 can be defined recursively by

$$\begin{aligned} V_i(x_{it}; \Gamma) =& A_i(x_{it})\big(m_i + \delta \mathbb{E}[V_i(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i)|x_{it}]\big) \\ &+ (1 - A_i(x_{it}))\delta \mathbb{E}[V_i(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i)|x_{it}], \end{aligned} \tag{8}$$

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

$$V_i(v_{it}, y_{it}, 0, m_i; \Gamma) = K \tag{9}$$

where K is the life-time value of a consumer that has fully repaid.[17] On date 0, the firm's expected net present value (NPV) from lending to consumer i under contract Γ is

$$\text{NPV}_i(\Gamma) = d_i + \delta \mathbb{E}[V(x_{i1}; \Gamma)|x_{i0}] - c, \tag{10}$$

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.

[16] Formally, we experimented with a version of our model that did not include these random utility shocks and were unable to match the observed distribution of maturity.

[17] K derives from future businesses between the firm and consumer that might also utilize the device as digital collateral. For example, the firm in our study issues subsequent cash loans that also leverage the lockout technology to consumers who have successfully repaid their initial loan and obtained ownership.

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.

4.1 Methodology

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

1. Consumer i's income is log-normally distributed and i.i.d. in each period: $\log(y_{it}) \sim \mathcal{N}(\log(\bar{y}_i) - \frac{\sigma^2}{2}, \sigma^2)$.
2. The average income of consumers is log-normally distributed in the population: $\log(\bar{y}_i) \sim \mathcal{N}(\log(\bar{y}) - \frac{\sigma_{\bar{y}}^2}{2}, \sigma_{\bar{y}}^2)$.
3. The random utility shocks are normally distributed: $\omega_{ij} \sim \mathcal{N}(0, \sigma_\omega^2)$ and i.i.d. across consumers and contracts.

We make several additional assumptions useful for identification. First, we assume that the lockout technology is perfectly effective (i.e., $\lambda = 1$). While a small fraction of consumers may be able to circumvent the lockout technology, this is unlikely to be a quantitative concern.[18] Second, we assume that consumers have log-utility (i.e., $\gamma = 1$). While maturity choices are informative about the discount factor, 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 half of its value each time depreciation materializes (i.e., $N_v = 2$). Thus, the first depreciation shock corresponds to moderate damage to the device (e.g., a cracked screen or battery deterioration) and the second shock renders the device unusable.

In addition, we normalize two parameters of the model. The firm's lifetime value of a fully-repaid consumer is zero (i.e., $K = 0$). We also normalize the fixed effect of the most popular 6-month contract to zero (i.e., $\xi_6 = 0$). These normalizations do not materially affect the estimation.

These assumptions leave 11 parameters for estimation: $\bar{y}$ (average mean income), $\sigma_{\bar{y}}$ (income dispersion), σ (income volatility), v_0 (initial usage value), ϕ (depreciation rate), β (discount factor), μ (liquidity cost), σ_ω (standard deviation of utility shock), and three fixed effects ξ_3, ξ_9, ξ_{12} for the 3-, 9-, and 12-month maturity contracts. We denote by Θ the set of these 11 structural parameters.

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

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 used in the estimation. The first set of moments captures take-up and maturity choices: the share of consumers selecting each maturity ($Takeup_3$, $Takeup_6$, $Takeup_9$, and $Takeup_{12}$). The second set of moments relates to the repayment behavior of consumers: the share of the amount owed repaid at maturity for each contract ($Repay_3$, $Repay_6$, $Repay_9$, and $Repay_{12}$). The third set of moments captures the overall dynamics of repayment: the share repaid in the first half of the time period from contract initiation to maturity compared to the second half (Δ_{repay}), the share of buyers who have fully repaid their loans at maturity (p_{perfect}), the probability of resuming payments in week t conditional on missing a payment in week $t-1$ (p_{resume}), and the share of buyers who do not complete contract repayment within two years since origination (p_{default}). Finally, we inform downpayment decisions by targeting the average downpayment ($DownPayment$).

We now summarize our estimation procedure and refer readers to Section B.1 in the Internet 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 the amount of liquidity withdrawn L_i.

We fix a treatment arm and set the contract terms to Γ^j, one of the contracts in the menu $\mathcal{M}_i$ of the treatment arm. 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 $A_i(x_{it})$ for each possible value of the state space. We then find consumers value for the contract, $W_i(\Gamma^j)$, which delivers consumers' optimal downpayment choice $d_i(x_{i0})$. We repeat this procedure for each contract in the menu of the treatment arm. Also using VFI to solve the outside option O_i (Equation (5)), we can then obtain consumers' take-up decision and preferred contract Γ_i^* (Equation (7)) in the menu $\mathcal{M}_i$ given an initial state x_{i0}. Next, we simulate a sample of 10^6 consumers for each treatment arm. Using the model solution from above, for each simulated consumer, we determine their contract choice, their downpayment choice given the selected contract, and their repayment behavior. Based on this behavior, we calculate the simulated moments. Repeating this procedure for each of the four treatment arms in the experiment used in the estimation, we obtain the 52 moments $m(\Theta) = m_1 - m_{52}$ for this set of structural parameters Θ.

We then minimize the distance between simulated moments $m(\Theta)$ and empirical moments m:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \, (m(\Theta) - m)' W (m(\Theta) - m), \tag{11}$$

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

where we use the inverse of a diagonal matrix with sample variances on the diagonal as the weighting matrix W.[20] Details on the algorithm used to estimate Θ can be found in Section B.4 in the Internet Appendix.

4.2 Estimated Parameters and Model Fit

Table 2 presents the parameter estimates. The average weekly income is similar across risk scores and ranges from \$34 to \$37. These income levels corresponds to just above the minimum wage in Mexico during our sample period.[21] Income volatility is signficant and increasing with risk score. The volatility of income for consumers in risk score 1 is 0.35 (i.e., a one-standard-deviation shock corresponds to 35% of their mean income). The volatility of income for consumers in risk score 4 is higher (0.41).

Consumers in risk score 1 have an initial usage value that is 24 times their marginal utility. While this value appears high, it is necessary to generate the large take-up rates we see in the data. The reason is the following. Given the estimated probability of depreciation of 3.0%,[22] our estimate for usage value implies that the average consumer in risk score 1 would be willing to pay a perpetual rent of 9.5% of their weekly income to acquire a phone.[23] However, for low-income consumers, the present value of this transfer is small in terms of dollars. Given the large estimated heterogeneity of mean income ($\sigma^2_{\bar{y}}$), this implies that a substantial share of borrowers in the left tail of the income distribution may not be willing to pay for the phone. For instance, for 12% of consumers in risk score 1, the present value of the perpetual transfer is below \$200, the typical purchase price of a phone in our sample. In practice, financing is costly, and the firm charges significant markups, which further reduces consumers' willingness to pay.[24] Yet, 60% of consumers in risk score 1 still purchase the

[20] In untabulated tests, we also conduct robustness analysis using alternative weighting matrices, including $W = (K_{\mathbf{mm}})^{-1}$, where $K_{\mathbf{mm}}$ is the variance-covariance matrix of data moments obtained via bootstrapping, and find the estimates to be similar.

[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 estimated depreciation rate ϕ is in line with survey evidence that shows that the average lifespan of smartphones in Mexico during our sample period is approximately 24 months. A report finds that 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%). Source: The Competitive Intelligence Unit and Usuarios de Servicios de Telecomunicaciones Cuarta Encuesta 2020 by Instituto Federal de Telecomunicaciones, Mexico.

[23] With i.i.d. income, the consumer's lifetime value without the phone is $\frac{\log(\bar{y})}{1-\beta}$. If she exchanges a perpetual rent of a share of t of her weekly income against ownership of the phone, her lifetime value becomes: $\frac{\log(\bar{y}(1-t))}{1-\beta} + \frac{v_0}{1-\beta(1-\phi)} + \frac{\beta\phi v_0}{2(1-\beta(1-\phi))^2}$, where ϕ is the phone's probability of depreciation. A transfer $t = 0.095$ makes the consumer indifferent.

[24] For example, financing at consumer's discount rate on a 6-month contract corresponds to a multiple of 1.04 for individuals in risk score 1 given their estimated time-preference, which is significantly lower than the a multiple charged by the lender, which ranges from 1.54 to 1.7.

phone. Without the high estimated usage value, matching this take-up rate would not be possible.

The estimated usage value decreases with the risk score. For consumers in risk score 4, usage value is 10 times the marginal utility evaluated at $\overline{y}$ and depreciation is 4.1%. Overall, the average consumer in risk score 4 has a smaller willingness to pay for the phone as a share of their income and demand for the phone in this group will be smaller.[25]

The discount factor ranges from 0.989 to 0.997, which corresponds to annual discount rates of 17% to 78%. Such time preferences are close to other estimates for poor consumers in developing countries.[26] The unit cost of withdrawing liquidity at date 0, μ, is similar across risk scores and ranges from 3.1 to 4.5. This μ implies that consumers in our sample face significant liquidity constraints, since they value an extra unit of liquidity withdrawal 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 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 the control arm to consumers in risk score 1, and simulate the model for each risk score. Panels A and B show the dynamics of repayment over time. Consumers in risk scores 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 share of what is owed) is 80%. Repayment for consumers in risk scores 3 and 4 is significantly worse: after origination, the fraction missing payments is around 15% (30%) for risk score 3 (4), and it rises to over 40% (55%) at maturity; repayment at maturity is around 75% (60%). Panel C shows the profitability on loans made to consumers decreases significantly with their risk scores: from 253% for consumers in risk score 1 to -11% for consumers in risk score 4.

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.

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

[25]For consumers in risk score 4, $t = 0.037$ and the present value of the perpetual transfer $t \times y_{it}$ in exchange for phone ownership is below $200 for 48% of these consumers.

[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%.

fonts. The empirical take-up rates are in blue, and the simulated ones are in red. The model almost exactly matches take-up rates both for targeted and untargeted arms.

Figure 5 plots the average repayment at maturity (as a share of what is owed) for each of the eight arms in the experiment, both overall (Panel A) and for each maturity separately (Panels B-E). Again, the model fit is excellent: simulated repayment rates fall within the confidence interval of estimated repayment rates in the data for 24 of the 32 arms-by-maturity cases. The main issues come from the Steep multiple arm, where the model underestimates repayment for 3-month contracts and overestimates it for the 12-month contract. This can be interpreted through the lens of selection into maturities: the Steep arm increases the relative price of the 12-month vs. 3-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 3-month contracts and only about 60% for 12-month contracts.

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 period from contract initiation to maturity (Panel A), the probability of resuming payment in week $t+1$ conditional on missing a payment in week t (Panel B), the share of consumers 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. It also matches the persistence of default well (Panel B), although it leads to a lower share of consumers that have still not fully repaid after two years (Panel C).

Finally, Figure 7 gives insight on the dynamics of repayment behavior. The probability of resuming payment exihibits a steady drop and the share of non-payers increases over time, likely reflecting gradual depreciation. When the number of weeks since contract initiation hits maturity, the share of non-payers significantly increases because a large fraction of consumers repay on time and the denominator, i.e., the number of contracts remaining in repayment, shrinks. The model is able to replicate these dynamic patterns well, despite not explicitly matching on them.

Table A2 completes the description of model fit by providing the exhaustive set of all moments targeted in our estimation, together with their simulated values.

4.3 Identification

In this section, we explore the mechanics of the model and identification. In Panel A of Table 3, we calculate how the simulated moments change by varying one parameter value while keeping all others fixed at their estimated values.[27] These local comparative statics shed light on both the mechanics of the model and as well as the identification of parameters and how they vary across risk scores.

To illustrate, first consider comparative statics with respect to usage value (v_0) and average income ($\bar{y}$). While both parameters affect overall take-up and repayment similarly, they have opposite effects on maturity choice: higher usage value makes lockout more costly, which makes longer maturity contracts (with lower weekly payments and less risk of being locked) more attractive; higher mean income shifts consumers toward toward shorter maturity contracts, as richer consumers can better afford these contracts with higher weekly payments but lower multiples.

Second, depreciation (ϕ) is a key driver of the difference in repayment between the first and second half of the contract, the probability of default, and the probability of resuming payments (once a phone is broken, the consumer will stop making payments). Higher depreciation also decreases take-up and shifts consumers into longer maturity contracts, where depreciation has the largest effect on repayment.

Third, the size of income shocks (σ) primarily affects the proportion of perfect repayers, as more volatile income increases the likelihood of consumers missing at least one payment. It also influences the probability of resuming payments and significantly impacts the repayment rate for short-maturity contracts, which require higher weekly payments.

Finally, consumers' discount factor (β) increases the take-up rate and affects maturity choices—more patient consumers are more likely to opt for all contracts except the 12-month option. The impact of the discount factor on repayment is mixed. While a higher β makes ownership more appealing and improves repayment, as evidenced by the positive slope of 3-month contract repayment relative to β, repayment for longer-maturity contracts decreases with β because lower-income consumers select into these options.

We next provide some intuition for how these comparative statics help explain the key parameter differences across risk scores. In order to do so, we first report how the moments differ across risk scores after controlling for the multiple and minimum downpayment (Table 4) using risk score 1 as the control group. Focusing first on risk score 4 (the third column of Table 4), several important observations emerge. First, risk score 4 exhibits worse overall repayment, a higher a default rate, a lower probability of resuming payment, and worse repayment in the second half of the contract. Additionally, consumers in risk score 4 exhibit greater selection on maturity: compared to risk score 1, they perform worse on the

[27]Because of space constraints, we do not show comparative statics for all 52 moments targeted in estimation. Instead, we summarize the local comparative statics using 13 moments that characterize take-up, downpayment and maturity choice, and repayment dynamics in the control treatment arm for one of the risk scores.

12-month contract relative to the 3-month contract. Qualitatively, all of these differences can be explained by a higher depreciation rate. However, a higher depreciation rate also reduces take-up and shifts customers toward longer maturity contracts. We do not observe these differences in Table 4.[28] Thus, we can interpret two of the other estimated parameter differences as "undoing" these unobserved effects associated with higher depreciation. First, to offset the (unobserved) reduction in take-up, the dispersion of the random utility shock, σ_ω, is larger for risk scores 4, which increases take-up due to the love of variety effect. Second, to offset the (unobserved) shift to the 12-month contract, the usage value (v_0) is lower for risk score 4, which makes longer maturity contracts less attractive. Ex-ante, it may be surprising that risk score 4 does not have lower average income. However, reducing average income would only exacerbate the shift into long maturity contracts, which explains why the estimated mean income is roughly the same.

The overall logic is similar when comparing the estimates of risk score 3 to risk score 1. However, for risk score 2, the logic is different. Consumers in risk score 2 are similar to risk score 1 in terms of the probability of resuming payment, the difference in share repaid during the first half of the contract, and the degree of selection on maturity. Thus, the estimated depreciation rate for risk scores 1 and 2 is roughly the same. Yet, repayment is significantly lower for risk score 2, so the estimation procedure uses other parameters—-such as a lower discount factor and higher income volatility—-to explain the lower repayment observed for risk score 2.

To further investigate our model's identification, Panel B of Table 3 reports the sensitivity matrix (Andrews et al., 2017), which linearly approximates how the parameters changes in response to a change in the empirical moment.

5 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 usage value that a consumer 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 consumer from missing a payment is less severe. Thus, a decrease in λ is akin to a lower collateral requirement. This affects firm

[28] Notably, the lower observed take-up rate for risk scores 4 is entirely explained by the fact that they face a higher minimum downpayment.

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, for risk score 1, the take-up rate increases from 62% to 91% and average repayment at maturity decreases from 82% 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 \$28. For $\lambda = 0.5$, the profit falls by \$39 with roughly equal amounts attributable to weaker incentives and weaker screening. For $\lambda = 0.2$, profit falls by \$108: 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 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 consumer 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 multiple and control downpayment arm as our "baseline" treatment group.

6.1 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' outside option include both the outside option in the model (buy with cash now, later or never), as well as a menu of four contracts with 100% required minimum downpayment that mimic the PAYGo contracts offered by the firm. By doing so, our measure excludes welfare gains that arise solely from a "love of variety" effect (Nevo (2003), Petrin (2002)).[29]

Our welfare measure, denoted by $\mathcal{W}_i$, is a standard money metric, defined as the percentage increase in weekly income over a two-year period in the no-financing benchmark that would deliver the same utility to the consumer as they enjoy from having access to the menu of PAYGo contracts.

