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

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Abstract

The rapid expansion of digital financial products in low- and middle-income countries has increased access to credit but raises important questions about their welfare effects. Pay-as-you-go (PAYGo) financing is one such product, relying on lockout technology that allows lenders to remotely disable the collateral's flow benefits when borrowers miss payments. This paper quantifies the welfare effects of PAYGo financing. We build a dynamic structural model of consumer behavior and estimate it using a large-scale, multi-arm 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 borrowers and those in the middle of the income distribution. Under plausible assumptions, PAYGo dominates traditional secured loans for all but the riskiest consumers. We explore contract design and show that variations of PAYGo contracts can deliver further welfare improvements.

1 Introduction

Consumer lending markets are fraught with economic frictions–moral hazard, adverse selection, and limited enforcement–that raise interest rates and limit access to credit. Recent technological innovations have fueled the growth of digital financial products aided by mobile phones, digital payments, and better data.[1][2] Yet despite this recent growth, little is known about their economic effects. What are the welfare implications of these products, and to what extent can technology mitigate traditional frictions? We address these questions in the context of a novel financial product: pay-as-you-go (PAYGo) financing.

PAYGo financing is a loan secured by the flow services of a durable good. A small down payment gives the borrower possession (e.g., of a smartphone), followed by frequent mobile payments. If a payment is missed, the embedded "lockout technology" allows the lender to remotely disable the device. Over the past decade PAYGo has grown rapidly, financing solar systems, smartphones, and other durables, with many lenders also offering follow-up loans or credit lines once initial contracts are completed.[3]

It is useful to compare PAYGo to secured lending, where collateral is repossessed after default. Collateral provides three functions: screening, repayment incentives, and insurance for the lender in case of default. PAYGo keeps the first two but drops the third. Its advantages are avoiding repossession costs—especially important when collateral is low-value—and offering more flexible repayment for borrowers with volatile incomes. Its disadvantages are the cost of lockout technology, the loss of insurance, and the ex-post inefficiency of disabling the good after missed payments. We relate PAYGo financing to other forms of consumer credit in more detail in Section 2.2.

Our goal is to quantify the welfare implications of PAYGo lending—specifically, how much borrowers gain from access and how PAYGo compares to more traditional contracts. We build a dynamic model with stochastic income, endogenous contract choice, and strategic repayment, and estimate it using a large-scale randomized experiment conducted by a fintech lender in Mexico. The experiment varied both multiples (financing costs) and minimum down payments, and we observe detailed post-purchase behavior. This design allows us to recover borrower preferences and income dynamics, quantify welfare gains, and run counterfactuals

[1]According to the World Bank, in 2021, 76% of adults worldwide had an account at a financial institution or through a mobile money provider, up from 51% 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 rose 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 had risen from 22% in 2018 to 38% in 2021, and African PAYGo solar companies received 72% of the sector's investment. Source: Off-Grid Solar Market Trends Report 2022 by GOGLA.

that highlight the underlying frictions.

Our partner for this study (the lender) is a leading PAYGo smartphone lender in emerging markets, serving low-income borrowers often excluded from traditional credit products.[4] Borrowers choose among four maturities (3, 6, 9, 12 months), each with a multiple that rises with maturity and a minimum down payment tied to a risk score. 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 down payments.

The experimental data reveals three stylized facts about consumer behavior that guide our modeling choices. First, demand varies sharply by risk score: low-risk consumers are highly elastic to multiples, while high-risk consumers shift into longer maturities when multiples rise. Second, we find evidence of asymmetric information and moral hazard: higher multiples lower repayment rates (especially among high-risk borrowers), while higher down payments improve repayment for most groups. Finally, there is strong selection on maturity—repayment rates are much lower on longer maturity contracts.

To account for these facts, we develop a structural model of contract choice and repayment. Consumers are rational agents facing a stochastic income process and differ ex ante by their expected and current income, which is privately observed and gives rise to adverse selection in both take-up and maturity choice. Longer maturities, with lower weekly payments, are more attractive to lower-income consumers. Repayment depends on income shocks: borrowers weigh the device's flow services against other consumption, and negative shocks raise the marginal utility of consumption and lower repayment likelihood.

We estimate the model using Simulated Method of Moments (SMM), targeting moments on take-up, maturity choice, and repayment observed in the pricing experiment. The model is therefore disciplined to replicate how consumers respond to variation in multiples and minimum down payments. We use four treatment arms for estimation and reserve the other four for validation. Given the heterogeneity evident in the reduced-form evidence, we estimate the parameters of the model separately for each risk score. For each score, 13 structural parameters are estimated using 52 moments. The model provides a good overall fit: with a few exceptions, it replicates consumer behavior—take-up, maturity, down payment, and repayment—both in- and out-of-sample. The estimates suggest that the average consumer earns close to the minimum wage, faces substantial income risk, values phone usage highly, and is liquidity constrained. As further validation, we recover higher income volatility and lower usage values for consumers the lender classifies as riskier ex-ante.

We next turn to counterfactual analyses to understand the economic consequences of

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

PAYGo financing. Our first exercise quantifies the welfare gains from access to PAYGo by comparing consumer welfare in the estimated model to a no-financing benchmark. Since some consumers may have alternative sources of credit, this benchmark should be viewed as an upper bound on welfare gains. We measure these gains as the percentage increase in income over a two-year horizon—the expected lifespan of the smartphone—that makes consumers indifferent between no financing and access to PAYGo contracts.

Our findings indicate sizable welfare gains, equivalent to a 3.4% average increase in income under the lender's baseline pricing. Gains are larger for less risky consumers and those with intermediate incomes: for instance, the average low-risk borrower experiences a 4.8% increase. At the same time, PAYGo is highly profitable for the lender, with annualized returns of 143–201% across risk scores. Such high profits suggest that imperfect competition may dissipate part of the potential welfare gains. We therefore consider a competitive pricing counterfactual in which prices are set so that the lender's internal rate of return (IRR) is 25% for each risk score. Under competitive pricing, multiples and down payments fall by 14% and 48% on average. Multiples decline most for low-risk borrowers, while down payments fall most for high-risk borrowers. Welfare gains are 79% higher than under baseline pricing, equivalent to a 6.0% income increase. These gains reflect both the intensive margin—takers face lower multiples—and the extensive margin, as take-up rises among liquidity-constrained borrowers.

Our second counterfactual compares PAYGo to a "traditional" secured loan, in which the lender repossesses smartphones after default. Such contracts are not observed in practice—likely because they are unprofitable—but they provide a useful benchmark for evaluating PAYGo's welfare effects. We compute competitive prices for secured loans under different repossession costs. As these costs rise, multiples and down payments increase, take-up declines, and repayment improves due to stronger screening. The net effect is that consumer welfare falls with higher repossession costs.

With reasonable repossession costs, PAYGo dominates secured lending for lower-risk consumers, while secured loans yield higher welfare for the riskiest. This reflects a key trade-off: secured lending provides stronger screening and repayment incentives, but repossession is more inefficient than lockout due to recovery costs and the lost value from reallocating the device. Low-risk consumers–who have higher usage value– have strong repayment incentives under PAYGo and see little benefit from the added discipline of secured lending, while the deadweight loss from repossession is large. For high-risk borrowers, the opposite holds: the stronger incentives of secured lending lead to a sharp reduction in prices, which outweighs the costs associated with repossession.

These 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 of payments before the device locks. Leniency improves insurance against income shocks but weakens screening and repayment incentives, raising competitive prices. Our quantitative analysis shows that welfare gains are hump-shaped in leniency. Starting from the standard PAYGo contract (no leniency), moderate leniency raises take-up because consumers value the added insurance while prices remain manageable. Beyond a point, however, further leniency drives prices high enough to reduce take-up. The optimal contract with leniency raises welfare by 5–14% compared to the standard PAYGo contract.

We next examine lock strength as another margin of insurance. In our setting, the phone is effectively unusable when locked, reflecting a strong lock. More forgiving versions are feasible—for example, disabling only certain features or locking the phone part of the week. We therefore consider contracts with varying degrees of lock strength. Weaker locks provide more risk-sharing but dilute repayment incentives. Empirically, the incentive effect dominates: across all risk scores, welfare gains under weaker locks are lower than under the standard PAYGo contract.

We entertain two variations of the PAYGo contract that provide consumers with stronger incentives for repayment (and thus lower prices) than PAYGo. The first variation locks consumers for multiple periods after each missed payments. The second variation requires consumers to pay a fee following a missed payment. For all risk scores, we find that neither variation improves welfare compared to the PAYGo contract.

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 down payment, maturity, and repayment, and our estimation relies on a large-scale, multi-arm experiment.

Credit markets are a canonical example of selection markets, where consumers differ both in their willingness to pay and in the costs they impose on lenders. The standard empirical IO approach models these dimensions directly, abstracting from deeper structural primitives. Einav et al. (2010) illustrate how this approach can be applied using exogenous price variation to conduct welfare analysis in insurance markets. DeFusco et al. (2022) extend this framework to quantify welfare losses arising from asymmetric information in an online consumer credit market. This approach is less suitable in our setting where consumers choose both maturity and down payment, which would necessitate strong functional form assumptions to identify their marginal willingness to pay. Second, the approach does not allow us to disentangle moral hazard from adverse selection (Section 5), nor does it facilitate counterfactual analyses of contract design (Section 6.3 and 7). We therefore adopt the alternative approach, which explicitly models the primitives underlying consumers' willingness to pay and lenders' costs. Unique features of the PAYGo contract and our detailed administrative dataset – including the full repayment history and post-purchase usage – allow us to estimate these primitives credibly.

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. Kluender (2023) finds that PAYGo insurance contracts increase take-up by relaxing liquidity constraints. While both findings suggest that PAYGo financing improves welfare, our paper offers a quantitative assessment of such welfare gains. Our paper also contributes to the literature on fintech and consumer welfare in developing countries. Prior work highlights 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, 2024; Agarwal et al., 2025) and to provide a remedy against financial repression (Buchak et al., 2021).[5] We emphasize the role of lock-out technology as a distinctive form of fintech in consumer lending. 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 that combines randomized controlled trials (RCTs) with structural modeling (see Todd and Wolpin, 2023 for a survey). RCTs enhance the credibility of structural methods in two ways. First, they allow for out-

[5]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).

of-sample model validation by using treatment or control groups as holdouts.[6] Second, they provide exogenous variation in treatment that can be used to identify and estimate key structural parameters.[7] Our paper leverages both. The experiment includes a total of eight arms. We use four arms for estimation and the remaining four for validation.

2 Background and Reduced-Form Evidence

2.1 Institutional Background

Smartphones have become a critical tool for economic development (Suri and Jack, 2016), yet remain expensive for many consumers in developing countries. Our partner is a fintech lender that offers PAYGo financing targeted at underbanked households without access to traditional credit. The firm installs a digital lock on financed phones: if a borrower misses a payment, the phone is disabled until payment is made, at which point full functionality is restored. This mechanism promotes repayment and allows the firm to serve consumers who would otherwise be excluded. The lender was an early pioneer in PAYGo smartphone financing and faced little direct competition during the period of our pricing experiment.

The contracts are defined by (1) maturity T, the number of weekly payments; (2) minimum down payment D; and (3) multiple θ. A consumer making a down payment $d_i \geq D$ on a phone priced at p finances $p - d_i$, repaid over T installments of $\theta(p - d_i)/T$. Consumers can make payments in-store or via mobile wallets. If a payment is missed, the phone locks until repayment, but the total number and size of payments remain unchanged. After T payments, the borrower owns the phone and the lock is permanently disabled. Consumers choose among maturities of 13, 26, 39, or 52 weeks. Multiples are the same across borrowers but increase with maturity. Minimum down payments vary with risk score $R \in \{1, 2, 3, 4\}$, with $R = 1$ the safest and $R = 4$ the riskiest.