Formally, for takers $\mathcal{W}_i$ solves:

$$W_i(\Gamma_i^*) + \xi_{\Gamma_i^*} + \omega_{i\Gamma_i^*} = B_i(\hat{y}_{i0}) \tag{12}$$

where

$$\hat{y}_{it} = \begin{cases} (1+\mathcal{W}_i)y_{it} & t \leq 104 \\ y_{it} & \text{otherwise} \end{cases} \tag{13}$$

For non-takers, $\mathcal{W}_i$ is 0.

$B_i(\hat{y}_{i0})$ corresponds to the consumer's value in the no-financing benchmark described above with the higher income process $\hat{y}_{it}$. We defer details on the computation of this benchmark and the welfare measure $\mathcal{W}_i$ to Section B.3 in the Internet Appendix.

We focus on welfare over a two-year period as it is commensurate with the expected lifespan of the phone. Note that $\mathcal{W}_i = 0$ for consumers that do not accept a contract. 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 $\mathcal{W}_{pop} \equiv \mathbb{E}[\mathcal{W}_i]$.[30]

Table 5 provides the welfare estimates across treatment groups and risk scores. For our baseline treatment group (risk score 1, control), we find that $\mathcal{W}_{taker} = 7.7\%$. That is, the average taker in the baseline treatment group is indifferent between (a) their preferred PAYGo contract, and (b) no access to financing but a 7.7% increase in income over the next

[29] In our model, welfare gains from the PAYGO contracts arise for two broad reasons: (1) because they allow consumers to finance phone consumption (2) because they allow consumers to get random utility draws. Our measure allows us to focus on (1) by including in the outside option a menu of contracts similar to the ones offered in the data but with a 100% downpayment requirement (and thus offering no financing to consumers).

[30] 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.

two years. The take-up rate in this treatment group is 63%, which implies an unconditional welfare effect of $\mathcal{W}_{pop} = 4.8\%$. The unconditional welfare gain decreases to 3.4% in the high multiple treatment arm, and increases to 5.2% in the low downpayment treatment arm.

The welfare effects are smaller for higher risk scores. For the control group, $\mathcal{W}_{pop}$ is 4.5% for risk score 2, 2.5% for risk score 3, and 1.2% for risk score 4. Averaging across the population of all risk scores in the control arm, we get $\mathcal{W}_{taker} = 6.2\%$ and $\mathcal{W}_{pop} = 3.4\%$.

Figure 9 plots the welfare effects by mean income ($\bar{y}_i$) for risk score 1. The welfare effects are concentrated among consumers with intermediate income, where $\mathcal{W}_{taker}$ can be as large as 12%. Welfare effects diminish to near zero 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 the poorest consumers, the contracts are too expensive and have no effect on their welfare.

6.2 Competitive Pricing

Firm profit across all risk scores and treatment groups is positive and economically significant (Table 5). Across the four risk scores, the NPV per contract ranges from $27-37 in the control arm with corresponding IRRs in the range of 143%-201%.[31] Firm profit is increasing in the multiple 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 consumer welfare. In this subsection, we quantify the potential welfare gains under the counterfactual of perfect competition among firms.

Solving for the competitive menu with different prices for each maturity 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, solving for the vector of prices that maximizes consumer welfare subject to a break-even constraint is computationally intensive.

We sidestep these issues by assuming that the multiples are proportional to those in the control arm. In other words, we characterize a competitive contract by a pair (d_c, m_c), where d_c is the minimum downpayment and m_c is a scalar. The competitive multiple for each maturity are the multiples in the control arm scaled by m_c. For each risk score, we solve the pair that maximizes consumer welfare subject to the lender's break-even constraint.

[31] 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.

In Table 6, we report the terms across all risk scores in the competitive pricing counterfactual. We include terms for the control group for comparison. Both the multiples and minimum downpayment under competitive pricing are lower than in any of the treatment arms, and significantly so except for the multiples of risk score 4. For instance, for risk score 1, the 6-month multiple and downpayment are 1.54 and 25% in the control group, while they are 1.24 and 10.6% 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 7.7% to 11.3%). In Figure 9, we plot the cross section of take-up rates (Panel A) and welfare effects (Panel B) for each level of mean income under competitive pricing and under the control arm. 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 5, we also report the welfare measures for the other three risk categories under competitive prices. Welfare $\mathcal{W}_{pop}$ for risk score 2, 3, and 4 increases from 4.5%, 2.5%, and 1.2% under the control arm to 8.3%, 4.2%, and 2.4% under competitive pricing. In Table 7, we investigate what proportions of the increases in welfare come from lower multiples or minimum downpayment. For risk scores 1 and 2, lower multiples provide about 2/3 of the welfare increase and lower minimum downpayments provide about 1/3. For risk score 3, the two contract terms have about equal contributions. For risk score 4, the welfare increase comes solely from the lower minimum downpayment. This suggests that the greater repayment risk for higher risk scores, due to more volatile income, lower usage value, and faster depreciation, limits the scope of competition's effects in lowering interest rates.

6.3 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 digitally 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 by a significant margin for reasonable assumptions about the repossession technology. To establish this finding, we first solve the consumer's problem (take-up and repayment) when facing a secured loan. Given the solution to the consumer's problem, we compute firm profit and competitive prices for secured loans under various assumptions about the repossession technology. We then evaluate consumer welfare from a secured loan and compare it to our findings in Section 6.2.

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 multiple) 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 consumer 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 consumer retains the device and the firm recovers nothing. A *frictionless* repossession technology is characterized by $c_{\text{repo}} = 0$ and $p_{\text{repo}} = 1$.

With this alternative contract, the consumer also enjoys the fixed and random utility shocks from the device estimated in Section 4. However, we assume that the consumer only enjoys these shocks while in possession of the device. We thus convert them to a per period flow value $\omega_{ij}^{\text{flow}} = (1-\beta)(\omega_{ij} + \xi_j)$ and assume the consumer receives $\omega_{ij}^{\text{flow}}$ each period until the device is repossessed.[32]

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 consumer 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 consumer is

$$\begin{aligned} &U_i^{\text{repo}}(v_{it}, y_{it}, n_{it}, m_i, a_{it}) \\ &= \max\Big\{ v_{it} + \omega_i^{\text{flow}} + u(y_{it} - m_i) + \beta \mathbb{E}[U_i^{\text{repo}}(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i, a_{it}) | x_{it}], \\ &v_{it} + \omega_i^{\text{flow}} + u(y_{it}) + \beta \mathbb{E}[U_i^{\text{repo}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, a_{it} + 1) | x_{it}] \Big\}. \end{aligned} \tag{14}$$

[32] If the shocks are instead received as a time 0 transfer, some consumers take up the contract solely to capture the instantaneous utility shocks and then immediately default and are repossessed. If the repossession technology is not too costly, this can also be profitable for the firm. Converting utility shocks to flows and assuming they are only realized while in possession of the device avoids this behavior.

The consumer 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 a period, the consumer gets to consume the value of the device in this period.

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

$$U_i^{\text{repo}}(v_{it}, y_{it}, n_{it}, m_i, \bar{a}) = p_{\text{repo}} \Pi_i(0, y_{it}) + (1 - p_{\text{repo}})(\Pi_i(v_{it}, y_{it}) + \omega_{ij} + \xi_j), \tag{15}$$

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

$$U_i^{\text{repo}}(v_{it}, y_{it}, 0, m_i, a_{it}) = \Pi_i(v_{it}, y_{it}) + \omega_{ij} + \xi_j, \tag{16}$$

which holds for all $a_{it} < \bar{a}$ and where $\Pi_i(v_{it}, y_{it})$ is defined as in Equation (3).[33] Consumers enjoy the per period flow value equivalent to the fixed and random utility shocks in perpetuity after she repays in full or after repossession fails.

Once we have solved for the consumer's value function, computing the value from an arbitrary contract and the consumer's outside option follows the same steps as in Section 3.4, with the exception that we do not include separate additive terms corresponding to random shocks and fixed effects to U_i^{repo}.

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

$$\begin{aligned} V_i^{\text{repo}}(x_{it}) =& A_i^{\text{repo}}(x_{it})\big(m_i + \delta \mathbb{E}[V_i^{\text{repo}}(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i, a_{it}) | x_{it}]\big) \\ &+ (1 - A_i^{\text{repo}}(x_{it}))\delta \mathbb{E}[V_i^{\text{repo}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, a_{it} + 1) | x_{it}], \end{aligned} \tag{17}$$

where $A_i^{\text{repo}}(x_{it})$ is the consumer's optimal repayment policy. The ownership boundary condition for the firm is analogous to Equation (9). The default boundary condition (i.e., $n_{it} \geq 1$, $a_{it} = \bar{a}$) is:

$$V_i^{\text{repo}}(v_{it}, y_{it}, n_{it}, m_i, \bar{a}) = p_{\text{repo}}(\kappa_{it} - c_{\text{repo}}) + (1 - p_{\text{repo}})(-c_{\text{repo}}). \tag{18}$$

The firm's NPV from lending to consumer i is analogous to Equation (10).

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

Welfare Comparison To facilitate our comparison to the welfare effects of PAYGo, we focus on competitive prices for the secured loan. Following the same approach as in Section 6.2, we solve for the zero-profit welfare-maximizing contract for a secured loan with multiples proportional to those in the control multiple / control downpayment arm of the experiment. 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 gains created under competitive prices by each technology relative to a no-financing benchmark, and compare them to the welfare gains generated by PAYGo derived in Section 6.2. Under competitive pricing, consumer welfare is equivalent to total welfare. Hence, using competitive pricing for this exercise enables us to identify the total *potential* surplus for each lending technology, whereas the lender's existing pricing schemes trade off consumer surplus creation and firm profit.

Figures 10 depicts prices, take-up, repayment, and welfare gains for the various contracts assuming that the chance of success $p_{\text{repo}} = 100\%$. As the repossession technology becomes more efficient (i.e., as c_{repo} decreases), in general the multiple and minimum downpayment fall, which is intuitive as it becomes easier for the lender to break even. The welfare gain from secured lending decreases with c_{repo}.

For consumers in risk score 1, a traditional secured loan with a repossession cost of $20.3 generates the same welfare gain as PAYGo financing. The welfare equivalent repossession cost increases with the risk score. In other words, PAYGo is likely to dominate secured lending for lower risk consumers but not necessarily for the riskiest ones. This finding illustrates a key trade-off between the two forms of financing. On the one hand, secured lending provides stronger screening and repayment incentives than PAYGo as a missed payment implies losing the usage value forever. On the other hand, conditional on default, the ex-post inefficiency of repossession are larger than lockout due to both the physical cost of repossessing collateral and the opportunity cost of permanently reallocating it to its next best user. Becuase lower risk consumers have a higher usage value (Table 2), they have a strong incentive to repay even under the PAYGo contract. Further, since their usage value is higher, the dead weight loss from reallocation created by repossession is large. As a result, for these low risk consumers, secured lending is dominated by PAYGo. The opposite is true for the riskiest consumers.[34]

[34]The quantitative finding that secured lending dominates for consumers in risk score 4 even for large repossession costs relies on the assumption that repossession always succeeds (i.e., $p_{\text{repo}} = 1$). A lower p_{repo} would increase the relative gains from PAYGo.

7 Contract Design

In this section, we explore whether the PAYGo contract can be improved upon to provide larger welfare gains.

7.1 Leniency

Many households in LMICs face significant income risk (Amuedo-Dorantes and Pozo, 2011). This risk implies that even consumers who deliver positive profit to the firm on average will occasionally be forced into non-strategic default. Locking such consumers out may create unnecessary welfare loss. While information asymmetries hinder the ability to contract on income realizations, the PAYGo contract can be amended to provide more leniency to consumers missing payments. Such a leniency policy may increase welfare by providing insurance against negative income shocks, but it will also reduce screening and incentives for repayment so that its overall effect on welfare gains is ambiguous. This section explores this trade-off quantitatively.

For this exercise, we consider a PAYGo contract with a leniency policy parameterized by $\bar{l}$, which is the cumulative number of payments a consumer can miss before the lock is initiated: the device remains unlocked until the consumer has missed $\bar{l}$ payments, at which point the device locks every week when the consumer misses a payment. The PAYGo contract described in Section 3 corresponds to $\bar{l} = 0$. The consumers problem with this amended contract is described in detail in Section A.1 in the Internet Appendix.

Consistent with intuition, Panel C of Figure 11 shows that more lenient contracts worsen repayment incentives (Panel D). As a result, higher multiples and minimum downpayment are required for the lender to break even as the policy becomes more lenient (Panel A and B). At low level of leniency, more lenient contracts increase take-up rates since consumers benefit from the increased insurance while prices remain moderate (Panel C). As leniency increases, this effect is reversed and more leniency leads to decreased take-up rates as prices become exceedingly high. Panel E shows that the welfare gains created by these contracts are hump-shaped with leniency and that they dominate the PAYGo contracts for lower levels of leniency. The optimal leniency policy is around 10 missed payments for risk scores 1, 2, and 3, and around 5 for risk score 4. The welfare gains at the optimal leniency contract are largest (smallest) for risk score 2 (4), and correspond to a 14% (5%) increase in welfare gain relative to the welfare gains created by the standard PAYGo contract.

7.2 Lock Strength

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 use of the lockout technology (e.g., where only certain features or apps on the phone are disabled or where the phone is locked only for a fraction of the week) is technologically feasible. In this subsection, we conduct a normative analysis on the strength of the lockout technology. In particular, we ask whether $\lambda = 1$ maximizes welfare.

We have seen in Section 5, that a higher λ alleviates both moral hazard and adverse selection, and thus increases lender profits, which makes lending sustainable for a greater number of consumers. However, conditional on a missed payment, a higher λ also destroys more surplus. In other words, a higher λ reduces risk sharing, but foster screening and repayment incentives. This section explores this trade-off quantitatively.

For this exercise, we consider a range of alternative contracts that use a technology $\lambda \in [0, 1]$. For each contract λ, we compute competitive multiples and minimum downpayment and evaluate the welfare gains created by this contract relative to the no-financing benchmark. The results are illustrated in Figure 12. The qualitative patterns are consistent across risk scores. A weaker lock results in higher default (Panel D) and thus in higher multiples and minimum downpayment (Panels A and B). The risk-sharing benefits obtained by a weaker lock are dominated by the increased costs of financing: overall, both take-up rates and welfare gains strictly increases with λ (Panel C and E), even for the riskiest consumers.

7.3 Stringency

Finally, we ask whether a more stringent contract with stricter consequences for missed payments can achieve higher welfare gains. We consider two variations of the standard PAYGo contract. In the first one, consumers are locked for additional periods after missing a payment. The consumer problem and the firm objective under this alternative contract are described in Section A.2 of the Internet Appendix. As in our previous counterfactuals, we calculate welfare gains for these alternative contracts under competitive pricing.

Figure 13 shows that these harsher contracts are dominated by the standard PAYGo contract. While the more stringent contracts lead to better repayments (Panel D), they reduce risk-sharing sufficiently that both take-up and welfare gains decrease with the number of periods locked (Panel C and E). This finding is consistent with our results in Section 7.1: if anything, the standard PAYGo contract provides too little insurance, not too much.

In our second extension, consumers have to pay a proportional fee, $f \times m$, (in addition to m) following a missed payment in order to unlock the device. After doing so, the device is unlocked and the next payment returns to its normal level m. Section A.2 of the Internet Appendix provides further details on this contract and the Bellman equation for consumers. Consistent with our earlier findings, Figure 14 shows that additional fees strictly reduce the welfare gains of PAYGo.