2.2 PAYGo Compared to Conventional Consumer Financing

Consumers typically rely on two main forms of credit to purchase durable goods. The first is unsecured credit, such as credit cards, which depends on a functioning credit scoring system and incentivizes repayment through future credit access. Credit cards are generally offered only to individuals with established credit histories. The second is secured credit, in which

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

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

collateral can be repossessed, providing incentives for borrowers to repay and security for lenders. Auto loans are a common example of secured credit in consumer finance.

PAYGo differs by embedding repayment enforcement directly into the good itself, allowing remote deactivation when payments are missed. The idea of restricting access for nonpayment is not new—telecom and utility providers often suspend service—but those are service contracts rather than financing. More comparable are smartphone installment plans offered by carriers, which also suspend service if payments are missed. Relative to these, PAYGo introduces two innovations.

The first is *technological*: the lockout system is embedded into the smartphone with patented software that is costless to deploy and resistant to tampering, as confirmed by our empirical analysis. Unlike carrier-offered smartphone installment plans in the U.S., where defaulted phones can often still be used via Wi-Fi or by jailbreaking, locked devices in our setting are nearly unusable aside from emergency calls and contract payments. The second is *contractual*: under PAYGo, borrowers face no penalties for missed payments and regain access immediately after repayment. By contrast, U.S. borrowers typically incur late fees, must clear arrears to restore service, and face damage to their credit scores. These features isolate repayment incentives that stem solely from the phone's usage value, strengthening the identification in our structural estimation and welfare analysis.

PAYGo is particularly well-suited to LMICs, where credit bureaus are underdeveloped and access to formal credit is limited. Our partner lender operates across Latin America, South Africa, and the Philippines. In India, similar lending models have emerged (e.g., DataCultr), and in sub-Saharan Africa, M-Kopa—an early PAYGo pioneer for solar systems—has expanded into smartphones, reaching more than five million customers.[8] A key challenge for some lenders is "phone flashing," where borrowers modify device software to bypass locks.[9] Our partner mitigates this by integrating advanced hardware and software security with manufacturers. While similar technologies (e.g., starter-interruption devices) exist in U.S. auto lending, PAYGo remains rare there—likely because of abundant unsecured credit and robust credit scoring systems.

2.3 Experimental Design and Data

Our study exploits a large-scale pricing experiment conducted by the lender in Mexico between November 2018 and June 2019. Consumers expressing interest in financing were randomly assigned to one of 4×2 treatment groups: four arms that varied the multiple θ

[8]https://african.business/2024/09/apo-newsfeed/leading-fintech-m-kopa-reaches-5-million-customers-unlocking-1-5bn-in-credit-across-5-markets

[9]https://www.standardmedia.co.ke/business/business/article/2001507606

and two arms that varied the minimum down payment D. Table 1 describes these terms. Panel A shows the four multiple arms: the Control arm corresponds to the baseline contract with the lowest multiples, the Medium and High arms increase multiples uniformly across maturities, and the Steep arm makes longer maturities relatively more expensive. Panel B shows the two down payment arms, which depend on the consumer's risk score. In the Lower arm, minimum down payments are reduced by five percentage points for risk scores 1–3 and by ten percentage points for risk score 4. Consumers were assigned uniformly across the four multiple arms (25% each) and, independently, had a 60% chance of being placed in the Control down payment arm and a 40% chance in the Lower arm.

The dataset contains information on demographics, treatment assignment, contract take-up and choice, and repayment behavior over a two-year horizon. In total, 28,786 consumers participated (Table 1). The typical consumer is 32 years old and predominantly male (85%). A majority have a bank account (57%), 21% hold a credit card, and more than half work in the formal private sector. Distribution across risk scores is 24% in risk score 1, 30% in risk score 2, 27% in risk score 3, and 20% in risk score 4. Table A1 in the Online Appendix shows that consumer characteristics are balanced across treatment arms.

In the experiment, 52% of consumers accepted a contract ("takers," Table A2 in the Online Appendix). The average phone price was \$206. Among takers, 29% chose a 3-month contract, 38% a 6-month contract, 22% a 9-month contract, and 11% a 12-month contract. Minimum down payments appear binding: over 80% of takers put down exactly the required minimum (Figure A1 in the Online Appendix). On average, takers made a down payment equal to 31% of the purchase price, financing \$143. They faced an average multiple of 1.70, which implies a weekly payment of \$9.8 over an average maturity of 28 weeks.

Repayment performance was far from perfect. On average, takers repaid 74% of the amount owed by contract maturity. Only 32% repaid in full by maturity, though 74% had repaid in full within two years. On average, full repayment took 114% of the contractual maturity. Panel B of Figure 1 shows a histogram of the share of payments missed across maturities, highlighting inconsistent repayment. About 22% of borrowers missed 50% or more of required payments by maturity, rising to nearly 40% for those on 12-month contracts. Both panels of Figure 1 demonstrate that repayment outcomes worsen with longer maturities.

The implied interest rates on PAYGo contracts are high. Across treatment groups, APRs range from 142% to 360%. Because nominal payments are fixed, however, effective APR declines when repayment is delayed. For example, a 6-month contract in the Control arm has a multiple of 1.54, corresponding to a weekly interest rate of 3.49% or an APR of 182% for on-time repayment. If a borrower pays only every other week, doubling the repayment horizon to a year, the effective bi-weekly interest rate is still 3.49%, but the implied APR falls to 91%.

2.4 Reduced-Form Evidence

This subsection summarizes key patterns in consumer behavior from the pricing experiment, using reduced-form regressions to capture how borrowers respond to variation in contract terms.

We estimate the following specification separately for each risk score R:

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

Here, average multiple$_i$ is the average multiple faced by consumer i in her assigned pricing arm, and $\mathbb{1}_{i \in \text{low min down}}$ is an indicator for assignment to the lower down payment arm. The Steep arm is excluded because it alters the multiple–maturity relationship in a non-uniform way, complicating comparisons. Outcomes Y_i^R include: (i) loan take-up, (ii) log loan maturity, (iii) log down payment, and (iv) the log share of the loan repaid at maturity.

We find that higher multiples significantly reduce take-up, with an average semi-elasticity across risk scores of -0.24 ($t = -5.1$). Low-risk consumers are most responsive, while take-up among risk score 4 borrowers shows little sensitivity (Panel A, Figure 2). One interpretation is that low-risk consumers have better outside options, such as cash financing, than high-risk ones. Conditional on take-up, higher-risk consumers (scores 3–4) respond to higher multiples by shifting into longer contracts (Panel B). These are more expensive overall but have lower weekly payments.[10] In contrast, down payment choices do not respond to multiples (Panel C). Finally, repayment falls with higher multiples: a 1% increase in the average multiple reduces the share repaid at maturity by -0.38 % ($t = -3.8$, Panel D). This elasticity is stable across risk scores. For high-risk consumers, it reflects moral hazard rather than adverse selection, since their take-up does not respond to multiples; for low-risk consumers, both channels may be at play.

Although we find evidence of adverse selection and moral hazard, the magnitude is smaller than in other contexts. For example, DeFusco et al. (2022) report that a one percentage point increase in APR in a Chinese fintech experiment raised missed payments by 0.096. In a comparable regression, we find a semi-elasticity of only 0.039, consistent with the idea that PAYGo contracts mitigate information frictions. This interpretation aligns with Gertler et al. (2024).

[10] Despite this shift, the net effect is positive: across risk scores, the elasticity of weekly payments to multiples is 0.60 ($t = 9.9$).

We also study the effect of minimum down payments on take-up, maturity, and repayment. For each risk score R we estimate:

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

where $\mathbb{1}_{i \in \text{price arm } l}$ indicates assignment to pricing arm $l \in \{\text{Control}, \text{Medium}, \text{High}, \text{Steep}\}$.

The elasticity of actual down payment to the minimum requirement is close to one and significant across risk scores (Panel G, Figure 2), unsurprising given that more than 80% of takers pay exactly the minimum. Higher minimum down payments reduce take-up (Panel E), especially among riskier, liquidity-constrained consumers. On average, higher down payments shorten maturities (Panel F) because they reduce the financed amount and lower weekly payments. Riskier borrowers—who typically prefer longer maturities—are then able to switch to shorter ones. Overall weekly payments fall despite the shift (elasticity = -0.40, $t = -25.6$).[11] Because higher down payments induce positive selection and reduce weekly payments, they also improve repayment across all risk scores (Panel H).

Finally, repayment dynamics vary by maturity. Panel A of Figure 1 shows that while weekly payments decline with maturity, repayment rates at maturity are substantially lower for longer contracts. Panel B shows the distribution of weeks in default, confirming that longer maturities exhibit more frequent and persistent nonpayment. Together, these results highlight maturity choice as an important channel of selection—something we explicitly incorporate into our structural model.

3 Model

3.1 Model Overview

A single firm produces a good that yields flow utility and offers a menu of PAYGo contracts varying in maturity and interest rate. Consumers have heterogeneous, privately observed stochastic income. Each consumer first decides whether to accept a contract and, if so, which one. Accepted contracts require a down payment to take possession of the device. In each subsequent period, after observing income, the consumer decides whether to pay. If a payment is missed, the device locks; once all required payments are made, it is permanently unlocked.

[11] Across risk scores, this elasticity confirms that higher down payments reduce weekly payments net of maturity adjustments.

3.2 Consumers

Consumers (indexed by i) are expected utility maximizers with time-separable, quasi-linear preferences over consumption and device usage: $u(c_{it}) + q_{it}$. Consumption utility follows CRRA, $u(c) = \frac{1}{1-\gamma}c^{1-\gamma}$, with relative risk aversion γ. Consumers discount the future at rate β. At each date t, consumer i receives income y_{it}, which follows a Markov process. At date 0, she may also withdraw liquidity L_i at unit cost μ_i, which can be used for the down payment or initial consumption.[12] Consumers do not have access to any external borrowing or savings technology.

3.3 The PAYGo Contract

A PAYGo contract is defined by the triple $\Gamma \equiv (D, T, \theta)$, where D is the minimum down payment, T is the maturity (the number of payments required), and θ is the multiple. Given Γ and a phone priced at p, a borrower who pays $d_i \geq D$ finances the balance $p - d_i$ with weekly installments of $m = \theta(p - d_i)/T$. If the borrower makes the scheduled payment in period t, the phone is unlocked and delivers usage value $q_{it} = v_{it}$. If the payment is missed, the phone locks and the consumer receives $q_{it} = (1 - \lambda)v_{it}$, where $\lambda \in [0, 1]$ measures the effectiveness of lockout technology. At the two extremes, $\lambda = 1$ implies perfect enforcement (no utility from the locked phone), while $\lambda = 0$ is equivalent to unsecured credit (utility unaffected by payment status). Once T payments are made, the borrower owns the device and it is permanently unlocked.

Each consumer begins with initial usage value $v_{i0} = \bar{v}$. In every period, the device depreciates with probability ϕ, reducing its usage value by $\bar{v}/N_v$. After N_v depreciations, the phone becomes worthless. Formally, if depreciation occurs in period t, usage value evolves according to

$$v_{it} = \max\{v_{i,t-1} - \bar{v}/N_v, 0\}.$$

The firm offers consumers a menu of PAYGo contracts that vary in maturity, multiple, and minimum down payment. Payments are made weekly.[13]

[12] Liquidity withdrawal at purchase is both plausible (e.g., consumers save to buy the phone) and necessary to match observed take-up and repayment patterns. Without it, down payments funded only by date 0 income would imply consumers are too wealthy to explain their repayment behavior.