8 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 the 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 3.4% 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 7.2% relative to a benchmark with no financing and also outperforms a reasonably calibrated traditional 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. Our quantitative analysis suggests that a leniency policy may result 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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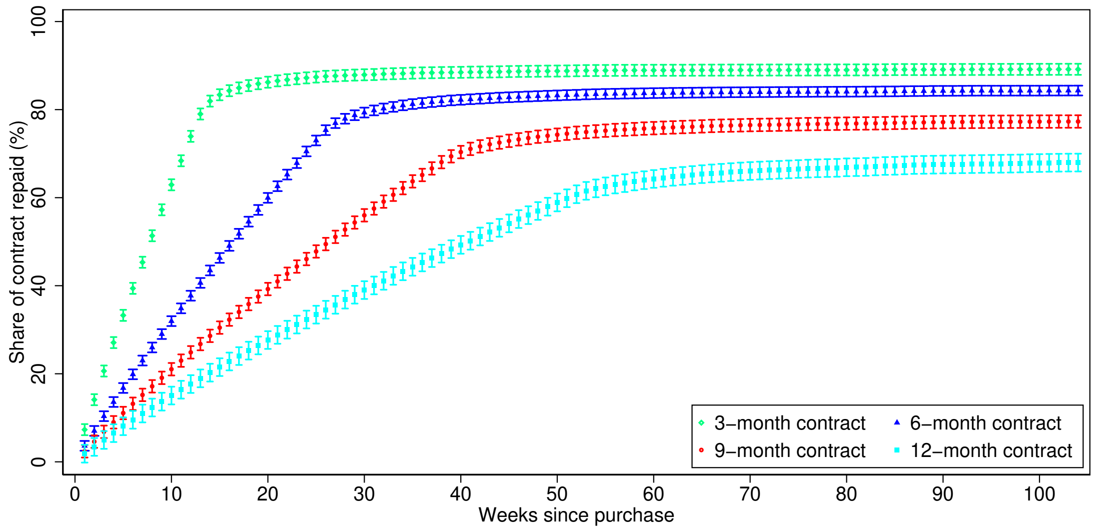
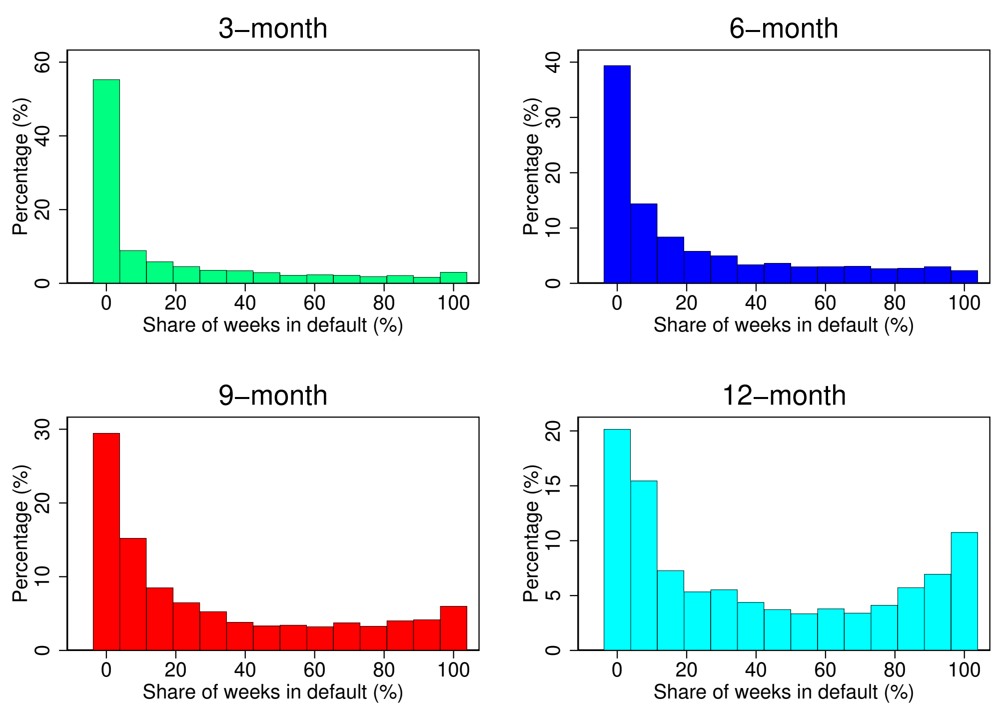
A Figures

Figure 1: Repayment by Maturity

Panel A: Dynamics of the share of contract repaid

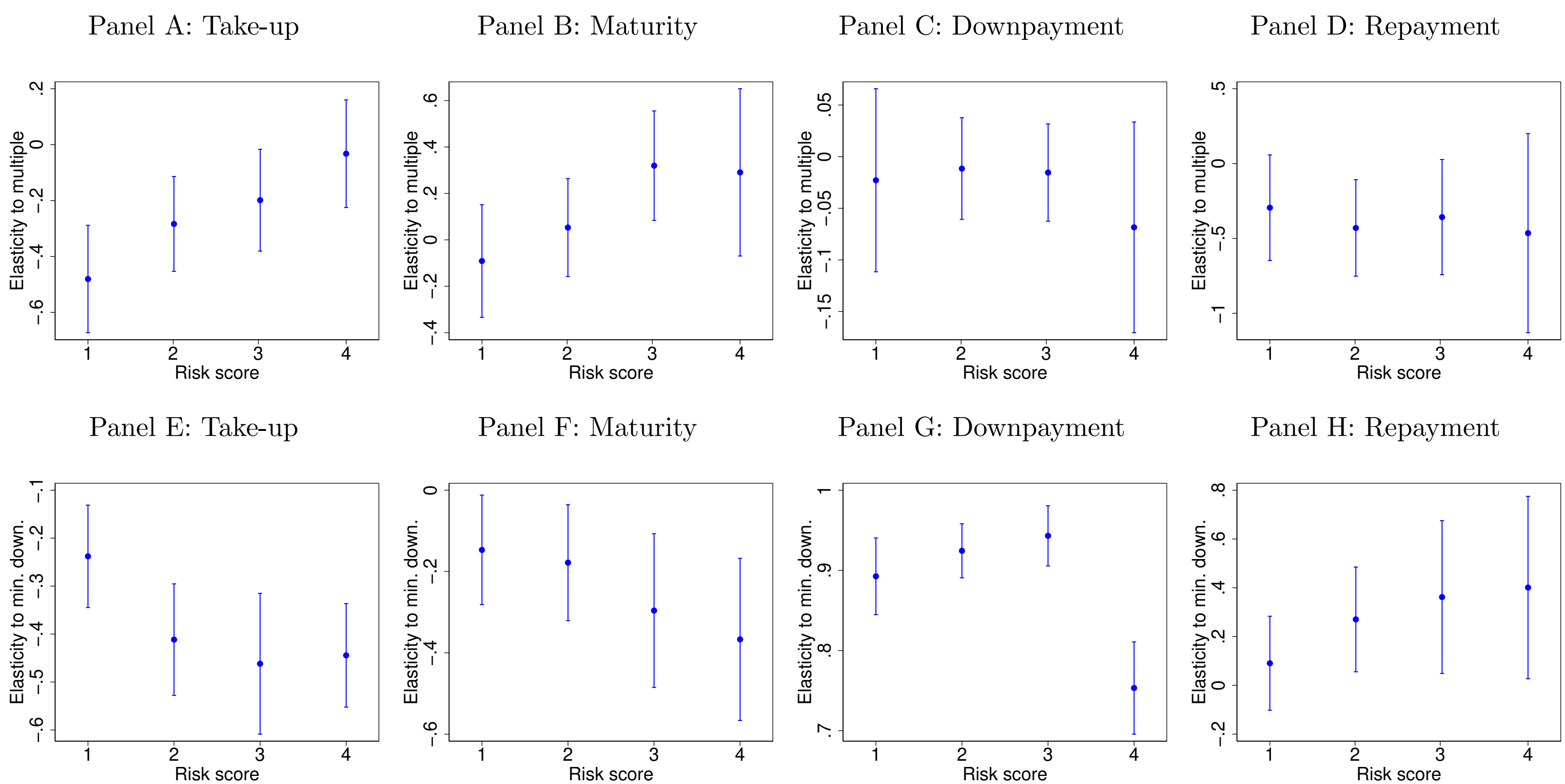


Panel B: Distribution of the share of weeks in default



Note: Panel A shows the share of contract repaid at each point in time. Panel B shows the distribution of the share 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.

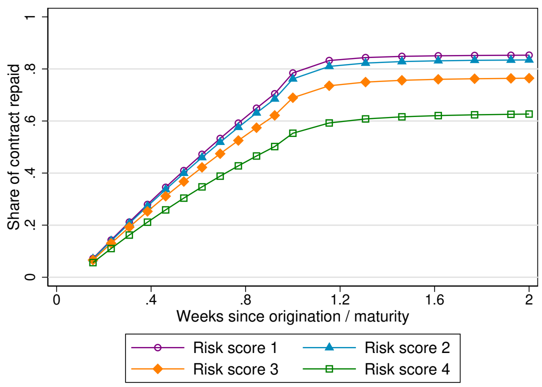
FIGURE 2: Elasticity to Average Multiple and Minimum Downpayment Across Risk Scores



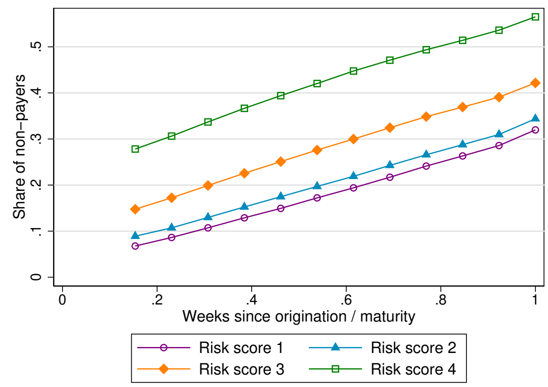
Note: In Panels A-D, for the Control, Medium and High pricing arms, we first construct the average multiple across maturity. For each risk score, we then regress a loan outcome on the log of the average multiple, controlling for the loan's downpayment arm. In Panels E-H, for each risk score, we regress a loan outcome on the log of the required minimum 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 consumer 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 3: Comparison Across Risk Scores, Holding Treatment Constant

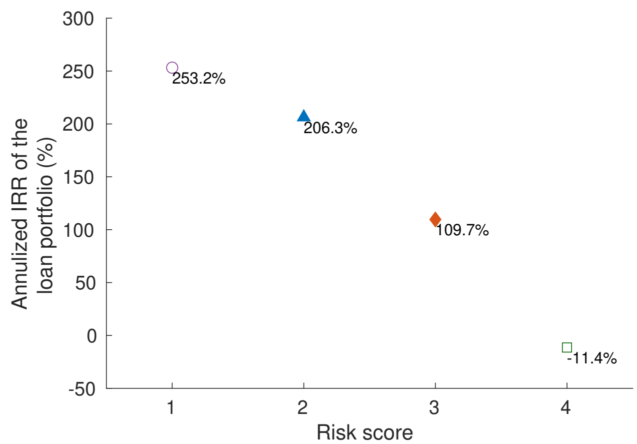
Panel A: Repayment



Panel B: Missed payments



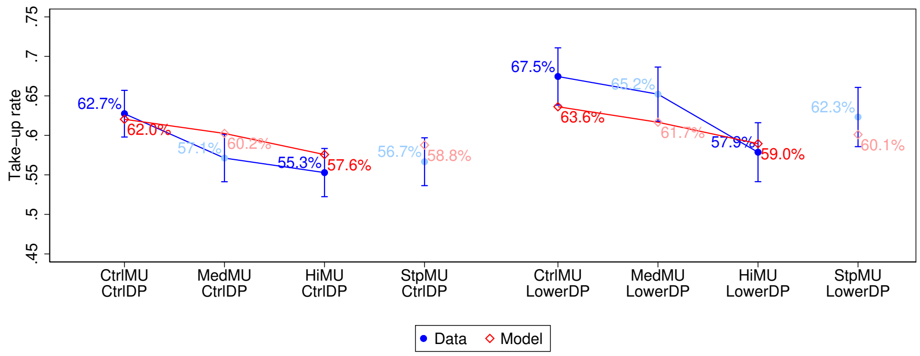
Panel C: IRR



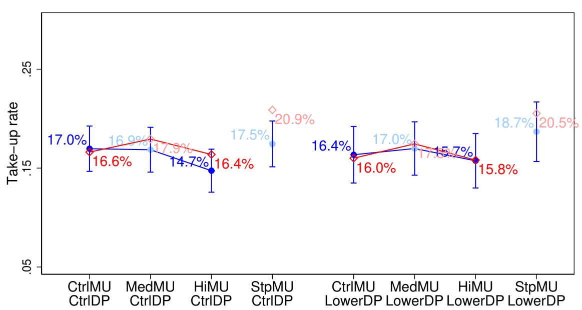
Note: We compare simulated consumer behavior across risk scores holding treatment fixed. We fix contract terms to those offered in the control multiple / control downpayment arm for risk score 1. We then simulate the behavior of consumers with different risk scores using the parameter estimates obtained in our SMM estimation. Panel A shows the simulated share of contract 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)

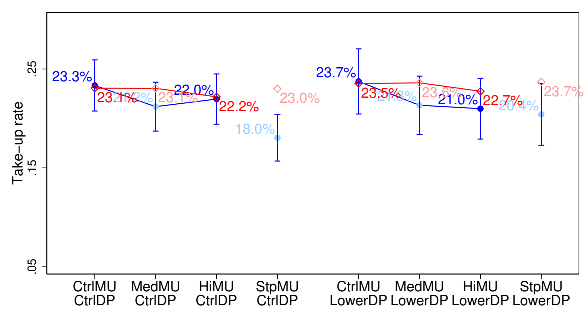
Panel A: Overall



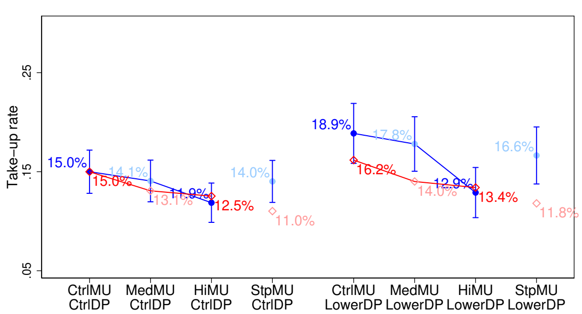
Panel B: 3-month contract



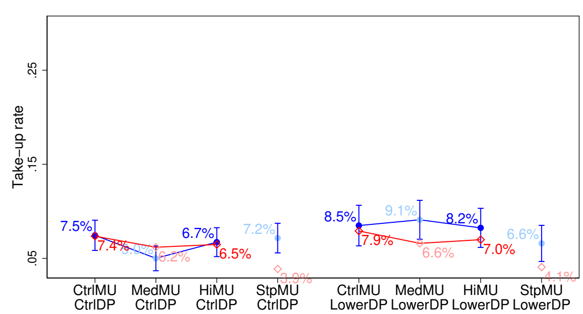
Panel C: 6-month contract



Panel D: 9-month contract



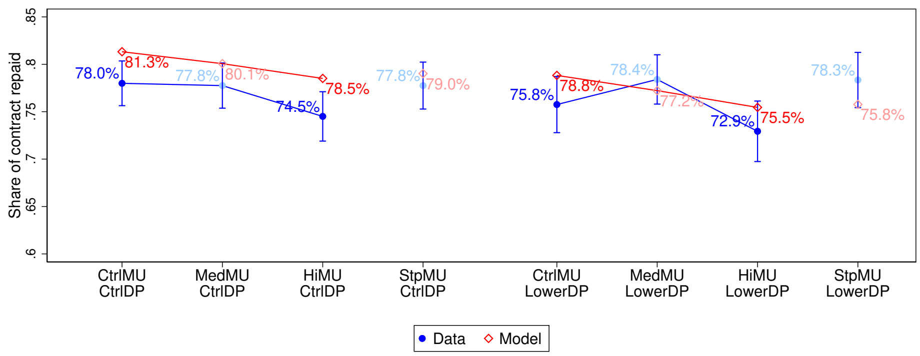
Panel E: 12-month contract



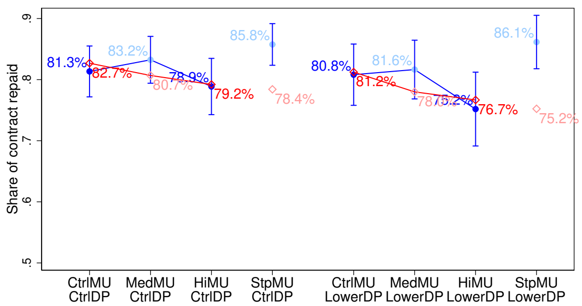
Note: This figure shows take-up rates in both actual data (in blue) and simulated data (in red) for risk score 1. Panel A reports the average take-up rate across maturity. Panel B, C, D, and E report take-up rates for the 3, 6, 9, and 12 month contracts respectively. The x-axis corresponds to the 8 experimental arms. CtrlMU (resp. MedMU, HiMU and StpMU) is the control multiple arm (resp. medium, high and steep). CtrlDP (LowerDP) is the control downpayment arm (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 - Share of Contract Repaid (Risk Score 1)