[13] Prepaying for future weeks is rare in the data and increases the effective interest rate, so we omit it from the model.

3.4 The Consumer's Problem

Consumers in the model make a sequence of decisions. First, they decide whether to accept one of the offered contracts or retain the option to purchase the device later with cash. If a contract is accepted, they choose the down payment. Thereafter, in each period, after privately observing their income and depreciation, the consumer decides whether to make the scheduled payment. We now formalize the consumer's problem and characterize its solution.

Repayment Decisions Fixing a contract Γ and down payment d_i, the payoff-relevant state variable is $x_{it} = (v_{it}, y_{it}, n_{it}, m_i)$, where n_{it} is the number of payments remaining and m_i the weekly payment. Let $U_i(x_{it}; \Gamma)$ denote the continuation value of consumer i under contract Γ (henceforth, the latter argument is suppressed).[14] While in repayment ($n_{it} \geq 1$), the Bellman equation is

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

The optimal policy is to make the payment if

$$\underbrace{\lambda v_{it}}_{\text{extra usage value}} + \beta \underbrace{\mathbb{E}[U_i(v_{i,t+1}, y_{i,t+1}, n_{it} - 1, m_i) - U_i(v_{i,t+1}, y_{i,t+1}, n_{it}, m_i) | x_{it}]}_{\text{future value of reducing obligations}} \geq \underbrace{u(y_{it}) - u(y_{it} - m_i)}_{\text{consumption cost}}.$$

In words, the consumer pays when the extra usage value from being unlocked plus the discounted expected benefit of having one fewer future payment exceeds the immediate utility cost of lower consumption. We denote the repayment decision by $A_i(x_{it})$. 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., permanent unlock):

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

Value of a Contract Given a contract Γ, the consumer chooses how much to put down and how much to consume at date 0, subject to (i) the budget constraint and (ii) the down payment requirement. This problem defines consumer i's ex-ante value of contract Γ, denoted

[14] The subscript i on the value function indicates dependence on consumer-specific characteristics (e.g., mean income) that are fixed over time and not included as state variables.

$W_i(\Gamma)$. Let $m(d_i) = \theta(p - d_i)/T$ be the weekly payment given down payment d_i. Then:

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

Here $\mu_i L_i$ is the cost of withdrawing L_i units of liquidity. We interpret μ_i as consumer i's shadow value of liquidity.[15] This setup allows consumers to trade off liquidity between down payments and consumption, without modeling a full intertemporal savings problem.

Outside Option If no contract is accepted, the consumer retains the option to buy the device with cash at price p at any future date t, or to never purchase it. The outside option is thus a real option with value

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

If the device is purchased with cash, the consumer chooses liquidity withdrawal and consumption accordingly. The value of cash purchase is

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

Maturity Choice: Contract Selection Each consumer faces a menu of contracts $\mathcal{M}_i = \{\Gamma^j\}_{j \in J}$, indexed by maturity j (the number of payments). Contracts with longer maturities involve lower weekly payments but higher multiples. Mirroring the classic logit demand system (Berry et al., 1995; Berry, 1994), each contract Γ^j has a fixed effect ξ_j, and consumers draw an idiosyncratic shock ω_{ij}. These terms capture unobserved heterogeneity and allow the model to match maturity choice.

If all contracts yield lower value than the outside option, i.e., if $\mathcal{M}_i^* \equiv \{\Gamma^j \in \mathcal{M}_i : W_i(\Gamma^j) + \xi_j + \omega_{ij} > O_i(y_{i0})\} = \emptyset$, the consumer does not take up. Otherwise, the consumer

[15] In our empirical specification, μ_i is higher for poorer consumers. Formally, we let μ_i be proportional to the marginal utility of consumption at mean income, i.e. $\mu_i = \mu \times u'(\bar{y}_i)$.

selects the contract from $\mathcal{M}_i$ that delivers the highest value,

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

In our setting, the shocks capture unmodeled heterogeneity in preferences (e.g., discount factors or usage values). Empirically, 37% of takers select the 6-month contract, even though its terms are nearly dominated by either the 3-month (lower multiple) or 9-month (lower payment) options.[16]

3.5 Firm Profit

The firm is risk-neutral and discounts at rate δ. Let $V_i(x_{it}; \Gamma)$ be the firm's expected gross profit from consumer i, conditional on contract Γ and state x_{it}. Profits evolve recursively: if the consumer pays ($A_i(x_{it}) = 1$), the firm receives m_i and continues with one fewer payment; if not, it collects nothing in that period and the number of payments owed is unchanged. Formally,

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

The terminal condition is

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

where K is the lifetime value of a fully repaid customer. In practice, K reflects future business opportunities: for example, in our setting the lender issues follow-up cash loans that also rely on the lockout technology.[17]

At date 0, the firm's expected net present value (NPV) from consumer i under contract Γ is

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

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

[16] Without shocks or additional heterogeneity, the model cannot match observed maturity and repayment patterns. One explanation is payment targeting, where consumers prefer maturities with payments in a targeted range (Argyle et al., 2020). A full microfoundation would require behavioral assumptions (e.g., budgeting heuristics or reference dependence) for which no canonical model exists. We therefore follow the discrete choice tradition and use random utility shocks to capture this unexplained variation.

[17] K derives from future transactions with consumers who have successfully repaid and obtained ownership. For instance, the lender in our study issues subsequent cash loans secured by the same lockout technology.

4 Estimation

We estimate the model by Simulated Method of Moments (SMM), targeting moments of take-up, down payment, maturity choice, and repayment from the pricing experiment.

4.1 Methodology

For estimation, we impose three parametric assumptions:

1. Each period, income is log-normally distributed and i.i.d.:
   $\log(y_{it}) \sim \mathcal{N}\big(\log(\bar{y}_i) - \frac{\sigma^2}{2}, \sigma^2\big)$. [18]

2. Mean income across consumers is log-normally distributed in the population:
   $\log(\bar{y}_i) \sim \mathcal{N}\big(\log(\bar{y}) - \frac{\sigma_{\bar{y}}^2}{2}, \sigma_{\bar{y}}^2\big)$.

3. Random utility shocks are $\omega_{ij} \sim \mathcal{N}(0, \sigma_\omega^2)$ and i.i.d. across consumers and contracts.

For identification, we make several additional assumptions. First, we assume the lockout technology is perfectly effective ($\lambda = 1$). Although a small fraction of consumers may be able to circumvent it, this is unlikely to matter quantitatively.[19] Second, we assume consumers have log utility ($\gamma = 1$). Because maturity choices are informative about discounting but not sufficient to disentangle risk aversion from time preference, fixing $\gamma = 1$ helps identify the discount factor. Third, we assume the device loses half its value with each depreciation shock ($N_v = 2$). The first shock reflects moderate damage (e.g., a cracked screen or battery deterioration), and the second 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.

Finally, we set the phone price $p = \$200$, which corresponds to the average phone price in our sample. In our baseline model, we assume that consumers cannot choose which phone model to purchase, despite the heterogeneity in models and prices observed in the data (see Table A2 in the Online Appendix). We adopt this simplifying assumption because the experimental variation applies only to financing terms, not to phone prices themselves. However, this modeling choice could potentially affect our welfare estimates: all else equal, consumer welfare from PAYGo financing could be higher in a setting where consumers can

[18] Similar results hold with persistent income, but persistence is not well identified and is omitted from the specification.

[19] The lender uses a patented Android-based technology, typically built into the device by the manufacturer.

also adjust the type of phone they buy in response to variations in financing terms. To address this, we also estimate an extended model with endogenous phone choice, calibrated to match the average price in each treatment arm. As shown in Online Appendix A.1, the welfare gains from PAYGo financing remain quantitatively similar in this extended model.

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

We estimate the model separately for each risk score using SMM. For each score, the estimation targets 52 moments, corresponding to 13 moments across the four treatment arms of the pricing experiment. The first set captures take-up and maturity choice: the share of consumers selecting each maturity ($Takeup_3$, $Takeup_6$, $Takeup_9$, $Takeup_{12}$). The second set captures repayment: the share repaid at maturity for each contract ($Repay_3$, $Repay_6$, $Repay_9$, $Repay_{12}$). The third set captures repayment dynamics: the share repaid in the first vs. second half of the contract (Δ_{repay}), the share fully repaid at maturity (p_{perfect}), the probability of resuming payment after a missed installment (p_{resume}), and the share of contracts not fully repaid within two years (p_{default}). Finally, we target the average down payment ($DownPayment$).

We now outline the estimation procedure (details in Online Appendix C). Starting from initial values of Θ, we discretize the state space $x_{it} = (v_{it}, y_{it}, n_{it}, m_i)$ and the initial decisions d_i (down payment) and L_i (liquidity withdrawal).

For a given treatment arm, we set contract terms Γ^j and solve the consumer's value function U_i using value function iteration (VFI) on the grid (Eq. 1).[20] This yields the optimal repayment policy $A_i(x_{it})$, the contract value $W_i(\Gamma^j)$, and the implied down payment choice $d_i(x_{i0})$. Repeating across all contracts in the menu and solving the outside option O_i (Eq. 5) delivers consumers' take-up decision and contract choice Γ_i^* (Eq. 7).

We then simulate 10^6 consumers per treatment arm. We compute contract choice, down payment, and repayment behavior for each simulated consumer using the model solution, and calculate the corresponding simulated moments. Repeating this across the four estimation arms yields 52 simulated moments $m(\Theta) = (m_1, \ldots, m_{52})$ for a given parameter vector Θ. We estimate Θ by minimizing the distance between simulated and empirical moments:

$$\hat{\Theta} = \arg\min_{\Theta}, (m(\Theta) - m)' W (m(\Theta) - m), \tag{11}$$

[20]Backward induction is not feasible since the terminal date depends on repayment behavior.

where W is the inverse of a diagonal matrix of sample variances.[21] Details of the estimation algorithm appear in Online Appendix C.4.

4.2 Estimated Parameters and Model Fit

Table 2 reports the parameter estimates. Estimated average weekly income is similar across risk scores, ranging from \$34 to \$37, just above Mexico's minimum wage during the sample period.[22] Income volatility is substantial and increases with risk score. For consumers in risk score 1, a one–standard deviation shock corresponds to about 35% of mean income (0.35); for those in risk score 4, volatility is considerably 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%,[23] 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.[24] 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, 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 average 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.[25] Yet, 60% of consumers in risk score 1 still purchase the 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,

[21] As a robustness check, we also use alternative weighting matrices, including $W = (K_{\mathbf{mm}})^{-1}$, where $K_{\mathbf{mm}}$ is the variance–covariance matrix of data moments obtained by bootstrapping. Results are similar.

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

[23] 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.

[24] 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.

[25] 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 multiple charged by the lender, which ranges from 1.54 to 1.7.

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.[26]

The estimated discount factor ranges from 0.989 to 0.997, implying annual discount rates between 17% and 78%. These time preferences are consistent with other estimates for poor households in developing countries.[27] The unit cost of withdrawing liquidity at date 0, μ, is similar across risk scores, ranging from 3.1 to 4.5. This implies consumers value an additional unit of liquidity about four times as much as an additional unit of contemporaneous consumption, consistent with severe liquidity constraints documented in reduced-form evidence on 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. In this exercise, we fix the contract menu to that offered in the control arm for risk score 1 and simulate the model for all risk scores. Panels A and B show repayment dynamics. Consumers in risk scores 1 and 2 behave similarly: about 10% miss payments shortly after origination, rising to 35% by maturity, with repayment of roughly 80%. Repayment is significantly worse for risk scores 3 and 4: 15% (30%) miss early, increasing to over 40% (55%) by maturity, with repayment falling to 75% (60%). Panel C shows profitability declines sharply with risk score, from 253% for risk score 1 to –11% for risk score 4.