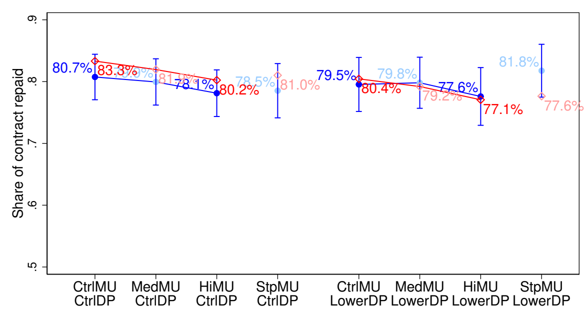
Panel A: Overall



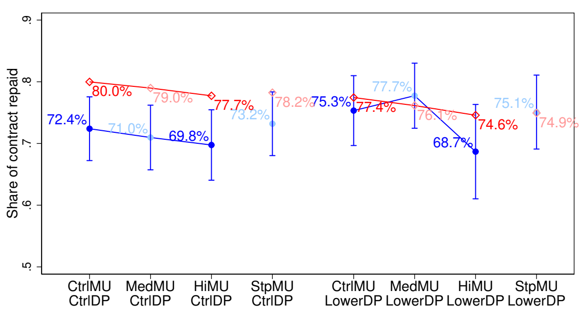
Panel B: 3-month contract



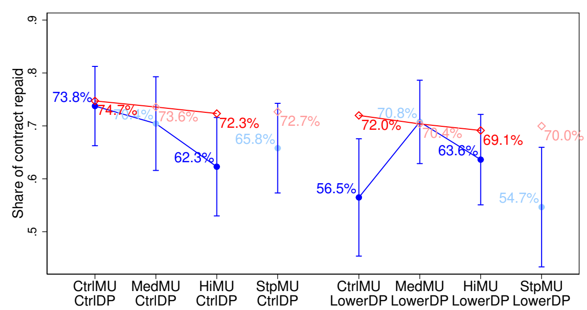
Panel C: 6-month contract



Panel D: 9-month contract



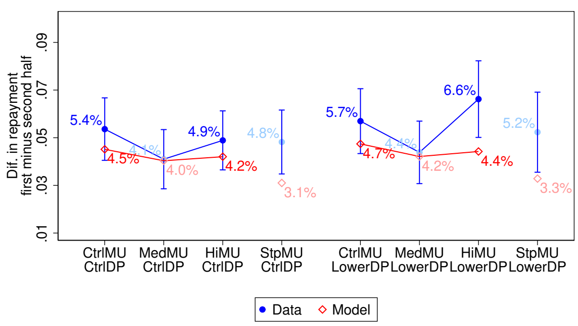
Panel E: 12-month contract



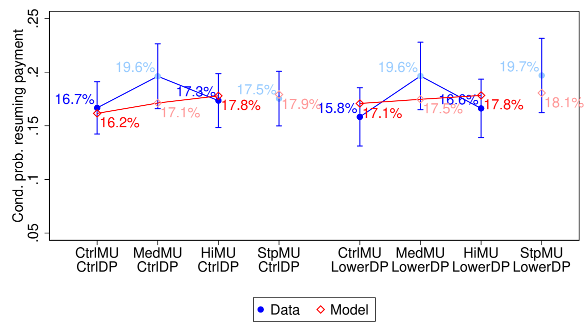
Note: This figure shows the average share of contract repaid at maturity in both actual data (in blue) and simulated data (in red) for risk score 1. Panel A reports the average share of contract repaid across maturity. Panel B, C, D, and E report the average share of contract repaid for the 3, 6, 9, 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 (LowerDP) is the control downpayment arm (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)

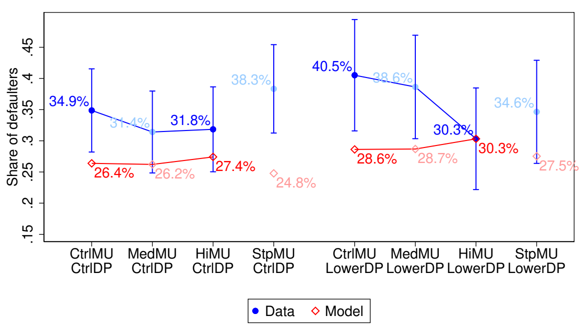
Panel A: Difference in repayment of first minus second half during maturity



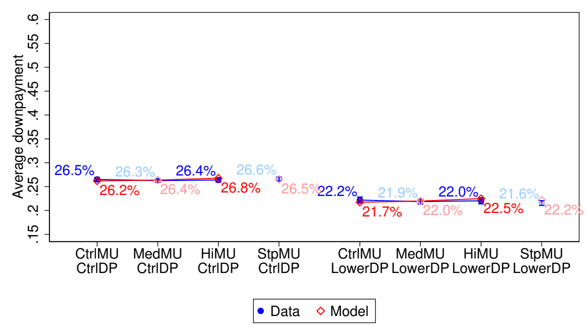
Panel B: Conditional prob. of resuming payment



Panel C: Share of consumers who did not fully repay in two years

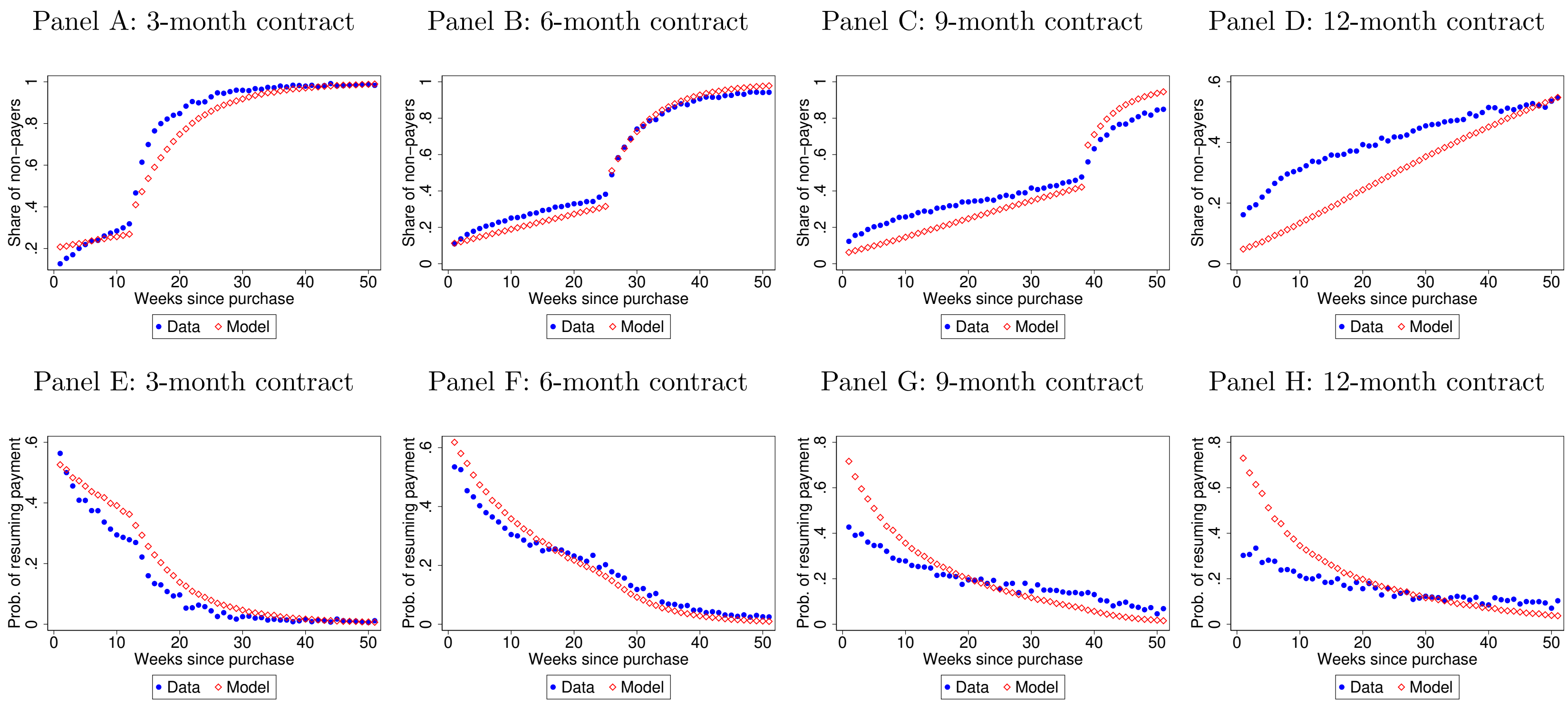


Panel D: Downpayment



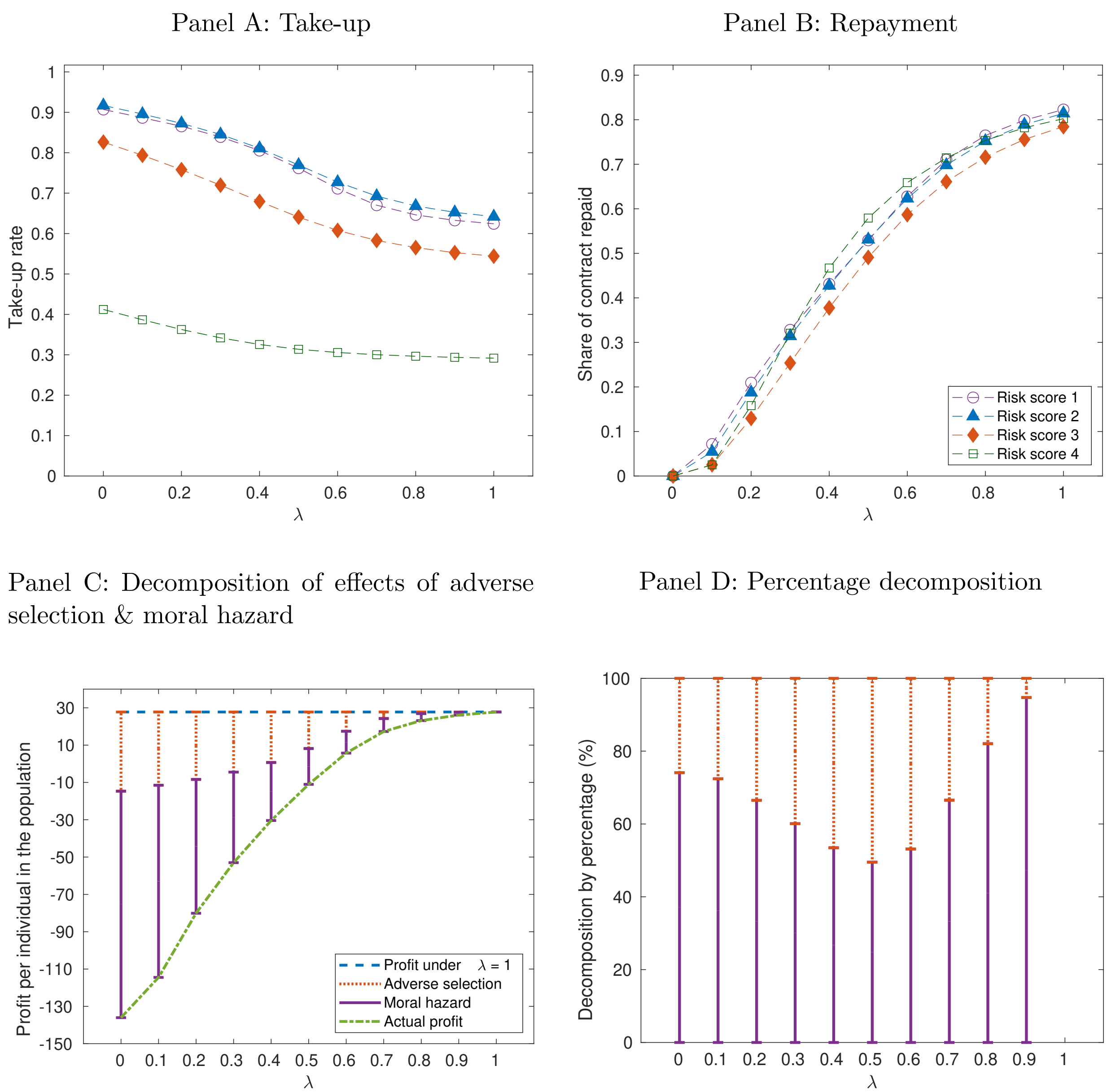
Note: This figure plots additional moments from actual data (in blue) and simulated data (in red) for risk score 1. Panel A shows the average difference in the share of the amount due repaid in the first half of the contract minus the share repaid in the second half. Panel B reports the probability of resuming payment in week t conditional on missing payment in week $t-1$. Panel C shows the share of consumers 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 (LowerDP) is the control downpayment arm (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 7: Model Fit - Repayment Dynamics



Note: In Panels A-D, we plot the dynamics of the share of non-payers in each week since purchase. In Panels E-H, we plot the dynamics of the probability of resuming payment conditional on not paying in the previous period in each week since purchase. In these plots we average across all risk scores and treatment arms.

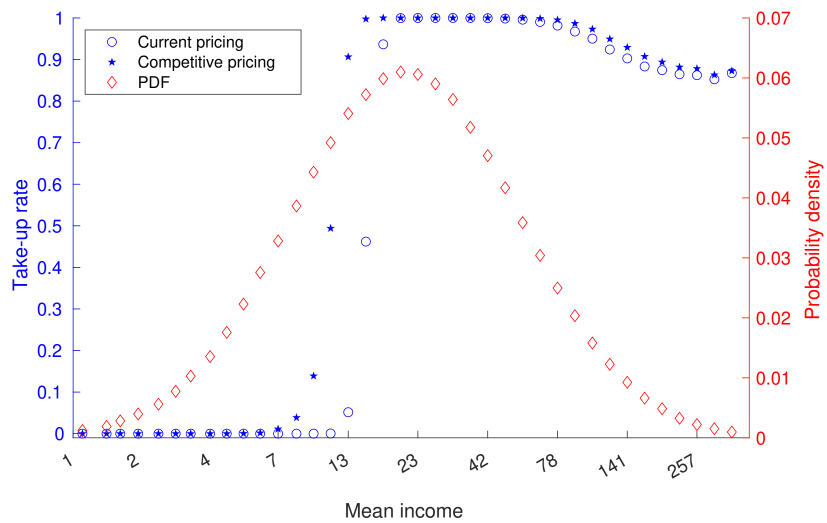
Figure 8: Decomposition of Effects of λ into Moral Hazard and Adverse Selection



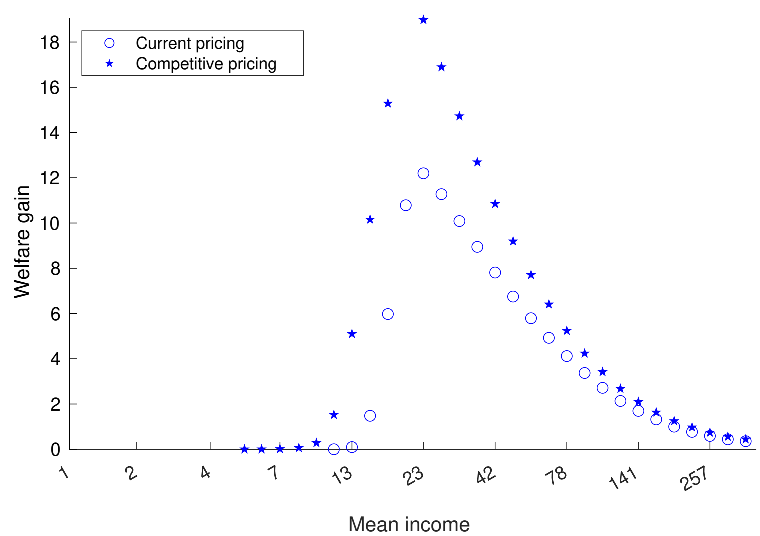
Note: We simulate the model assuming consumers face the menu of contracts offered in the control multiple / control downpayment arm and varying the efficiency of the lockout technology, λ, from 0 (no lockout) to 1 (full lockout, as in the baseline estimation). Panel A shows the take-up rates for each value of λ. Panel B shows the average share of contract repaid 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 A2 in the Appendix. Panel D provides the percentage decomposition of the profit loss into adverse selection (the upper segment) and moral hazard (the lower segment) for risk score 1.