Model Fit We visually (and exhaustively) assess the fit of the model for consumers in risk score 1 in Figures 4 and 5. The model fit is similar across risk scores (see Figure A5 in the Online Appendix).

Figure 4 shows average take-up rates for all eight experimental arms, overall (Panel A) and by maturity (Panels B–E). Estimation arms are shown in solid font and validation arms in transparent font; empirical rates are in blue and simulated rates in red. The model closely matches take-up across both estimation and validation 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 with model fit stem from the (out-of-sample) Steep multiple arm,

[26]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.

[27]For instance, Carvalho (2010) uses consumption responses to randomized transfers in Mexico's PROGRESA program and, assuming risk aversion of 1 and a real interest rate of 5%, estimates an annual discount rate of 78%.

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 moderate selection into maturities leading to repayment rates that are only modestly lower for 12-month contracts, whereas selection appears to be 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.

Figures A3 and A4 in the Online Appendix show that the model closely replicates additional moments and repayment dynamics: it matches the down payment distribution, captures persistence of default and repayment timing, and reproduces the rise in non-payers at maturity due to mass repayment and shrinking denominators. Table A3 in the Online Appendix reports the full set of targeted moments alongside their simulated values and the SMM errors.

4.3 Identification

In this subsection, we use local comparative statics to illustrate the mechanics of the model and the sources of identification. Panel A of Table A4 in the Online Appendix reports how simulated moments change when varying one parameter while holding the others fixed.[28] These exercises clarify how each parameter maps into consumer behavior.

- **Usage value (v_0) and average income ($\bar{y}$):** Both raise take-up and repayment but affect maturity in opposite directions. A higher v_0 makes being locked more costly and thus increases demand for longer maturities with smaller weekly payments. By contrast, a higher $\bar{y}$ enables larger weekly payments and shifts consumers toward shorter maturities with lower overall financing costs.

- **Depreciation (ϕ):** Higher depreciation lowers repayment in the second half of contracts, raises default, and reduces the probability of resuming payments. It also reduces take-up and shifts consumers toward longer maturities, where repayment performance is most sensitive to depreciation.

- **Income volatility (σ):** Higher income volatility lowers the share of perfect repayers and reduces repayment on short maturities with high weekly payments. In constrast with depreciation, higher income volatility increases the probability of resuming payments.

[28] Because of space constraints, we summarize comparative statics using 13 moments that capture take-up, down payment, maturity choice, and repayment dynamics in the control treatment arm for one risk score.

- **Discount factor (β):** A higher discount factor increases take-up and demand for most maturities (except the 12-month). Its effect on repayment is mixed: higher patience improves repayment on short maturities but worsens repayment on long ones, as lower-income consumers self-select into them.

We next use these insights to explain how parameter estimates differ across risk scores. Table 3 compares moments across risk scores after controlling for multiples and down payments, using risk score 1 as a benchmark. Consumers with risk score 4 exhibit worse overall repayment, higher default, lower probability of resuming payments, and weaker repayment in later periods. Qualitatively, these outcomes are consistent with higher depreciation. Yet higher depreciation also depresses take-up and pushes borrowers into longer maturity contracts, which we do not observe.[29]. Therefore, other parameters must offset these unobserved effects. Indeed, the dispersion of utility shocks is larger for risk score 4, which raises take-up via a love-of-variety effect, while usage value is lower, which dampens demand for long contracts. Mean income is similar across the two risk scores; reducing it would increase demand for longer maturity contracts, inconsistent with the data.

Understanding the estimates for risk score 3 follows a similar logic, though the differences are less pronounced. The comparison between risk scores 2 and 1 is different. Consumers in in risk score 2 do not display evidence of higher depreciation: their repayment profile over the contract horizon, their probability of resuming, and their maturity selection resemble risk score 1. Yet they repay significantly less overall. The estimation therefore attributes the weaker repayment of risk score 2 to other parameters: a lower discount factor, which reduces the future value of ownership and weakens repayment incentives, and higher income volatility, which increases the probability of missing payments even for otherwise solvent borrowers. Relative to risk score 1, risk score 2 consumers are equally attached to the phone but less patient and face more unstable income, which explains why repayment is systematically lower despite similar depreciation dynamics.

Finally, Panel B of Table A4 in the Online Appendix reports the sensitivity matrix (Andrews et al., 2017), which linearly approximates how parameter estimates shift in response to changes in the empirical moments.

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

[29]The lower take-up rate for risk score 4 is explained entirely by higher minimum down payments.

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 profit through two channels. First, more consumers–especially riskier ones–take up the loan. 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 6 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 6, 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 down payment 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 down payment 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 can buy the phone with cash at any date in the future. They also have access to a menu of four contracts with 100% required minimum down payment that mimic the PAYGo contracts offered by the firm. Effectively, this allows consumers to buy the phone without financing and obtain the same utility shock that they would get from each of the PAYGo contracts in the menu they are offered. By doing so, our welfare measure excludes the gains that arise from the random utility shocks due to the "love of variety" effect (Nevo (2003), Petrin (2002)).[30]

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. We focus on welfare over a two-year period as it is commensurate with the expected lifespan of the phone in our setting, as suggested by the estimated depreciation rate.

For takers, $\mathcal{W}_i$ solves:

$$\max_{\Gamma^j \in \mathcal{M}_i} W_i(\Gamma^j) + \xi_j + \omega_{ij} = B_i(\hat{y}_{i0}) \tag{12}$$

where

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

and $B_i(\hat{y}_{i0})$ corresponds to the consumer's value in the no-financing benchmark described above with the augmented income process $\hat{y}_i$. For non-takers, $\mathcal{W}_i = 0$. We defer details on the computation of this benchmark and the welfare measure $\mathcal{W}_i$ to Section C.3 in the Online Appendix. We report 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 $\mathcal{W}_{pop} \equiv \mathbb{E}[\mathcal{W}_i]$.[31]

[30] In our model, welfare gains from the PAYGo financing arises for two broad reasons: (1) because they allow consumers to finance phone consumption, and (2) because they allow consumers to get random utility draws. Our welfare measure allows us to focus on (1) by including in the outside option a menu of contracts with the same utility shocks but no access to financing.

[31] 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

Table 4 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 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 down payment 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 7 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.

6.2 Competitive Pricing

Firm profit across all risk scores and treatment groups is positive and economically significant (Table 4). 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%.[32] Firm profit is increasing in the multiple and remains significantly above zero even in the Lower down payment treatment groups. 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 equilibrium in a model with adverse selection, perfect competition, and where firms offer a menu of different prices for each maturity is not trivial. 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 on average, 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.

income and hence captured by the no-financing benchmark.

[32]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.

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 for each risk score by a pair (d_c, m_c), where d_c is the minimum down payment 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.

In Panel A of Table 5, 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 down payment 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 down payment 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 7, 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 4, 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 Panel B of Table 5, we investigate what proportions of the increases in welfare come from lower multiples or minimum down payment. For risk scores 1 and 2, lower multiples provide about 2/3 of the welfare increase and lower minimum down payments 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 down payment. 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 Comparison to Secured Lending

In this subsection, we compare lockout-enabled PAYGo to a traditional secured loan in which the lender repossesses the collateral after default. The advantage of secured lending is that the lender recovers collateral value, whereas lockout yields no recovery. The disadvantage of a secured loan is that the repossession is costly and may ultimately fail. Moreover, the consequences to consumers from defaulting are more severe than the consequences from missing payments under a PAYGo contract.

To analyze this benchmark, we solve the consumer's take-up and repayment problem under a secured loan, compute firm profits, and derive competitive prices for a range of repossession technologies characterized by $(c_{\text{repo}}, p_{\text{repo}})$, where c_{repo} is the lender's cost of repossession and p_{repo} is the probability of success. Details of the model are in Section B.1 in the Online Appendix. To facilitate our comparison to PAYGo, we focus on competitive prices for the secured loan and compare consumer welfare to our findings in Section 6.2.

Figure 8 reports prices, take-up, repayment, and welfare assuming $p_{\text{repo}} = 1$. As c_{repo} falls, both multiples and down payments decline, making secured loans more attractive. For low-risk consumers (risk score 1), PAYGo and secured lending deliver equal welfare when repossession costs about \$20.3. The welfare-equivalent repossession cost rises with risk score, implying that PAYGo dominates secured lending for safer borrowers but not necessarily for the riskiest. This reflects a central trade-off: secured loans provide stronger screening and repayment incentives but create larger ex-post inefficiencies, since repossession is both costly and permanently reallocates the device. Because lower-risk consumers have higher usage value, they already have strong repayment incentives under PAYGo and the deadweight loss from repossession dominates. For high-risk consumers, by contrast, the stronger repayment incentives of secured lending outweighs the inefficiency of repossession.[33]

7 Contract Design

In this section, we explore whether the PAYGo contract design 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

[33] If $p_{\text{repo}} < 1$, PAYGo becomes even more favorable. For instance, with $p_{\text{repo}} = 75\%$, PAYGo financing matches secured lending at repossession costs of \$22.7, \$21.8, \$19.1, and \$48.5 for risk scores 1–4, respectively. With $p_{\text{repo}} = 50\%$, PAYGo dominates secured lending for all risk scores and any non-negative cost of repossession.

repayment so that its overall effect on welfare gains is ambiguous. This subsection 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 B.2 in the Online Appendix.

Consistent with intuition, Panel D of Figure 9 shows that more lenient contracts worsen repayment incentives. As a result, higher multiples and minimum down payment are required for the lender to break even as the policy becomes more lenient (Panels 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 higher for lower risk scores. The welfare gains at the optimal leniency contract range from 5% to 14% relative to 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., locking only certain apps or features) 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 fosters screening and repayment incentives.

To quantify this trade-off, we evaluate contracts with $\lambda \in [0, 1]$, computing competitive terms and welfare relative to a no-financing benchmark. As shown in Figure A6 in the Online Appendix, a weaker lock raises default and requires higher multiples and down payments. The insurance they provide is outweighed by financing costs: across all risk scores, take-up and welfare gains rise monotonically with λ, making the strongest lock welfare-maximizing.

It is perhaps surprising that leniency can raise welfare whereas a weak lock cannot. Both policies insure consumers against income shocks and weaken enforcement, but they do so in different ways. A leniency policy provides intertemporal insurance by allowing households to defer payments when income is low, shifting obligations into the future while preserving repayment incentives. A weak lock, by contrast, weakens enforcement in every period regardless of income. This distinction explains why leniency can improve welfare, whereas a weaker lock cannot.

7.3 Stringency

Finally, we ask whether more stringent contracts with harsher consequences for missed payments could improve welfare. We examine two variations of the standard PAYGo contract: one in which borrowers are locked for additional periods after a missed payment (Section B.3 in the Online Appendix), and another in which they must pay a proportional fee, $f \times m$, on top of the regular payment m to unlock the phone following a missed payment.

Figure A7 in the Online Appendix shows that locking borrowers for multiple periods raises repayment rates but reduces risk-sharing, leading to lower take-up and welfare. Figure A8 in the Online Appendix illustrates that penalty fees likewise diminish welfare gains. Overall, we find that stricter punishments do not improve efficiency: the standard PAYGo contract already provides too little insurance, and harsher terms only exacerbate this.

8 Conclusion

Pay-as-you-go (PAYGo) financing has rapidly expanded as a credit model in low- and middle-income countries (LMICs). Its defining feature is lockout technology, which allows lenders to remotely and cheaply disable collateral when borrowers miss payments. Using data from a large-scale pricing experiment combined with a structural model, we quantify the welfare implications of PAYGo financing.

Our results show that PAYGo generates substantial welfare gains. Relative to a no-financing benchmark, observed contracts raise welfare by 3.4%—equivalent to an income increase of 3.4% over two years. Because these terms also yield high lender profits, this understates potential gains. Under competitive pricing, welfare gains rise to 7.2% and exceed those from a reasonably calibrated secured loan.

We explore contract design by considering several variations of the PAYGo contract that involve either more insurance or stronger repayment incentives. A leniency policy—allowing borrowers to miss several payments before lockout—delivers higher welfare, as the added risk-sharing outweighs weaker incentives and screening. By contrast, stricter designs such as penalty fees do not improve outcomes. These findings underscore the importance of how lockout technology is applied and point to the value of further research on its optimal use in financial contracting.

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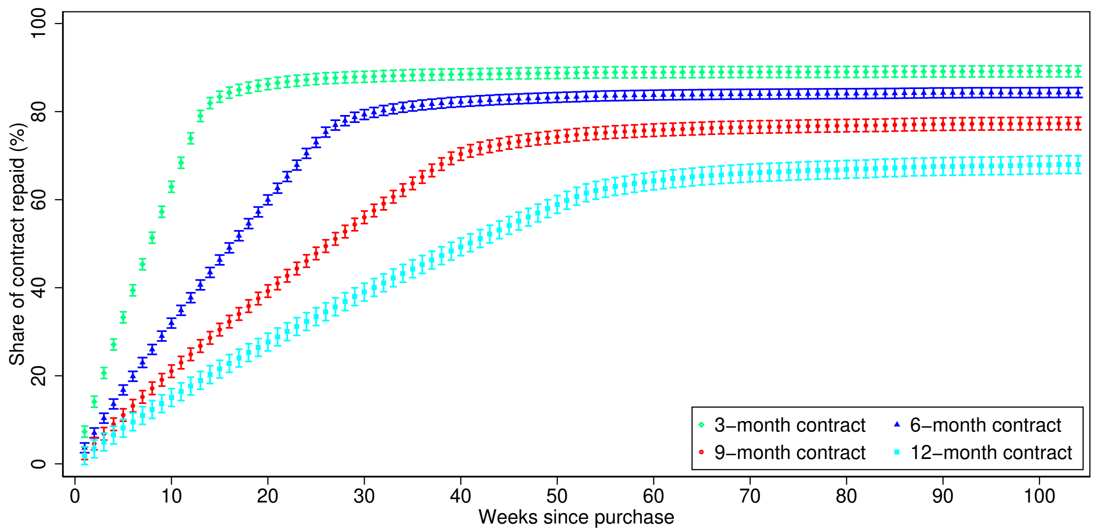
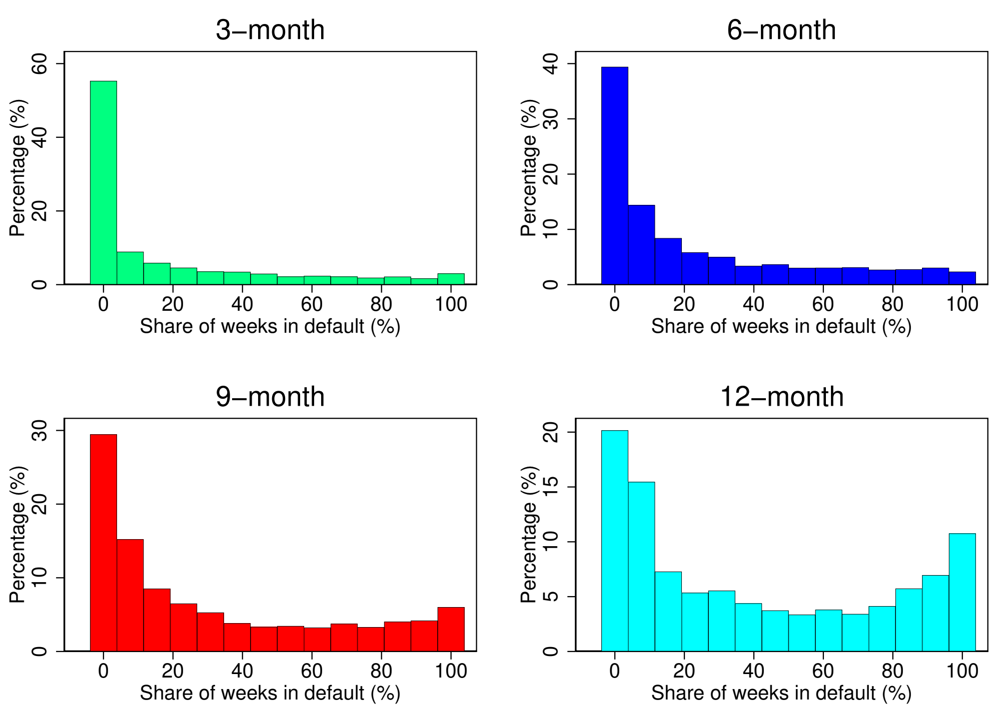
A Figures

Figure 1: Repayment by Maturity

Panel A: Dynamics of the Share of Contract Repaid

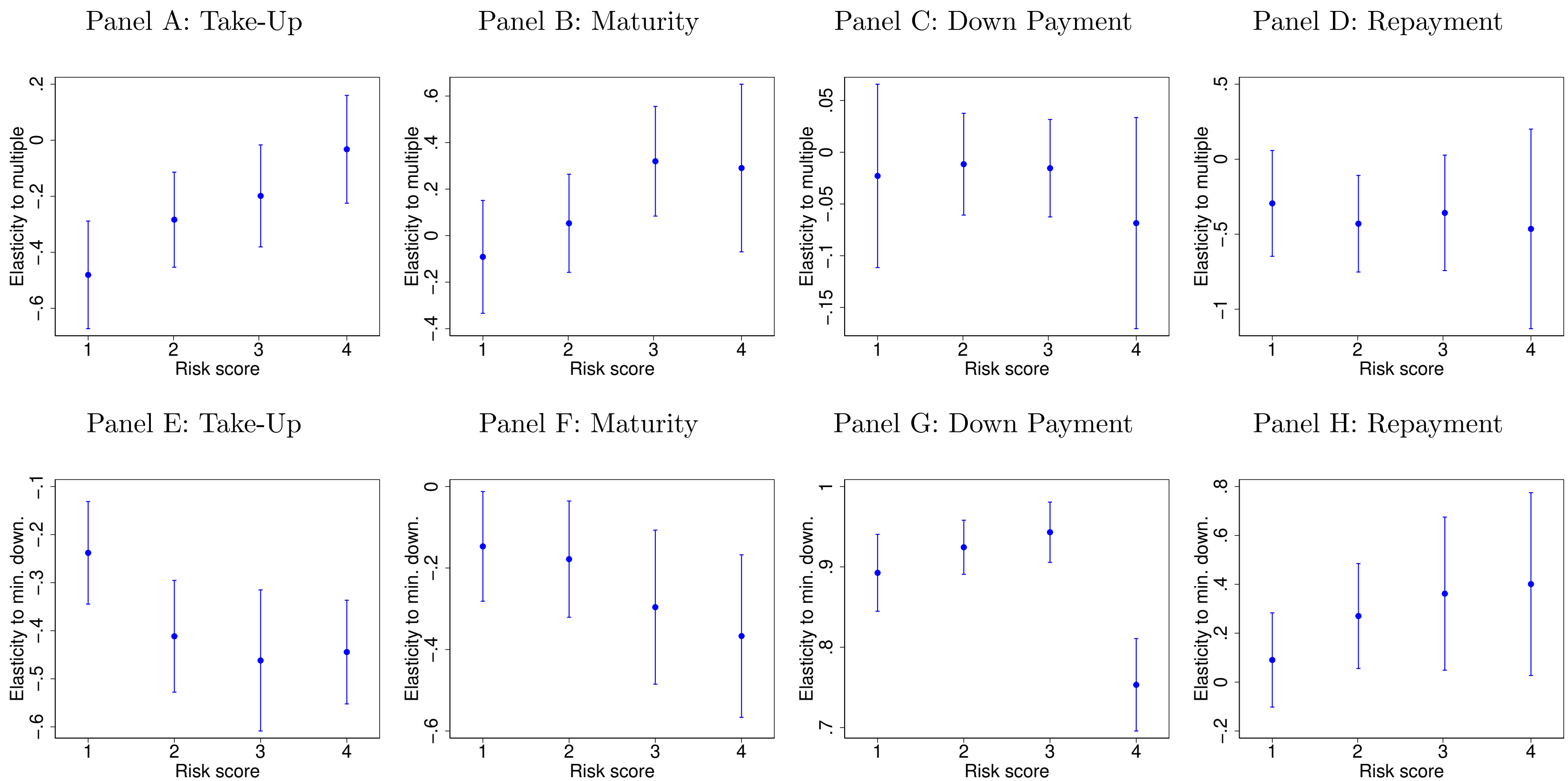


Panel B: Distribution of the Share of Weeks in Default



Note: Panel A shows the share of the contract repaid over time. Panel B shows the distribution of weeks in default (locked) from initiation to maturity. Repayment is averaged across risk scores and treatment groups within each maturity.

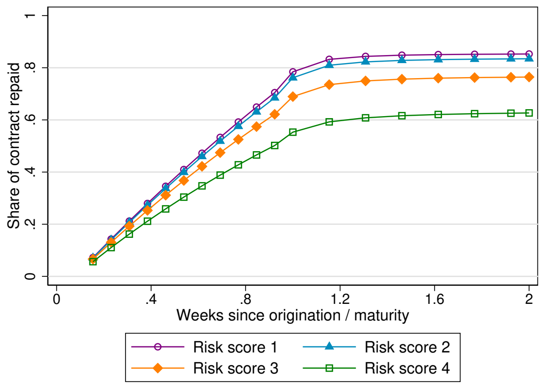
Figure 2: Elasticity to Average Multiple and Minimum Down Payment Across Risk Scores



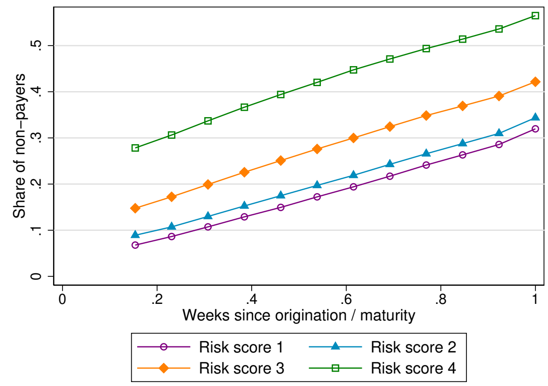
Note: Panels A–D show elasticities with respect to the average multiple; Panels E–H show elasticities with respect to the minimum down payment. Dependent variables are: take-up (A, E), log maturity (B, F), down payment (C, G), and share repaid at maturity (D, H). Elasticities are estimated separately for each risk score, with 95% confidence intervals. To construct these, we regress loan outcomes on log(average multiple) (Panels A–D) or on log(minimum down payment) (Panels E–H), controlling for the other contract dimension.