Figure 9: Take-up and Welfare by Income, Risk Score 1

Panel A: Take-up rates

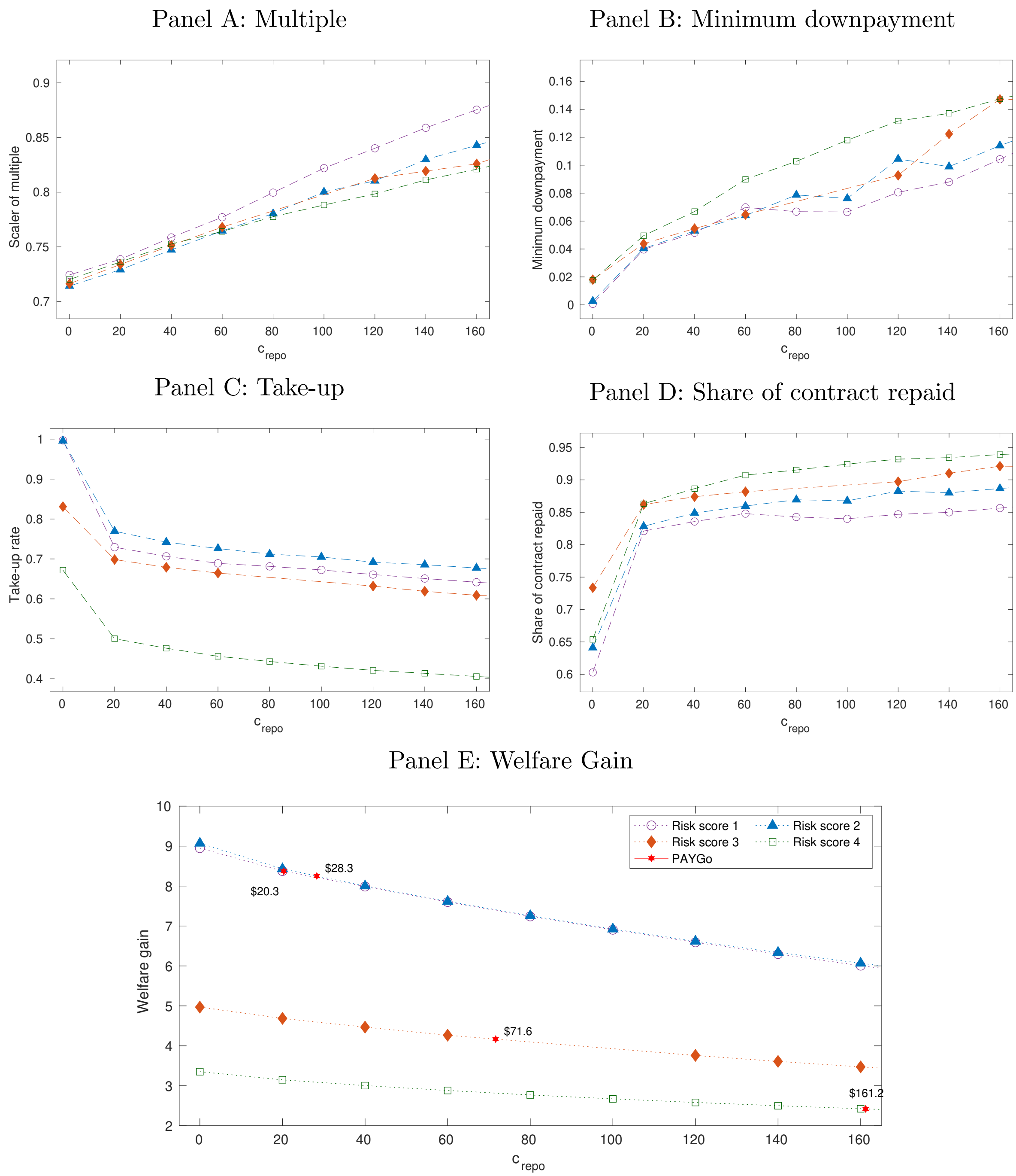


Panel B: Welfare gain $\mathcal{W}_{pop}$



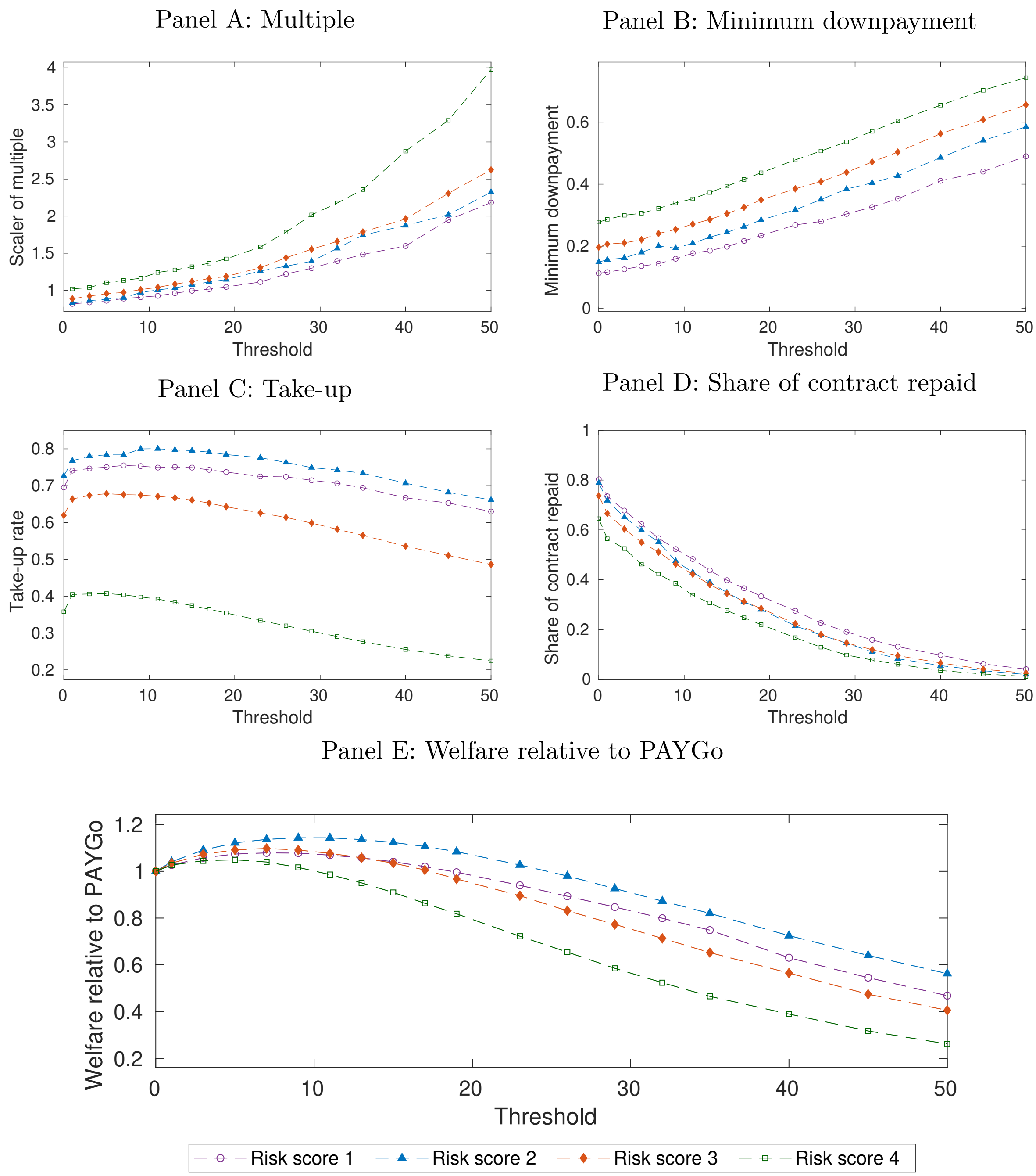
Note: We simulate the model assuming consumers face (1) the contract menu offered in the control multiple / control downpayment arm (2) the contract menu with competitive prices assuming that the multiples are proportional to those in the control multiple / control downpayment arm. Panel A reports the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

Figure 10: Traditional Secured Lending with $p_{\text{repo}} = 100\%$



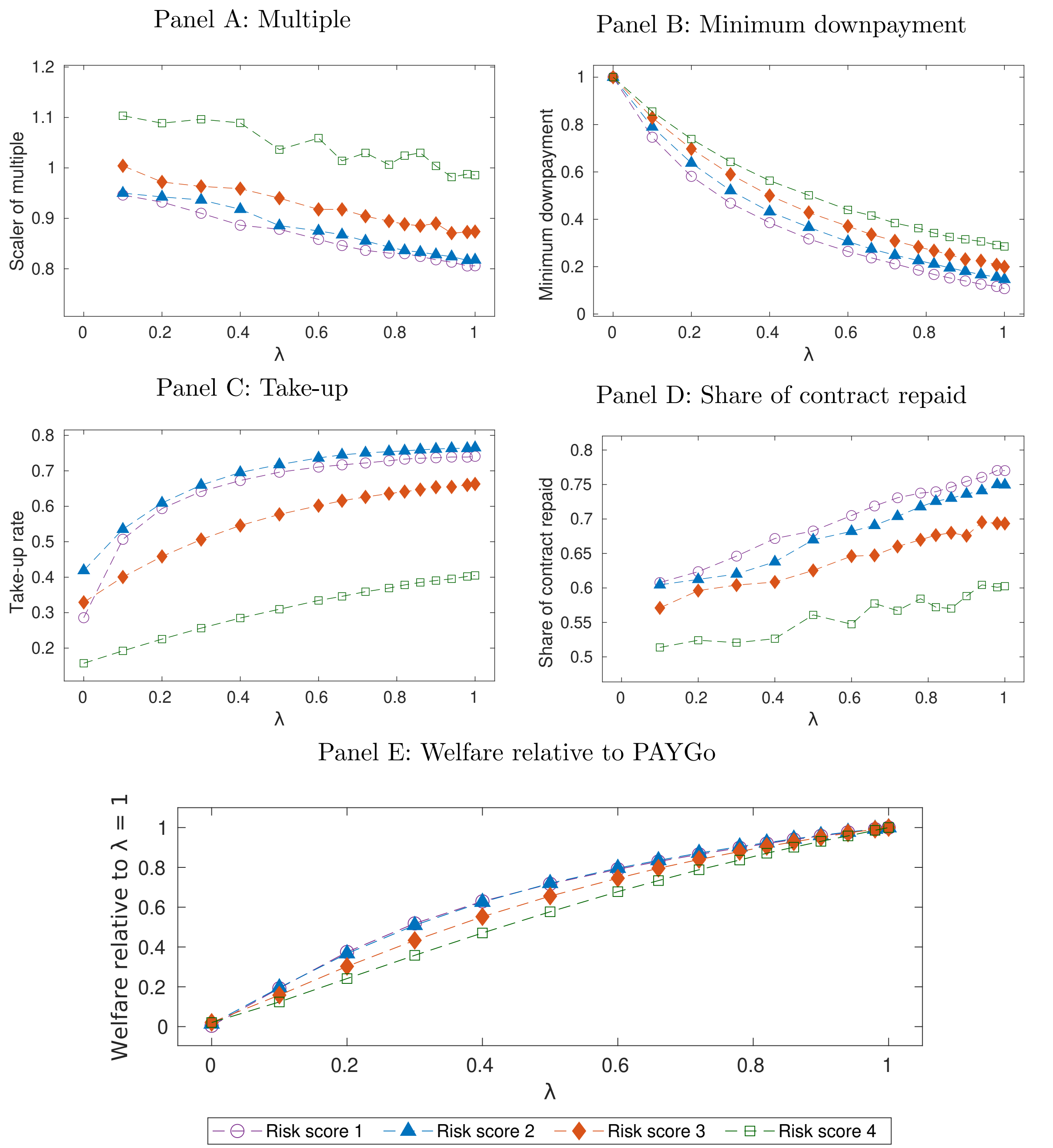
Note: We consider traditional repossession technologies with chance of success $p_{\text{repo}} = 100\%$ and vary the cost of repossession c_{repo}. For each risk score and technology, we find the competitive prices in a market where multiples are proportional to those in the control multiple / control downpayment arm of the experiment. Panel A reports the competitive multiple. Panel B reports the competitive minimum downpayment, Panel C the average take-up rate, Panel D the average share of contract repaid at maturity, and Panel E the welfare gains $\mathcal{W}_{pop}$. We also label the repossession cost that delivers the same welfare as PAYGo for each risk score in Panel E.

Figure 11: PAYGo Variation: Leniency for Missed Payments



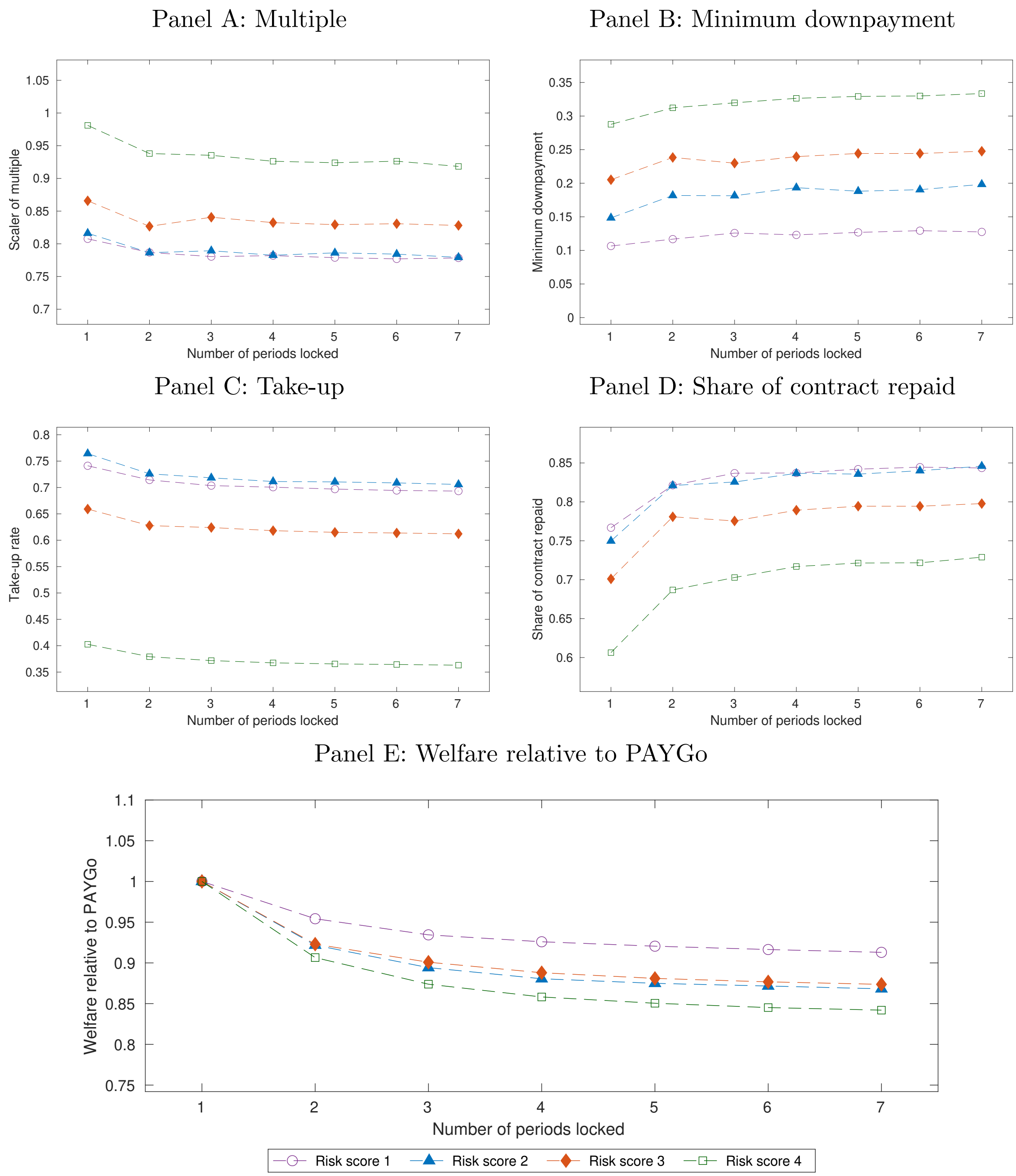
Note: We let the lender use a leniency policy and initiate lockout only after the number of cumulative missed payments exceeds a threshold. Then for each risk score and technology, we find the competitive prices in a market where multiples are proportional to those in the control multiple / control downpayment arm of the experiment. Panel A reports the competitive multiple across risk scores and thresholds for the initiation of lockout. Panel B reports the competitive minimum downpayment, Panel C the average take-up rate, Panel D the average share of contract repaid at maturity, and Panel E the welfare gain $\mathcal{W}_{pop}$ relative to PAYGo.