FIGURE 3: Simulated Repayments Holding Treatment Constant Across Risk Scores

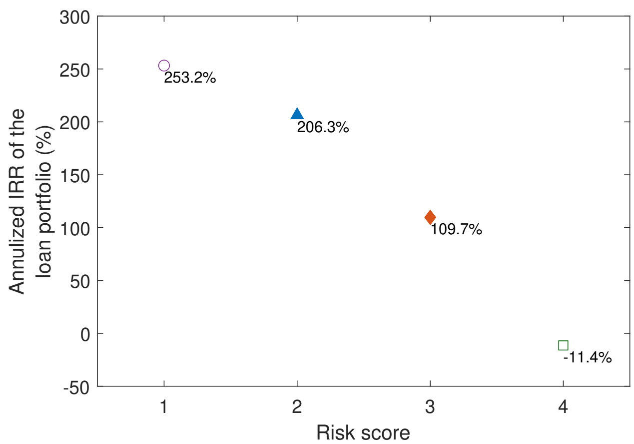
Panel A: Simulated Repayment



Panel B: Simulated Missed Payments



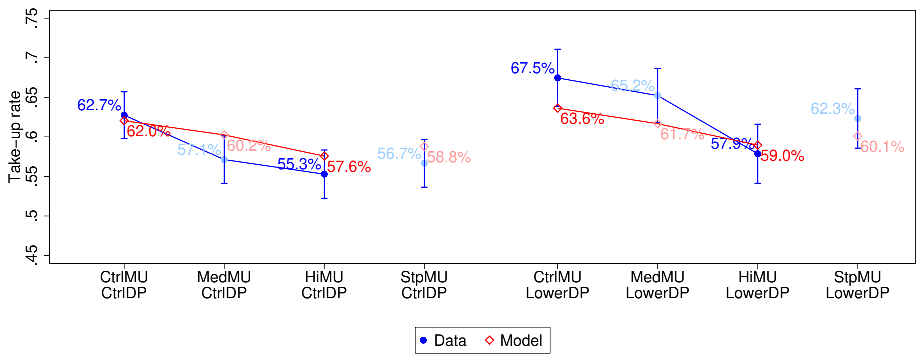
Panel C: Simulated IRR



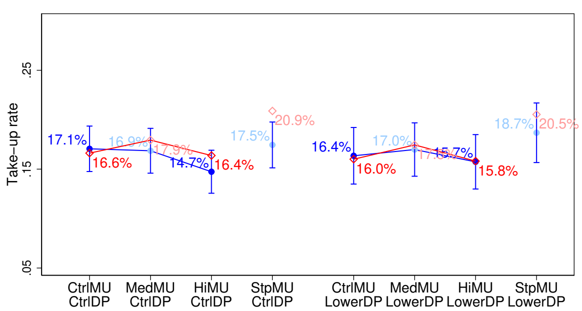
Note: This figure compares simulated consumer behavior across risk scores holding contract terms fixed to those of the control multiple / control down payment arm for risk score 1. Panel A shows the simulated share repaid over time, Panel B the share of non-payers, and Panel C the IRRs of the simulated loan portfolios. Simulations use parameter estimates from our SMM estimation. Annualized IRRs based on actual consumer behavior are reported in Table 4.

FIGURE 4: Model Fit – Take-Up Rates, Risk Score 1

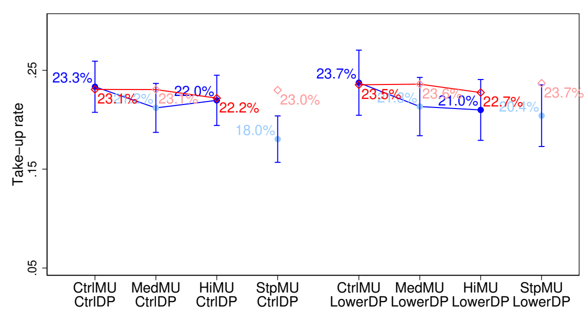
Panel A: Overall



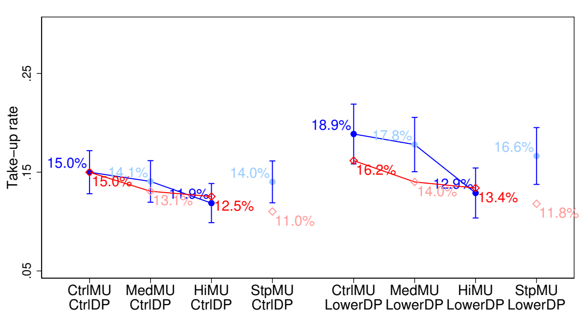
Panel B: 3-Month Contract



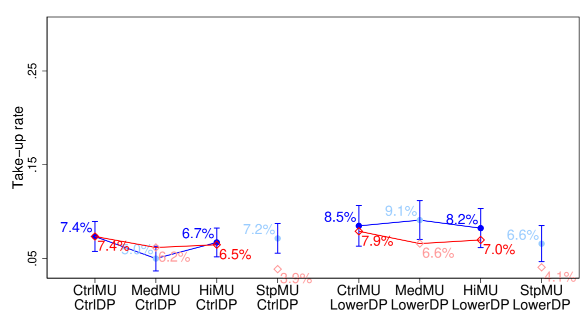
Panel C: 6-Month Contract



Panel D: 9-Month Contract

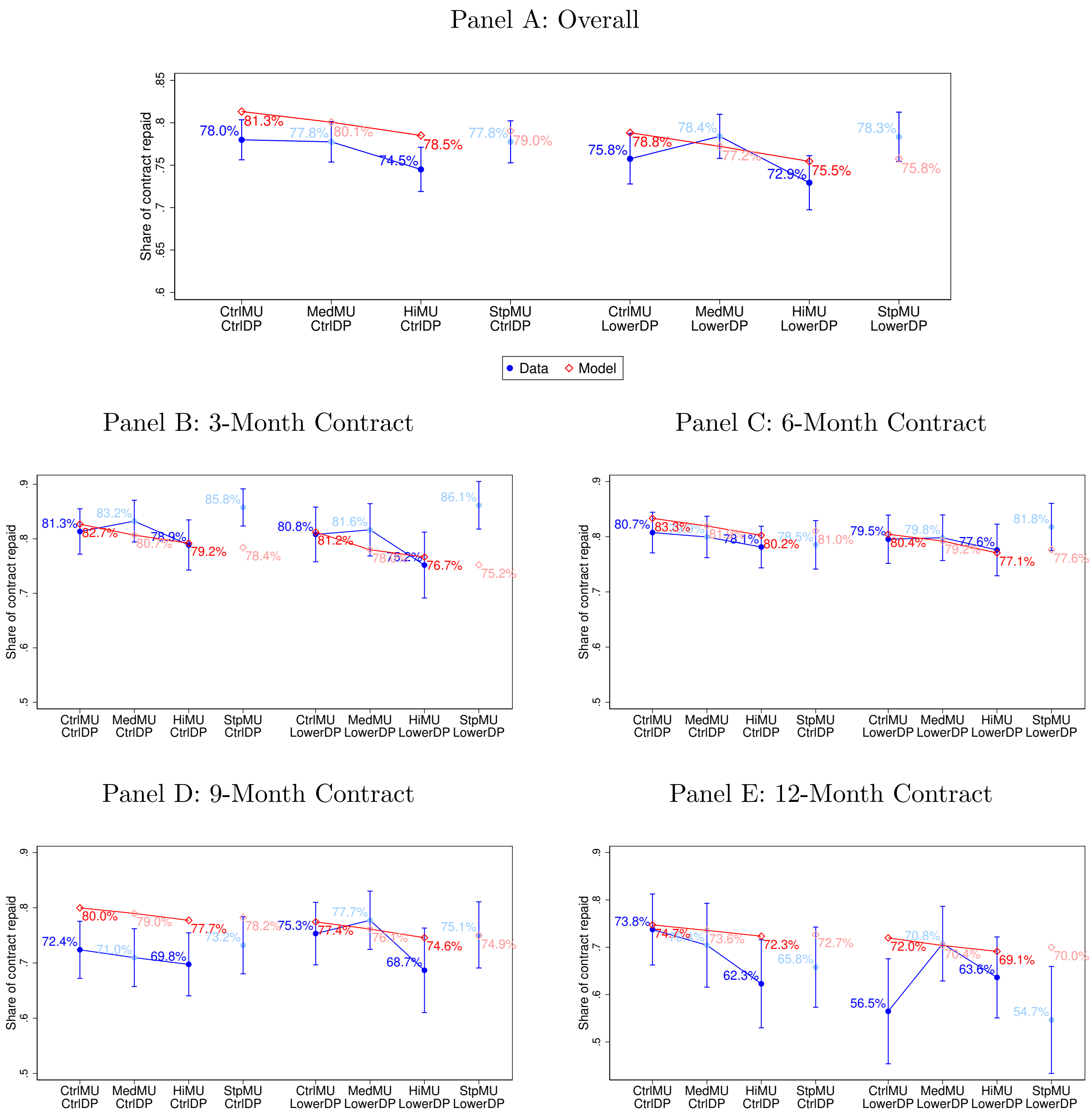


Panel E: 12-Month Contract



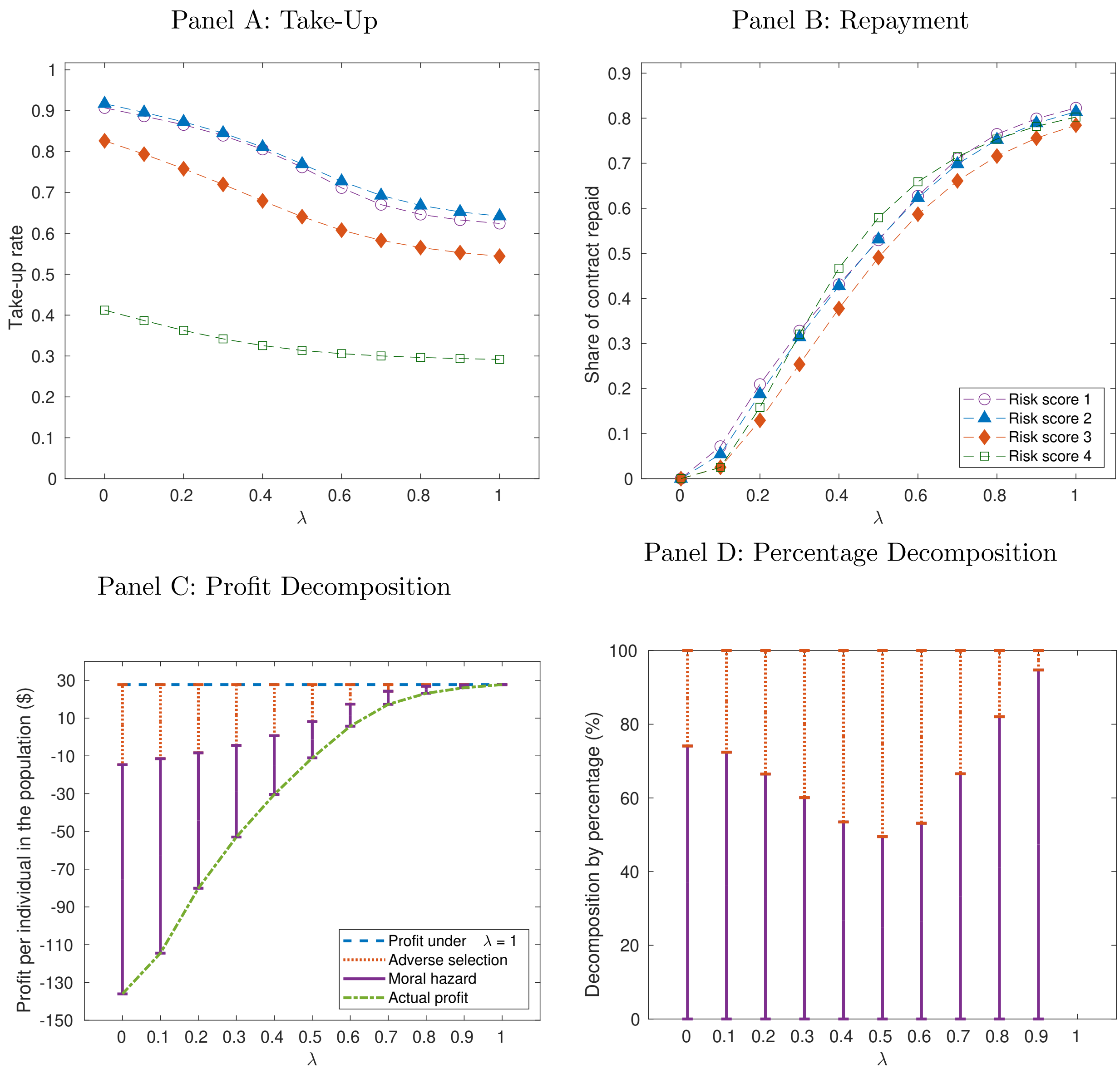
Note: This figure compares actual (blue) and simulated (red) take-up rates for risk score 1. Panel A aggregates across maturities; Panels B–E show results for the 3-, 6-, 9-, and 12-month contracts. The x-axis shows the 8 experimental arms: CtrlMU, MedMU, HiMU, StpMU (multiple arms) and CtrlDP, LowerDP (down payment arms). Treatment groups used in estimation are shown in solid color; validation groups in transparent. Vertical bars indicate 95% confidence intervals.

Figure 5: Model Fit – Share of Contract Repaid, Risk Score 1



Note: This figure compares actual (blue) and simulated (red) shares of contract repaid at maturity for risk score 1. Panel A aggregates across maturities; Panels B–E show results for the 3-, 6-, 9-, and 12-month contracts. Experimental arms are labeled as in Figure 4. Treatment groups used in estimation are solid; validation groups transparent. Vertical bars show 95% confidence intervals.

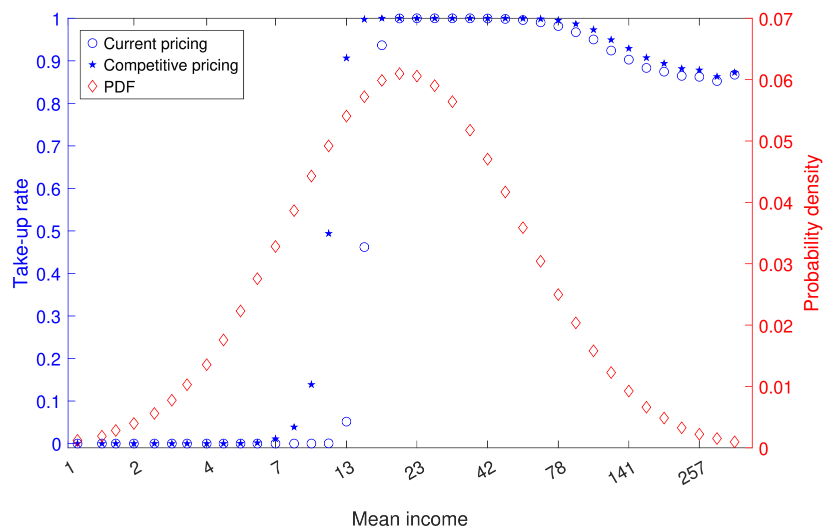
FIGURE 6: Effect of λ on Moral Hazard and Adverse Selection, Risk Score 1



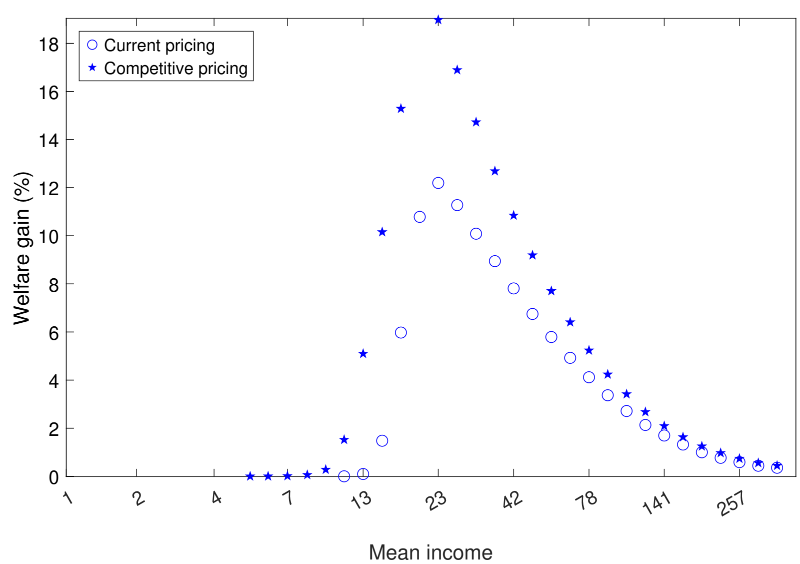
Note: This figure shows how take-up, repayment, and profits vary with lockout efficiency λ, ranging from 0 (no lockout) to 1 (full lockout, baseline). Panel A shows take-up rates; Panel B the average share of contract repaid. Panel C decomposes profit losses from lower λ into (a) weaker screening (profit differences due to changes in taker composition) and (b) weaker incentives (worse repayment by takers). Panel D shows the percentage decomposition into adverse selection (upper segment) and moral hazard (lower segment). Results are for risk score 1; analogous results for risk scores 2–4 are in Figure A2 in the Online Appendix.

Figure 7: Take-Up and Welfare by Income, Risk Score 1

Panel A: Take-Up Rates



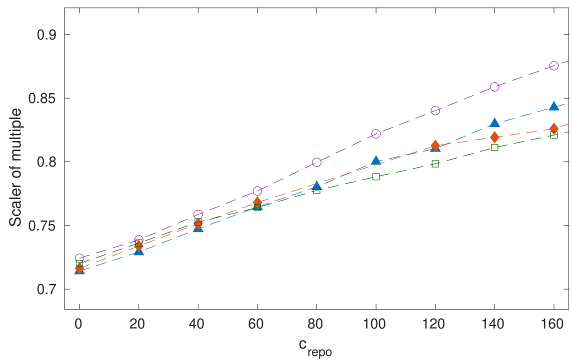
Panel B: Welfare Gain $\mathcal{W}_{taker}$



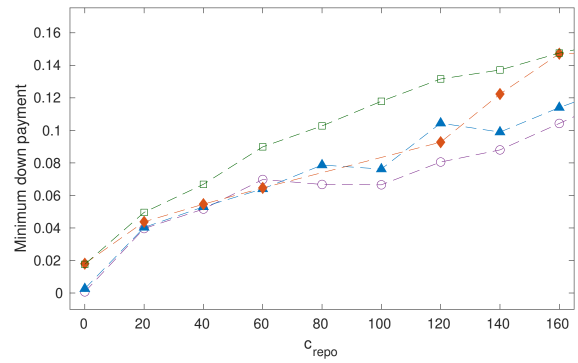
Note: This figure compares take-up and welfare gains under control-arm and competitive pricing for risk score 1. Panel A shows take-up by mean income, with competitive pricing (stars) and actual pricing (circles). Red diamonds show the income distribution. Panel B shows welfare gains $\mathcal{W}_{taker}$ by mean income under both pricing regimes.