Figure 12: PAYGo Variation: Less Stringent Lockout



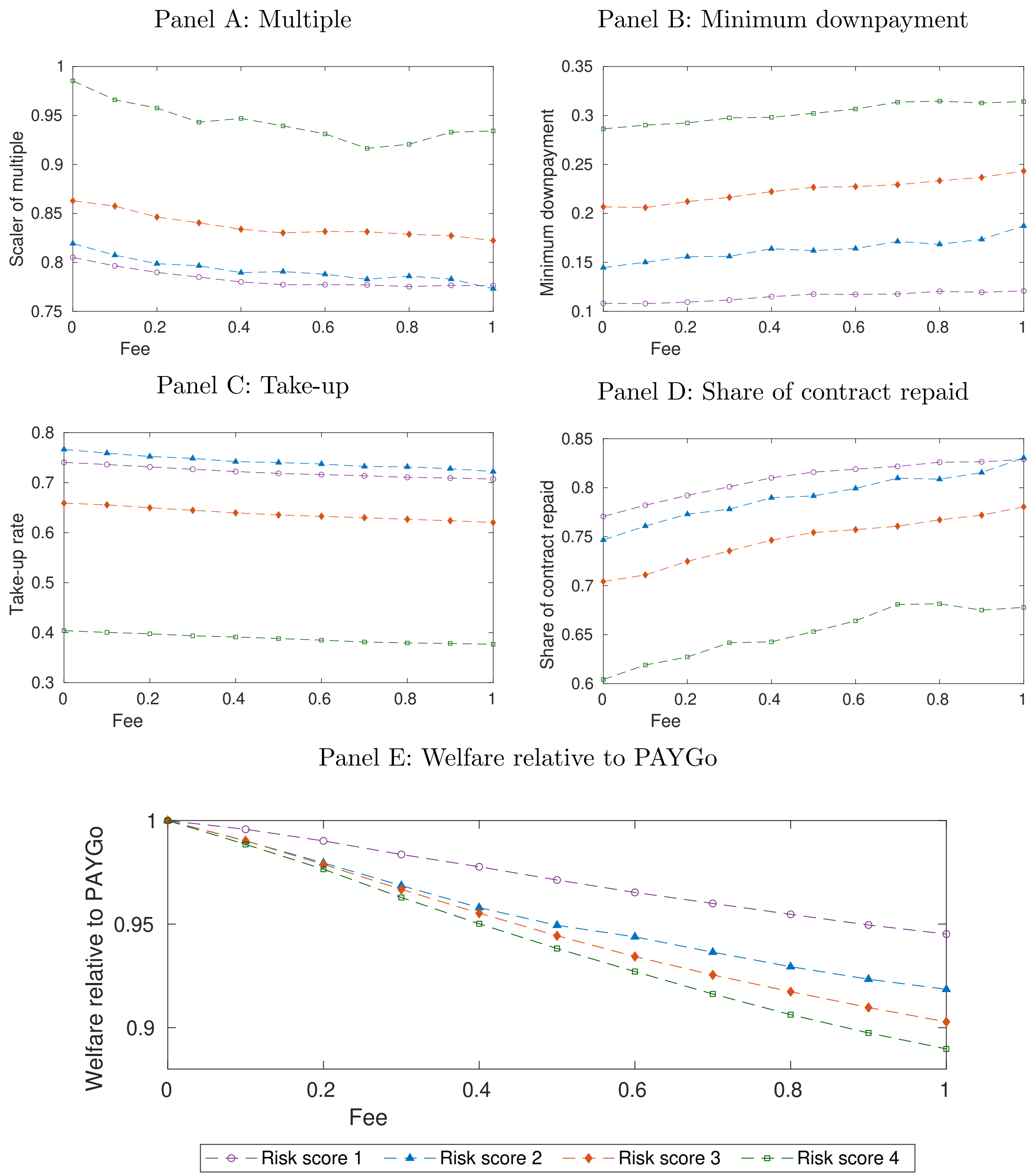
Note: For each risk score and technology, we find the competitive prices in a market where multiples are proportional to those in the control multiple / control downpayment arm of the experiment. This calculation is done using the baseline parameter estimates and assuming various values for λ, the efficiency of the lockout technology. For each value of λ, we then simulate a sample of consumers facing these competitive prices. Panel A reports the ratio of competitive multiples to those in the control multiple / control downpayment arm across risk scores and values of λ. Panel B reports the competitive minimum downpayment, Panel C the average take-up rate, Panel D the average share of contract repaid at maturity, and Panel E the welfare gain $\mathcal{W}_{pop}$ relative to PAYGo.

Figure 13: PAYGo Variation: Additional Periods Locked after Missed Payments



Note: We let the lender maintain the lock on the device for multiple periods after each missed payment. Then for each risk score and technology, we find the competitive prices in a market holding the multiples proportional to those in the control multiple / control downpayment arm of the experiment. Panel A reports the scaler of competitive multiples relative to multiples in the control multiple / control downpayment arm. Panel B reports the competitive minimum downpayment, Panel C the average take-up rate, Panel D the average share of contract repaid at maturity, and Panel E the welfare gain $\mathcal{W}_{pop}$ relative to PAYGo.

Figure 14: PAYGo Variation: Fees for Missed Payments



Note: We let the lender use a policy under which the borrower is required to pay a fee when missing a payment. Then for each risk score and technology, we find the competitive prices in a market where multiples are proportional to those in the control multiple / control downpayment arm of the experiment. Panel A reports the competitive multiple across risk scores and thresholds for the initiation of lockout. Panel B reports the competitive minimum downpayment, Panel C the average take-up rate, Panel D the average share of contract repaid at maturity, and Panel E the welfare gain $\mathcal{W}_{pop}$ relative to PAYGo.

B Tables

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	Pricing Treatment	# of Consumers 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 consumers in each treatment arm of the pricing experiemnt.

Table 2: Parameter Estimates

	(1) Risk score 1	(2) Risk score 2	(3) Risk score 3	(4) Risk score 4
Income process parameters:				
$\bar{y}$ (average mean income, weekly in \$)	33.7	34.8	37.3	35.5
	(1.7)	(1.8)	(2.6)	(5.4)
$\sigma_{\bar{y}}$ (dispersion of mean income)	0.98	0.87	0.86	0.97
	(0.04)	(0.06)	(0.06)	(0.14)
σ (income volatility)	0.35	0.38	0.37	0.41
	(0.01)	(0.01)	(0.02)	(0.03)
Device value parameters:				
v_0 (initial usage value)	24.1	23.6	15.7	10.3
	(3.1)	(2.4)	(1.7)	(1.3)
ϕ (prob. of depreciation, weekly)	0.030	0.030	0.034	0.041
	(0.001)	(0.001)	(0.001)	(0.002)
Other customer preference parameters:				
β (discount factor, weekly)	0.997	0.989	0.995	0.996
	(0.003)	(0.003)	(0.006)	(0.006)
μ (liquidity cost)	4.07	3.07	3.28	4.54
	(0.11)	(0.03)	(0.02)	(1.30)
σ_ω (std. dev. of random utility shock)	130.1	185.3	255.6	299.9
	(23.7)	(27.1)	(22.2)	(83.5)
ξ_3 (fixed effect for 3 month)	13.6	-6.3	-47.8	18.2
	(8.4)	(9.2)	(10.8)	(15.4)
ξ_9 (fixed effect for 9 month)	-78.4	-96.2	-124.8	-177.0
	(16.4)	(15.5)	(16.4)	(48.9)
ξ_{12} (fixed effect for 12 month)	-110.6	-158.5	-222.4	-285.7
	(29.6)	(25.8)	(27.4)	(77.5)

Note: This table reports the model's parameter estimates. To ease interpretation, v_0, σ_ω, ξ_3, ξ_9, and ξ_{12} are scaled by the marginal utility evaluated at the population average mean income (i.e., $u'(\bar{y})$). For instance, the true value for v_0 in risk score 1 is $24.1 \times u'(33.7)$. As discussed in Section 3, μ_i is proportional to the consumer's marginal utility at its mean income, i.e. $\mu_i = \mu \times u'(\bar{y}_i)$, where μ is the value reported in the table. Standard errors are calculated using the delta method discussed in Section B.5 and reported in the parentheses.

Table 3: Jacobian Matrix and Sensitivity Matrix, Risk Score 1

Panel A: Jacobian matrix (J)

	$\bar{y}$	$\sigma_{\bar{y}}$	σ	v_0	ϕ	β	μ	σ_ω	ξ_3	ξ_9	ξ_{12}
$Takeup_3$	0.12	-0.11	0.03	-0.04	-0.03	1.46	-0.02	-0.01	0.01	0.02	0.02
$Takeup_6$	0.02	-0.14	-0.01	0.07	-0.07	2.69	-0.02	-0.04	-0.01	0.03	0.03
$Takeup_9$	-0.04	-0.12	-0.03	0.14	-0.08	2.54	-0.03	0.03	-0.00	-0.09	0.02
$Takeup_{12}$	-0.04	-0.07	-0.02	0.08	0.00	-1.11	-0.02	0.08	-0.00	0.02	-0.11
$Repay_3$	-0.00	0.01	-0.11	0.08	-0.03	0.15	-0.04	-0.03	-0.00	-0.00	-0.00
$Repay_6$	0.03	-0.00	-0.06	0.02	-0.04	-0.87	0.03	-0.01	-0.00	0.00	-0.00
$Repay_9$	0.01	-0.00	-0.04	-0.00	-0.06	-1.32	0.02	-0.00	-0.00	-0.00	0.00
$Repay_{12}$	0.01	0.00	-0.02	0.00	-0.06	-0.93	0.02	-0.00	-0.00	-0.00	0.00
Δ_{repay}	-0.04	-0.01	-0.01	0.04	0.12	-0.08	0.00	0.02	-0.01	-0.02	-0.02
p_{perfect}	0.06	0.04	-0.21	0.04	-0.04	-2.02	0.03	-0.02	-0.00	-0.00	0.00
p_{resume}	-0.04	-0.01	0.16	-0.01	-0.21	2.56	-0.02	-0.01	0.00	0.01	0.01
p_{default}	-0.05	-0.00	0.03	0.01	0.19	0.22	-0.01	0.03	-0.00	-0.01	-0.02
$DownPayment$	0.13	0.14	0.11	-0.03	0.00	0.48	-0.16	-0.00	0.00	0.00	-0.00

Panel B: Sensitivity matrix ($\Lambda = (J'WJ)^{-1}J'W$)

	$\bar{y}$	$\sigma_{\bar{y}}$	σ	v_0	ϕ	β	μ	σ_ω	ξ_3	ξ_9	ξ_{12}
$Takeup_3$	0.35	0.20	0.23	1.75	0.35	-0.00	0.25	1.87	18.26	2.12	2.35
$Takeup_6$	-0.08	0.07	0.82	3.20	0.32	-0.04	-0.09	3.77	-6.48	6.79	7.43
$Takeup_9$	0.74	-1.49	-0.74	-3.50	-0.44	0.05	-0.27	-4.50	-10.43	-8.18	-7.24
$Takeup_{12}$	0.96	-1.36	-1.26	-4.49	-0.66	0.07	-0.08	-3.95	-14.57	-5.84	-10.45
$Repay_3$	-0.43	-0.92	1.17	1.18	0.41	-0.07	-0.76	-8.19	12.72	-4.14	-5.27
$Repay_6$	1.13	-1.48	-1.17	-5.10	-0.57	0.06	-0.21	-7.16	-16.21	-8.33	-10.99
$Repay_9$	-0.48	-0.43	0.13	0.04	-0.29	-0.04	-0.49	0.06	-0.66	0.24	1.07
$Repay_{12}$	-0.44	-0.08	0.56	1.27	-0.14	-0.06	-0.39	0.54	3.24	1.30	2.34
Δ_{repay}	-0.23	0.01	0.65	1.40	0.52	-0.03	-0.14	-0.68	2.79	0.35	0.72
p_{perfect}	0.80	1.91	-1.06	1.68	-0.19	0.04	1.07	7.29	-0.44	5.22	6.10
p_{resume}	-0.10	0.19	0.12	-0.59	-0.66	0.02	0.22	0.28	-1.50	-0.39	-0.89
p_{default}	-0.74	1.17	1.42	5.02	1.09	-0.06	0.16	4.06	16.27	6.01	7.73
$DownPayment$	3.00	1.64	1.17	1.77	0.19	0.03	0.82	0.12	-7.18	-0.56	-1.15

Notes: This table reports the scaled Jacobian and Sensitivity matrices for risk score 1. The Jacobian matrix J is multiplied by the parameter estimates, divided by the standard deviations of the moment, and divided by 100. Therefore, the first entry in Panel A, 0.12 is interpreted as a 1% change in $\bar{y}$ leads to $0.12 \times$ standard deviation change in $Takeup_3$. The sensitivity matrix Λ is multiplied by the standard deviations of moments, divided by the parameter estimates, and multiplied by 100. Therefore, the first entry in Panel B, 0.35 is interpreted as a 1 SD change in $Takeup_3$ leads to 0.35% change in $\bar{y}$.

Table 4: Moment Comparison across Risk Scores

	ΔRisk score 2	ΔRisk score 3	ΔRisk score 4	Risk score 1
Overall take-up	0.073***	0.039***	–0.030	0.600
	(7.99)	(3.15)	(–1.32)	
3-month	0.006	–0.010	–0.031*	0.167
	(0.89)	(–1.09)	(–1.83)	
6-month	0.043***	0.041***	0.012	0.213
	(5.78)	(4.07)	(0.64)	
9-month	0.019***	0.008	–0.005	0.149
	(3.11)	(0.97)	(–0.33)	
12-month	0.005	0.000	–0.006	0.072
	(1.18)	(0.00)	(–0.57)	
Average maturity	0.135*	0.209**	0.070	6.626
	(1.86)	(2.03)	(0.35)	
Overall repayment, at maturity	–0.049***	–0.097***	–0.142***	0.768
	(–5.97)	(–8.26)	(–6.18)	
3-month	–0.048***	–0.082***	–0.102***	0.819
	(–3.49)	(–4.30)	(–2.78)	
6-month	–0.050***	–0.100***	–0.177***	0.795
	(–3.90)	(–5.52)	(–4.96)	
9-month	–0.033*	–0.069***	–0.114**	0.730
	(–1.86)	(–2.61)	(–2.15)	
12-month	–0.063**	–0.146***	–0.227***	0.656
	(–2.19)	(–3.54)	(–2.72)	
Dif. in repayment, first minus second half	0.006	0.018***	0.024**	0.051
	(1.49)	(3.07)	(2.02)	
Share of perfect repayers	–0.079***	–0.139***	–0.216***	0.420
	(–6.27)	(–7.69)	(–6.08)	
Cond. prob. of resuming payment	–0.013	–0.048***	–0.077***	0.178
	(–1.58)	(–4.30)	(–3.61)	
Share of defaulters	0.052***	0.127***	0.190***	0.222
	(4.57)	(7.83)	(5.95)	
Average downpayment	–0.003**	–0.000	0.014***	0.246
	(–2.58)	(–0.06)	(4.76)	

Note: This table reports the results of regressing sample moments used in the estimation on dummy variables for each risk score, controlling for the multiple treatment arm and the minimum required downpayment. Each row corresponds to a regression and each of the first three columns report the corresponding fixed effect for the risk score. Consumers in risk score 1 serve as the reference group: their sample average is reported in the last column. The regression with the conditional probability of resuming payment as the outcome variable is weighted using the frequency of missing payments.

Table 5: 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					
CtrlMultipleCtrlDown	62.8%	7.7%	4.8%	37.3	201%
HighMultipleCtrlDown	55.3%	5.9%	3.4%	64.5	444%
CtrlMultipleLowerDown	67.5%	8.1%	5.2%	36.3	176%
Competitive Pricing	74.1%	11.3%	8.4%	0.0	25%
Risk score 2					
CtrlMultipleCtrlDown	61.3%	7.0%	4.5%	34.8	181%
HighMultipleCtrlDown	55.8%	5.1%	3.0%	59.7	391%
CtrlMultipleLowerDown	68.4%	7.4%	4.9%	35.5	164%
Competitive Pricing	76.4%	10.8%	8.3%	0.0	25%
Risk score 3					
CtrlMultipleCtrlDown	50.9%	4.6%	2.5%	26.8	143%
HighMultipleCtrlDown	48.9%	3.6%	1.8%	53.7	326%
CtrlMultipleLowerDown	59.7%	4.9%	2.7%	22.8	109%
Competitive Pricing	65.9%	6.3%	4.2%	0.0	25%
Risk score 4					
CtrlMultipleCtrlDown	26.2%	4.3%	1.2%	28.3	196%
HighMultipleCtrlDown	26.0%	3.9%	1.1%	37.0	239%
CtrlMultipleLowerDown	38.2%	5.1%	1.7%	14.4	82%
Competitive Pricing	40.5%	6.0%	2.4%	0.0	25%

Note: This table reports welfare gains and profitability of contracts for each experimental arm and under 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 6: Competitive Terms

	By maturity				
	(1) 3 month	(2) 6 month	(3) 9 month	(4) 12 month	(5) Overall
Risk score 1					
Ctrl multiple	1.36	1.54	1.64	2.00	
Ctrl minimum downpayment					25.0%
Competitive multiple	1.10	1.24	1.32	1.62	
Competitive minimum downpayment					10.6%
Risk score 2					
Ctrl multiple	1.36	1.54	1.64	2.00	
Ctrl minimum downpayment					30.0%
Competitive multiple	1.11	1.26	1.34	1.63	
Competitive minimum downpayment					14.9%
Risk score 3					
Ctrl multiple	1.36	1.54	1.64	2.00	
Ctrl minimum downpayment					35.0%
Competitive multiple	1.18	1.33	1.42	1.73	
Competitive minimum downpayment					20.5%
Risk score 4					
Ctrl multiple	1.36	1.54	1.64	2.00	
Ctrl minimum downpayment					50.0%
Competitive multiple	1.37	1.55	1.65	2.01	
Competitive minimum downpayment					28.1%

Note: This table reports the competitive terms assuming that the firm provides all four contracts and holds the multiples proportional to those in the control multiple / control downpayment arm of the experiment. It also reports the actual multiple and minimum downpayment in the control multiple / control downpayment arm of the experiment.

Table 7: Decomposition of Effects of Competition

	(1) $\mathcal{W}_{pop}$ under Ctrl	(2) $\Delta(\mathcal{W}_{pop})$ from competitive multiple	(3) $\Delta(\mathcal{W}_{pop})$ from competitive minimum downpayment	(4) $\mathcal{W}_{pop}$ under competitive terms
Risk score 1	4.8% (*62.6%*)	1.8% (*67.6%*)	1.2% (*69.4%*)	8.4% (*74.1%*)
Risk score 2	4.5% (*64.3%*)	1.9% (*69.3%*)	1.3% (*72.0%*)	8.3% (*76.4%*)
Risk score 3	2.5% (*54.3%*)	0.6% (*57.8%*)	0.9% (*62.7%*)	4.2% (*65.9%*)
Risk score 4	1.2% (*28.9%*)	-0.0% (*28.9%*)	1.2% (*40.6%*)	2.4% (*40.5%*)

Note: This table reports the effects of the change in welfare and take-up due to competitive multiple, competitive minimum downpayment, or both. Column (1) reports $\mathcal{W}_{pop}$ and take-up rates (in parentheses) under the control multiple / control downpayment arm of the experiment. Column (2) reports $\mathcal{W}_{pop}$ and take-up rates if the multiple is set to the competitive level while the minimum downpayment is the same as under the control multiple / control downpayment arm. Column (3) reports $\mathcal{W}_{pop}$ and take-up rates if the minimum downpayment is set to the competitive level while the multiple is the same as under the control multiple / control downpayment arm. Column (4) reports $\mathcal{W}_{pop}$ and take-up rates under competitive multiple and minimum downpayment.

Internet Appendix

A Counterfactual Models

A.1 PAYGo with a Leniency Policy

The Consumer's Problem The state variable is now $x_{it} = (v_{it}, y_{it}, n_{it}, m_i, l_{it})$, where l_{it} denotes cumulative number of payments missed. Let $U_i^{\text{leniency}}(x_{it}; \Gamma)$ denote the value function of consumer i under a PAYGo contract Γ with a leniency policy, which is henceforth suppressed. While in repayment and before hitting the threshold (i.e., for $n_{it} \geq 1$, $l_{it} < \bar{l}$), the Bellman equation for the consumer is

$$U_i^{\text{leniency}}(v_{it}, y_{it}, n_{it}, m_i, l_{it}) = \max \Big\{ v_{it} + u(y_{it} - m_i) + \beta \mathbb{E}[U_i^{\text{leniency}}(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i, l_{it}) | x_{it}], \\ v_{it} + u(y_{it}) + \beta \mathbb{E}[U_i^{\text{leniency}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, l_{it} + 1) | x_{it}] \Big\}. \tag{19}$$

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

There are two boundary conditions: lockout and ownership. If $l_{it} = \bar{l}$ then the consumer transitions into a standard PAYGo contract and the boundary condition is:

$$U_i^{\text{leniency}}(v_{it}, y_{it}, n_{it}, m_i, \bar{l}) = U_i(v_{it}, y_{it}, n_{it}, m_i), \tag{20}$$

which holds for all $n_{it} \geq 1$ and $U_i(v_{it}, y_{it}, n_{it}, m_i)$ is defined as in Equation (1). The other boundary condition is ownership (i.e., $n_{it} = 0$):

$$U_i^{\text{leniency}}(v_{it}, y_{it}, 0, m_i, l_{it}) = \Pi_i(v_{it}, y_{it}), \tag{21}$$

which holds for all $a_{it} < \bar{a}$ and where $\Pi_i(v_{it}, y_{it})$ is defined as in Equation (3).[35] Once we have solved for the consumer's value function, the value from an arbitrary contract and computing the consumer's outside option follows that same steps as in Section 3.4.

[35] Differently from the case of traditional repossession, $n_{it} = 0$ and $l_{it} = \bar{l}$ is reachable and the consumer value equals ownership. It is not used as a boundary condition here as this state can only be reached after a consumer transitions into a standard PAYGo contract.

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

$$\begin{aligned} V_i^{\text{leniency}}(x_{it}) =& A_i^{\text{leniency}}(x_{it})\big(m_i + \delta\mathbb{E}[V_i^{\text{leniency}}(v_{i,t+1}, y_{i,t+1}, n_{it}-1, m_i, l_{it})|x_{it}]\big) \\ &+ (1 - A_i^{\text{leniency}}(x_{it}))\delta\mathbb{E}[V_i^{\text{leniency}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, l_{it}+1)|x_{it}], \end{aligned} \tag{22}$$

where $A_i^{\text{leniency}}(x_{it})$ is the consumer's optimal repayment policy. The terminal boundary condition for the firm is analogous to Equation (9). The boundary condition for initiating lockout (i.e., $n_{it} \geq 1$, $l_{it} = \bar{l}$) is:

$$V_i^{\text{leniency}}(v_{it}, y_{it}, n_{it}, m_i, \bar{l}) = V_i(v_{it}, y_{it}, n_{it}, m_i). \tag{23}$$

The firm's NPV from lending to consumer i is analogous to Equation (10).

A.2 PAYGo with Extra Punishment for Non-Payment

The Consumer's Problem The state variable is now $x_{it} = (v_{it}, y_{it}, n_{it}, m_i, a_{it})$, where a_{it} denotes the number of periods that the consumer's device will remain locked. Let $U_i^{\text{punish}}(x_{it}; \Gamma)$ denote the value function of consumer i under a PAYGo contract Γ with extra punishment for non-payment, which is henceforth suppressed. While in repayment and not locked (i.e., for $n_{it} \geq 1$ and $a_{it} = 0$), the Bellman equation for the consumer is

$$\begin{aligned} U_i^{\text{punish}}(v_{it}, y_{it}, n_{it}, m_i, 0) = \max\Big\{& v_{it} + u(y_{it} - m_i) + \beta\mathbb{E}[U_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it}-1, m_i, 0)|x_{it}], \\ & u(y_{it}) + \beta\mathbb{E}[U_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, \bar{a}-1)|x_{it}]\Big\}. \end{aligned} \tag{24}$$

While in repayment and locked (i.e., for $n_{it} \geq 1$ and $a_{it} \geq 1$), the Bellman equation for the consumer is

$$\begin{aligned} U_i^{\text{punish}}(v_{it}, y_{it}, n_{it}, m_i, a_{it}) = \max\Big\{& u(y_{it} - m_i) + \beta\mathbb{E}[U_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it}-1, m_i, a_{it}-1)|x_{it}], \\ & u(y_{it}) + \beta\mathbb{E}[U_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, \bar{a}-1)|x_{it}]\Big\}. \end{aligned} \tag{25}$$

If a consumer misses a payment, she will be locked for $\bar{a}$ consecutive periods starting from the current period, irrespective of whether she repays in the next $\bar{a}-1$ periods. The boundary condition is ownership (i.e., $n_{it} = 0$):

$$U_i^{\text{punish}}(v_{it}, y_{it}, 0, m_i, a_{it}) = \Pi_i(v_{it}, y_{it}), \tag{26}$$

where $\Pi_i(v_{it}, y_{it})$ is defined as in Equation (3).

Firm Profit While in repayment and not locked (i.e., for $n_{it} \geq 1$ and $a_{it} = 0$), the Bellman equation for the firm's value function is:

$$\begin{aligned} V_i^{\text{punish}}(x_{it}) = & A_i^{\text{punish}}(x_{it})\big(m_i + \delta\mathbb{E}[V_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i, 0)|x_{it}]\big) \\ & + (1 - A_i^{\text{punish}}(x_{it}))\delta\mathbb{E}[V_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, \bar{a} - 1)|x_{it}] \end{aligned} \tag{27}$$

where $A_i^{\text{punish}}(x_{it})$ is the consumer's optimal repayment policy. While in repayment and locked (i.e., for $n_{it} \geq 1$ and $a_{it} \geq 1$), the Bellman equation for the firm's value function is:

$$\begin{aligned} V_i^{\text{punish}}(x_{it}) = & A_i^{\text{punish}}(x_{it})\big(m_i + \delta\mathbb{E}[V_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i, a_{it} - 1)|x_{it}]\big) \\ & + (1 - A_i^{\text{punish}}(x_{it}))\delta\mathbb{E}[V_i^{\text{punish}}(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i, \bar{a} - 1)|x_{it}] \end{aligned} \tag{28}$$

where $A_i^{\text{punish}}(x_{it})$ is the consumer's optimal repayment policy. The terminal boundary condition for the firm is analogous to Equation (9). The firm's NPV from lending to consumer i is analogous to Equation (10).

B Computation

B.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 $\bar{y}e^{-\frac{\sigma_{\bar{y}}^2}{2} + 3\times\sigma_{\bar{y}}}$. 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 amount of liquidity that the consumer withdraws. That linearly spaced grid ranges from

\$0 to \$250 and has size $\textit{GridSizeLiq} = 100$. Finally, we construct four grids for the four maturity-choice shocks, each of size $\textit{GridSizeUShock} = 9$. In the repayment stage, we use a grid for the current usage value of size $\textit{GridSizeVtoV0} = 3$, i.e., the device provides its initial usage value, half of initial value, or 0 to the consumer.

Repayment Stage. We first solve for ownership value $\Pi_i(v, y)$, where v is the usage 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 mean income $\bar{y}_i$ (as it affects the expected dynamics of income). It is thus solved separately for each point on the 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 (usage value, current income, number of remaining payments on the contract), we find consumers' value function as the limit of

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

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 mean income on the grid, it is solved for $\textit{GridSizeD} \times 4 \times \textit{GridSizeYLRM}$ 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 $O(v, y)$ via VFI. We start by obtaining the terminal value if the consumer chooses to buy with cash

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

where L is the amount of liquidity that the consumer withdraws, c is her consumption and the budget constraint is: $c + p = y + L$. This problem is solved separately for each point on the mean income grid (hence the i subscript).

Finally, we calculate $O_i(y)$ as the solution of the following VFI: $O_i^k(y) = \max \Big\{ u(y) + \beta \mathbb{E}[O_i^{k-1}(y')|y], G_i(y) \Big\}$. Again, this step is done for each point on the grid for 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 and the amount of liquidity to withdraw. These along with income pin down her consumption. We then select the optimal downpayment and the amount of liquidity to withdraw, which also delivers the value of choosing contract j, $W_i(x;\Gamma^j) + \xi_j + \omega_j$. 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 (10) and obtain the firm's NPV.

B.2 Simulation

We simulate a sample of 10^6 consumers and their dynamics from $t = 0$ to $t = 104$ weeks. We always fix random seed in the simulation. We draw the time-invariant characteristics $\bar{y}_i$ 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 steady 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 $y_0/\bar{y} \times \bar{y}$. 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 $y_0/\bar{y} \times \bar{y}$. By comparing the highest $W_i(\Gamma^j)+\xi_j+\omega_{ij}$ to O_i, we obtain both the consumer's take-up decision and maturity choice.

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

To simulate the repayment dynamics, we first draw a sequence of usage values v_{it}/v_{i0} for takers. Then, we linearly interpolate the value function if a consumer chooses to repay from the grids of $y_0/\bar{y} \times v_t/v_0 \times \bar{y} \times d \times n$ to the simulated consumer dynamics. We do the same for the value function if the consumer chooses not to repay. Comparing the simulated value when a consumer repays or not yields the simulated repayment dynamics. This simulation is done sequentially from $t = 1$ to $t = 104$.

B.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: $W(\Gamma^*)+\xi_{\Gamma^*}+\omega_{\Gamma^*} = B(\hat{y}_0)$ where $B(\hat{y}_0)$ is the value of the benchmark with the higher income process $\hat{y}_t$. $\hat{y}_t = (1+\mathcal{W})y_t$ if $t \leq 104$ and y_t otherwise.

Per definition, $B(\hat{y}_0)$ is the maximum among the outside option in the model and the values from a menu of contracts with 100% required minimum downpayment, both with the higher income process. We denote the former as $\hat{O}(\hat{y}_0)$ and the latter as $\hat{W}_i(\Gamma^{j,\text{down}=100\%}), j \in J$. $\hat{O}(\hat{y}_0)$ entails the solution of a dynamic programming problem where the consumer chooses whether to buy with cash optimally in each period, Hence, neither $\hat{O}(\hat{y}_0)$ or $B(\hat{y}_0)$ can be represented as an analytical function of $\mathcal{W}$ and no closed-formed solution exists for our welfare measure. Instead, we solve for it numerically for each consumer type (defined by its date-0 income y_{i0} and its mean income $\bar{y}_i$). Given the large size of possible consumer types, we minimize computing time by solving on a discrete grid: we define an extra grid for the proportional increase in income of size *GridSizeExtraInc* = 200 that ranges from 0% and 100%, and calculate the value of a consumer under the benchmark for welfare who enjoys an increase in income over a period of two years ($0 \leq t \leq 104$) for every level on this grid.

Computing $\hat{O}(\hat{y}_0)$ is different than computing the outside option since the proportional increase in income affects consumers for a finite horizon of two years. We first define the option value as $\hat{O}(\hat{y}_t, t)$. As the proportional increase in income exists for a finite period, this option value depends on the time t. For $t > 104, \hat{O}(\hat{y}_t, t) = O(y_t)$. 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

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

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

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

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 $\mathcal{W}$ is received only for two years. $\hat{\Pi}(v_{t+1}, \hat{y}_{t+1}, t+1)$ is also calculated via backward induction. We next solve for $\hat{W}_i(\Gamma^{j,\text{down}=100\%}), j \in J$ which is an aggregation of date 0 value of putting 100% downpayment and future value of phone ownership under the altered income process $\hat{y}_t$. The solution of the latter also uses backward induction.

With $\hat{O}(\hat{y}_0)$ and $\hat{W}_i(\Gamma^{j,\text{down}=100\%}), j \in J$, we solve for $B(\hat{y}_0)$. $\mathcal{W}$ corresponds to the increase such that $B(\hat{y}_0)$ is the closest to $W(\Gamma^*) + \xi_{\Gamma^*} + \omega_{\Gamma^*}$. Using a grid size of 200 for $\mathcal{W}$ allows us to minimize computational error. We obtain $\mathcal{W}$ on the grid for consumer types and then get $\mathcal{W}$ for every consumer in our simulations through linear interpolation.

B.4 The TikTak Algorithm

Our SMM uses the TikTak algorithm, which has 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^{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^*}.

B.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 $(J' K_{\mathbf{mm}}^{-1} J)^{-1}$.

B.6 Competitive Terms

Competitive terms correspond to the multiple and minimum downpayment requirement that maximize welfare per individual, $\mathcal{W}_{pop}$, while leaving zero profit for the firm. To solve for competitive terms, we use a penalty method with multiple starts. We define an objective function with penalty coefficient η $\Lambda(M|\eta) = \mathcal{W}_{pop}(M) - \eta \times \mathbb{E}[\text{NPV}|M]^2$, 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 $N_\star = 10$ sets of contracts terms 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 maximization for $\Lambda(M|\eta_1)$, then use the resulting contract as a starting point to maximize $\Lambda(M|\eta_2)$, and repeat until η_{N_η}. This delivers a set of 10 optimal contracts (corresponding to each of the initial 10 contracts) and the zero-profit welfare-maximizing contract corresponds to the best of these 10 contracts.

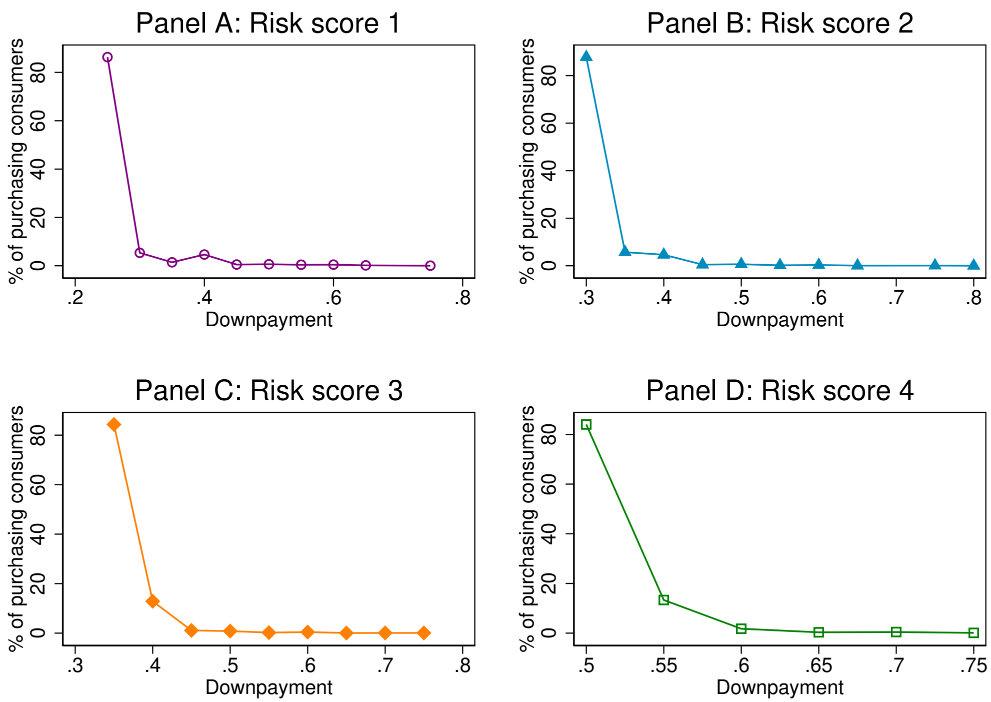
We verify this solution with a brute force method. For each level of downpayment from 0 to 1 on a grid of size 200, we solve for the multiple that yields zero profit. As multiple and downpayment are complements in profit, the zero-profit-line in a 2-D plane of multiple and downpayment is downward sloping. We then calculate $\mathcal{W}_{pop}$ for each point on this zero-profit line. The competitive terms 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.

B.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 uses 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.

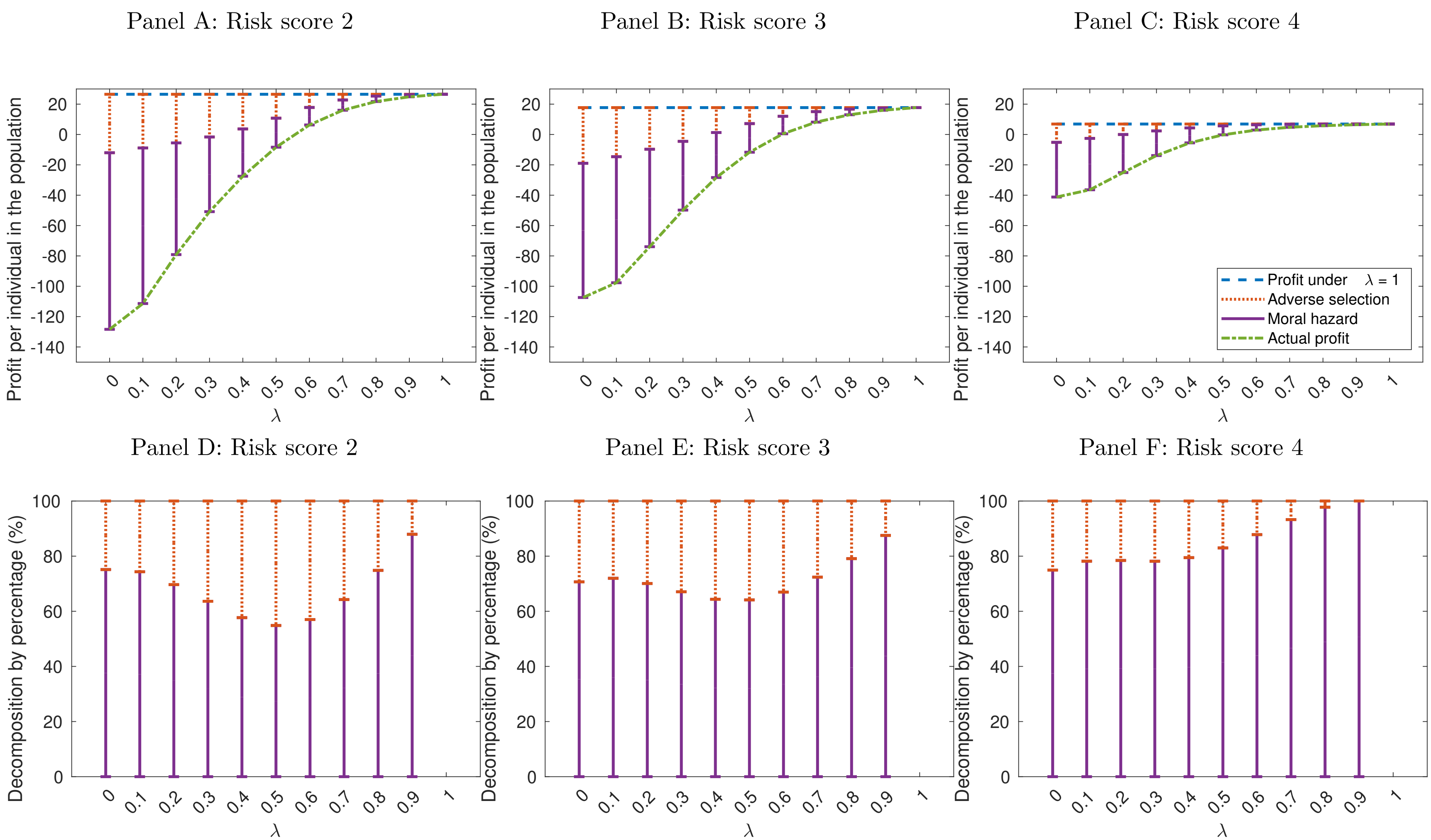
C Additional Figures

Figure A1: Histogram of Downpayments by Risk Score



Note: The figure reports the histogram of selected downpayment in the control multiple / control downpayment arm 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.

Figure A2: Decomposition of Effects of λ into Moral Hazard and Adverse Selection



Note: This figure replicates Panels C and Panel D in Figure 8 for risk scores 2, 3, and 4. Panel A shows the take-up rates for each λ. Panel B shows the average share of contract repaid at maturity. Panel C decomposes the loss in overall profit due to (a) weaker screening and (b) weaker incentives.

D Additional Tables

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 at maturity	180.2	117.9	160.6	11.4	403.8	208.2	187.8	166.7	115.2
Total amount paid at maturity / Amount due	0.74	0.32	0.88	0.05	1.00	0.77	0.74	0.71	0.71
If fully repaid at maturity	0.32					0.36	0.31	0.29	0.30
If fully repaid within two years	0.74					0.77	0.75	0.70	0.70
Time taken to complete / Maturity	1.14	0.44	1.02	0.82	1.86	1.12	1.16	1.14	1.11

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 consumer, 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.

Table A2: 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				
3 month	17.0%/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%
	16.6%/16.4%/16.0%/15.8%	*16.9%/16.2%/16.7%/16.2%*	*15.2%/14.4%/15.6%/14.9%*	*11.7%/11.3%/13.2%/12.8%*
	(0.3/-1.4/0.2/-0.1)	(0.4/-1.8/0.3/0.6)	(0.6/-0.9/0.7/-1.6)	(0.9/-1.4/-0.2/-0.1)
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%
	23.1%/22.2%/23.5%/22.7%	*23.8%/22.3%/24.4%/23.0%*	*21.5%/20.0%/22.4%/20.9%*	*10.9%/10.3%/12.3%/11.7%*
	(0.2/-0.2/0.1/-1.1)	(-0.6/0.0/0.3/0.2)	(-0.3/-1.1/0.3/0.5)	(-2.0/-0.7/2.2/3.1)
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%
	15.0%/12.5%/16.2%/13.4%	*15.1%/13.1%/15.9%/13.7%*	*11.8%/10.4%/12.4%/10.9%*	*4.3%/4.0%/5.1%/4.6%*
	(0.0/-0.6/1.8/-0.4)	(-1.5/-1.2/2.3/1.7)	(-2.1/0.2/1.5/1.0)	(-1.6/0.6/2.1/1.2)
12 month	7.5%/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%
	7.4%/6.5%/7.9%/7.0%	*7.9%/7.1%/8.4%/7.5%*	*5.5%/4.9%/5.8%/5.1%*	*2.0%/1.8%/2.3%/2.1%*
	(0.1/0.3/0.5/1.3)	(-0.7/0.1/-0.7/1.4)	(-2.0/1.9/0.4/2.9)	(-1.0/0.9/1.0/1.5)
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%
	62.0%/57.6%/63.6%/59.0%	*63.7%/58.6%/65.4%/60.3%*	*54.0%/49.7%/56.2%/51.9%*	*28.9%/27.4%/33.0%/31.2%*
	(0.5/-1.5/2.0/-0.6)	(-1.8/-2.1/1.8/2.6)	(-2.1/-0.6/2.0/1.2)	(-1.8/-0.9/2.7/3.1)
Repayment				
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%
	82.7%/79.2%/81.2%/76.7%	*79.6%/75.9%/76.0%/71.4%*	*77.1%/73.1%/72.6%/67.7%*	*82.3%/78.9%/72.7%/67.7%*
	(-0.7/-0.2/-0.2/-0.5)	(0.9/1.2/0.6/1.8)	(0.6/0.4/-0.8/3.7)	(-0.7/-1.5/0.5/2.1)
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%
	83.3%/80.2%/80.4%/77.1%	*83.4%/80.7%/80.6%/77.1%*	*80.6%/76.9%/76.9%/72.5%*	*81.7%/78.8%/74.9%/70.5%*
	(-1.6/-1.2/-0.4/0.2)	(-3.6/-2.3/-0.4/-2.8)	(-3.8/-3.3/-1.8/0.1)	(-1.9/-4.2/-2.9/-0.5)
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%
	80.0%/77.7%/77.4%/74.6%	*81.0%/78.5%/78.7%/75.6%*	*77.9%/74.6%/75.5%/71.3%*	*76.8%/74.2%/72.3%/68.4%*
	(-3.5/-3.2/-0.8/-1.9)	(-4.4/-4.5/-4.1/-2.0)	(-4.4/-1.7/-2.0/-4.0)	(-1.7/-3.2/-2.5/-0.1)
12 month, at maturity	73.8%/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%
	74.7%/72.3%/72.0%/69.1%	*75.2%/72.9%/73.1%/70.4%*	*71.4%/68.6%/69.2%/65.7%*	*68.9%/67.2%/65.4%/62.2%*
	(-0.3/-2.8/-3.7/-1.3)	(-4.0/-4.9/-2.9/-2.7)	(-1.3/-2.7/-2.4/-1.7)	(-1.3/-0.5/-0.0/-2.8)
All loans, at maturity	78.0%/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%
	81.3%/78.5%/78.8%/75.5%	*80.8%/77.9%/78.0%/74.4%*	*78.1%/74.5%/74.6%/70.2%*	*80.3%/77.4%/72.9%/68.5%*
	(-3.2/-3.4/-2.3/-1.7)	(-5.3/-4.7/-3.0/-2.7)	(-4.4/-3.8/-3.3/-0.7)	(-2.4/-5.2/-2.7/0.0)
Dif. in repayment 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%
	4.5%/4.2%/4.7%/4.4%	*4.6%/4.4%/4.8%/4.5%*	*5.2%/5.0%/5.2%/5.0%*	*4.7%/4.6%/4.8%/4.5%*
	(1.5/1.2/1.4/3.1)	(-0.2/1.9/-0.3/2.7)	(-1.5/0.7/0.8/3.0)	(-1.4/0.3/2.0/-0.5)
Share of perfect repayers	42.7%/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%
	42.8%/37.9%/39.2%/34.5%	*41.9%/36.7%/37.7%/32.8%*	*37.5%/32.1%/33.0%/27.9%*	*40.8%/35.3%/29.9%/25.0%*
	(-0.1/0.3/0.9/0.7)	(-0.2/1.8/0.7/-0.2)	(1.4/0.7/-0.9/2.0)	(2.1/-0.3/0.0/1.6)
Cond. prob. of resuming payment	16.6%/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%
	16.2%/17.8%/17.1%/17.8%	*15.4%/17.1%/16.3%/17.2%*	*13.2%/14.3%/13.8%/14.0%*	*9.8%/11.2%/11.9%/12.3%*
	(-0.0/0.7/1.2/1.1)	(-2.4/1.9/-0.7/2.2)	(-1.0/-0.1/-0.9/1.2)	(-2.0/0.5/-0.1/0.3)
Share of defaulters	21.9%/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%
	26.4%/27.4%/28.6%/30.3%	*26.8%/28.3%/29.2%/31.3%*	*30.7%/32.9%/33.5%/36.4%*	*30.3%/31.9%/35.4%/38.6%*
	(-2.4/-1.8/-2.0/-1.6)	(-2.5/-1.7/-3.6/-0.7)	(-2.4/-1.6/-1.0/-1.3)	(-2.7/0.6/0.7/-2.3)
Downpayment				
Average downpayment	26.6%/26.5%/22.2%/22.0%	31.1%/30.8%/26.0%/26.2%	36.0%/36.0%/31.0%/31.0%	51.0%/50.6%/41.8%/42.4%
	26.2%/26.8%/21.7%/22.5%	*30.7%/31.1%/26.0%/26.5%*	*35.7%/36.0%/31.0%/31.4%*	*50.7%/51.0%/41.1%/41.6%*
	(1.8/-0.9/1.4/-1.1)	(2.9/-1.2/0.1/-1.3)	(1.7/-0.2/0.1/-1.5)	(0.9/-1.1/1.6/1.6)
Error	88.2	190.2	161.3	130.9

Note: This table reports the sample moments along with simulated moments for each risk score. 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.