FIGURE 8: Traditional Secured Lending with $p_{\text{repo}} = 100\%$

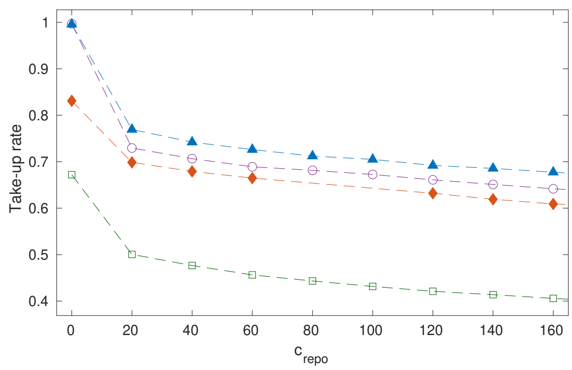
Panel A: Multiple



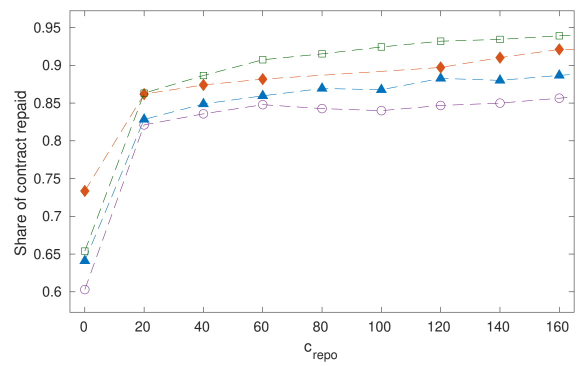
Panel B: Minimum Down Payment



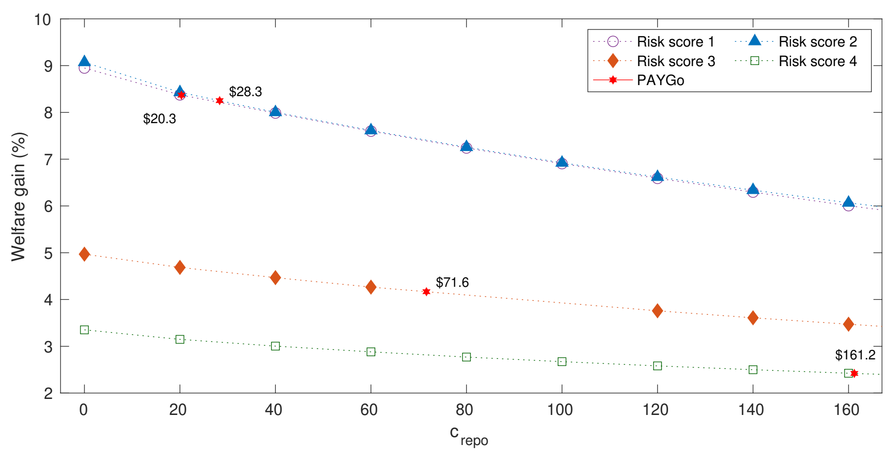
Panel C: Take-Up



Panel D: Share of Contract Repaid

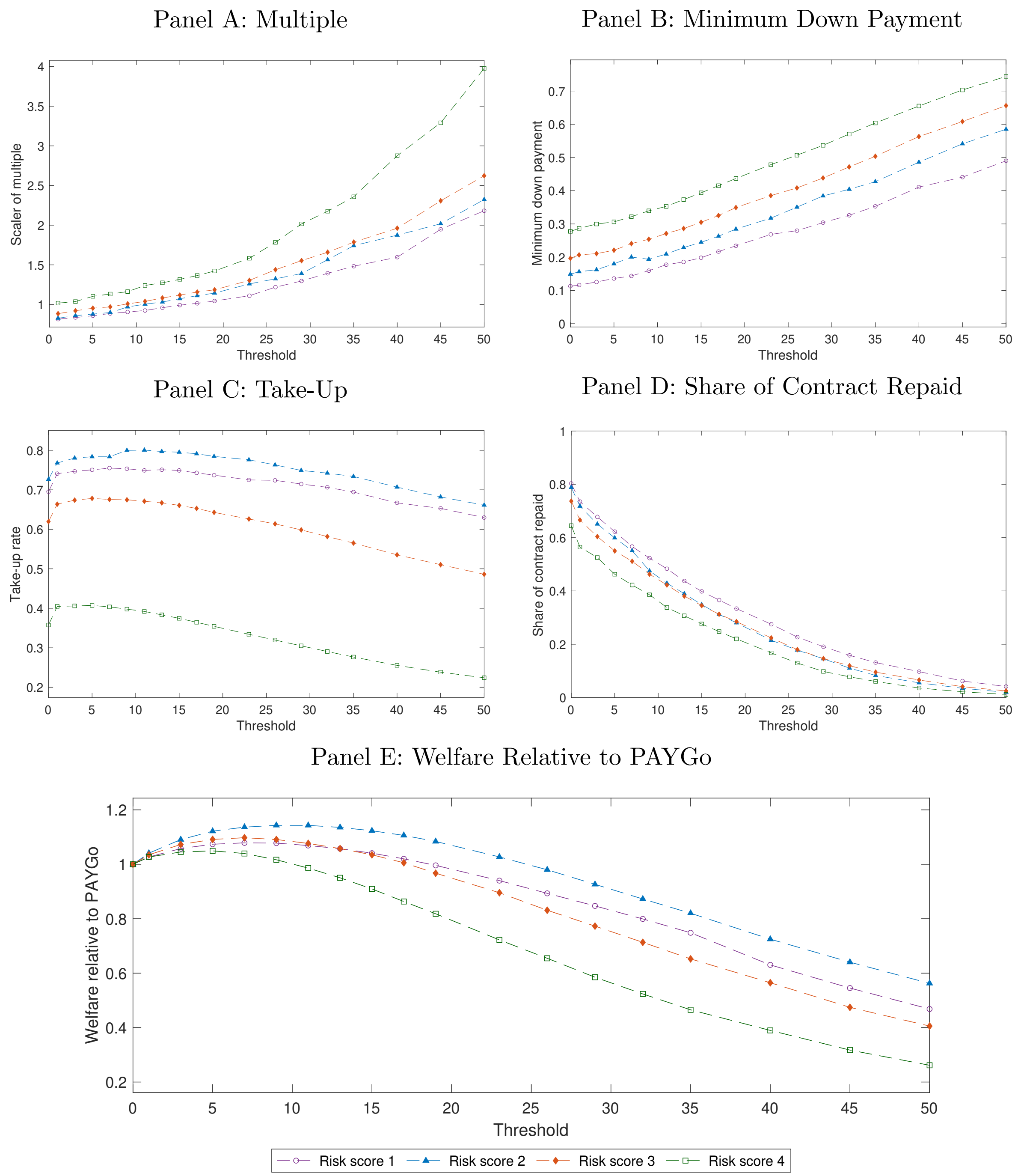


Panel E: Welfare Gain



Note: This figure shows competitive terms under secured lending with $p_{\text{repo}} = 100\%$ and varying repossession costs c_{repo}. Panel A shows multiples, Panel B minimum down payments, Panel C take-up rates, Panel D repayment, and Panel E welfare gains $\mathcal{W}_{pop}$. Panel E also labels the repossession cost that yields the same welfare as PAYGo. Competitive terms are computed assuming multiples remain proportional to those in the control-arm contracts.

FIGURE 9: PAYGo Variation: Leniency for Missed Payments



Note: This figure shows competitive terms under PAYGo with leniency, where lockout is triggered only after the number of missed payments reach the threshold. Panel A shows multiples, Panel B minimum down payments, Panel C take-up rates, Panel D repayment, and Panel E welfare gains $\mathcal{W}_{pop}$ relative to standard 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: Down Payment 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

Down Payment Treatment	Pricing Treatment	# of Consumers in 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 summarizes the pricing experiment. Panel A reports the multiples by maturity and pricing arm. The multiple measures loan cost; weekly payment equals $\frac{\text{Multiple}\times(\text{Phone Price}-\text{Down Payment})}{\text{Maturity}}$. Multiples are identical across risk scores. Panel B shows the two down payment arms by risk score. Panel C reports the number of consumers in each treatment group.

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 consumer 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 marginal utility at the population average mean income ($u'(\bar{y})$). For example, 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 a consumer's marginal utility at mean income, i.e., $\mu_i = \mu \times u'(\bar{y}_i)$, where μ is the reported value. Standard errors are calculated using the delta method (see Section C.5 in the Online Appendix) and appear in parentheses.

Table 3: 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 down payment	–0.003**	–0.000	0.014***	0.246
	(–2.58)	(–0.06)	(4.76)	

Note: This table reports regressions of sample moments on risk score dummies, controlling for multiple treatment arm and minimum down payment. Each row corresponds to one regression. Columns 1–3 show fixed effects for risk scores 2–4; risk score 1 is the reference group, with its average in the last column. The regression with the conditional probability of resuming payment as the dependent variable is weighted by the frequency of missed payments.

Table 4: Welfare and Profitability by 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	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	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	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	25

Note: This table reports welfare gains and profitability by experimental arm and under competitive pricing. Column (1) shows the take-up rate; Column (2) $\mathcal{W}_{taker}$, the welfare gain conditional on purchase; Column (3) $\mathcal{W}_{pop}$, the unconditional welfare gain; Column (4) the NPV per contract over two years; and Column (5) the annualized IRR for a portfolio of contracts in each arm over two years.

Table 5: Competitive Pricing Counterfactual

Panel A: Competitive Terms

	Multiple by Maturity (1) 3-Month	(2) 6-Month	(3) 9-Month	(4) 12-Month	(5) Min. Down (%)
Risk score 1					
Control multiple	1.36	1.54	1.64	2.00	
Control minimum down payment					25.0
Competitive multiple	1.10	1.24	1.32	1.62	
Competitive minimum down payment					10.6
Risk score 2					
Control multiple	1.36	1.54	1.64	2.00	
Control minimum down payment					30.0
Competitive multiple	1.11	1.26	1.34	1.63	
Competitive minimum down payment					14.9
Risk score 3					
Control multiple	1.36	1.54	1.64	2.00	
Control minimum down payment					35.0
Competitive multiple	1.18	1.33	1.42	1.73	
Competitive minimum down payment					20.5
Risk score 4					
Control multiple	1.36	1.54	1.64	2.00	
Control minimum down payment					50.0
Competitive multiple	1.37	1.55	1.65	2.01	
Competitive minimum down payment					28.1

Panel B: Decomposing the Welfare Gains from Competition

	(1) $\mathcal{W}_{pop}$ under Ctrl (%)	(2) $\Delta(\mathcal{W}_{pop})$ from competitive multiple (%)	(3) $\Delta(\mathcal{W}_{pop})$ from competitive minimum down payment (%)	(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: Panel A reports competitive terms assuming the firm offers all four contracts with multiples proportional to those in the control multiple / control down payment arm. It also shows the actual multiple and minimum down payment in the control arm. Panel B reports changes in welfare and take-up due to competitive multiples, competitive minimum down payments, or both. Column (1) shows $\mathcal{W}_{pop}$ and take-up (in parentheses) under the control arm. Column (2) shows outcomes if only the multiple is competitive, Column (3) if only the minimum down payment is competitive, and Column (4) if both are competitive.

Online Appendix

A Extensions

A.1 A Model with Phone Choice

As an extension, we allow consumers to choose which phone model to purchase. We assume that the initial usage value $\bar{v}$ is proportional to the list price of the phone, i.e., $\bar{v} = \nu p$, where ν is the normalized initial usage value and p is the phone price. In the take-up stage, consumers choose whether to buy, which maturity to take, how much to put as a down payment, and the price of the phone to purchase. We solve for the consumer value of purchasing a \$100, \$150, \$200, \$250, or \$300 phone. These price points correspond to the range of phone price observed in the data. Next, we interpolate consumer value along the dimension of phone price to obtain value from more granular phone price choices. Holding model parameters fixed, allowing for phone choice increases welfare by allowing consumers to optimize their phone consumption. However, the parameters of the model also adjust. Therefore, the welfare implications of endogenous phone choice are not clear ex ante. We estimate this model by targeting the moments listed in Section 4.1, as well as the average phone price chosen in each treatment arm of the financing experiment. Parameter estimates are reported in Table A5, and Figure A9 summarizes model fit. The model replicates the average phone price observed in the data. Table A6 reports the implied welfare gains from PAYGo financing, which are quantitatively very similar to the estimates in the baseline model (Table 4).

B Counterfactual Models

B.1 A Traditional Secured Loan

The Secured Loan Contract and Repossession Technology 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 $p_{\text{repo}} = 1$. Note that $\kappa_{it} - c_{\text{repo}}$ captures the lender's (net) value for the collateral.

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.[34]

The Consumer's Problem 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

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

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).[35] Consumers enjoy the per-period flow value equivalent to the fixed effects 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

[34]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.

[35]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.

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).

B.2 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

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

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 is below $\bar{l}$ 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 $l_{it} < \bar{l}$ and where $\Pi_i(v_{it}, y_{it})$ is defined as in Equation (3).[36] 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.

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).

B.3 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

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

[36] 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.

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

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

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).

C Computation

C.1 Model Solution

The consumer's problem has two stages: take-up and repayment. In the take-up stage, the consumer decides whether to accept a PAYGo contract, and if so, chooses the maturity and down payment. In the repayment stage, she decides each week whether to make the scheduled payment. We describe our solution method beginning with the repayment stage.

Discretization We solve the model numerically on discretized grids. We use a grid of $\bar{y}_i$ with *GridSizeYLRM* $= 16$ points and a grid of $y_{it}/\bar{y}_i$ with *GridSizeYtoYLRM* $= 15$ points. For $\bar{y}_i$, the endpoints are $\bar{y}e^{-\frac{\sigma_{\bar{y}}^2}{2}-3\sigma_{\bar{y}}}$ and $\bar{y}e^{-\frac{\sigma_{\bar{y}}^2}{2}+3\sigma_{\bar{y}}}$. For $y_{it}/\bar{y}_i$, the endpoints are $\exp(\mathbb{E}[\log(y_{it}/\bar{y}_i)] \pm 3\,\mathrm{Std}[\log(y_{it}/\bar{y}_i)])$. Interim points are spaced evenly.

For take-up, we use a grid of down payments (*GridSizeD* $= 10$) ranging from the minimum to 100% in equal steps. Liquidity withdrawal is defined on a linear grid from \$0 to \$250 of size *GridSizeLiq* $= 100$. We also construct four grids for the maturity-choice shocks, each with *GridSizeUShock* $= 9$ points. In the repayment stage, usage value is discretized on *GridSizeVtoV0* $= 3$ points: the initial usage value, half the initial value, and zero.

Repayment Stage We first solve for ownership value $\Pi_i(v, y)$, where v is usage value and y is income. The flow value is $f_{\mathrm{o}} = v + u(y)$. Starting from $\Pi_i^0(v, y) = 0$, we iterate

$$\Pi_i^k(v, y) = f_{\mathrm{o}} + \beta\mathbb{E}[\Pi_i^{k-1}(v', y')|v, y],$$

which converges to a unique fixed point. The subscript i indicates dependence on $\bar{y}_i$, so we solve separately for each $\bar{y}_i$ grid point.

Next, we solve the repayment problem. The flow utility if the consumer pays is $f_{\mathrm{p}} = v + u(y - m)$; if not, $f_{\mathrm{np}} = (1 - \lambda)v + u(y)$. Starting from $U_i^0(v, y, n)$, we iterate

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

with $U_i^k(v, y, 0) = \Pi_i(v, y)$. Because this problem depends on down payment d_i (through m), maturity, and $\bar{y}_i$, it is solved *GridSizeD* $\times 4 \times$ *GridSizeYLRM* times.

Outside Option Before contract choice, we solve for the outside option. The value if the consumer buys with cash is

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

subject to $c + p = y + L$. This is solved for each $\bar{y}_i$.

The option value is then

$$O_i^k(y) = \max\{u(y) + \beta\mathbb{E}[O_i^{k-1}(y')|y], G_i(y)\},$$

again for each $\bar{y}_i$.

Take-Up Stage For each contract j, we compute the value of PAYGo given each down payment and liquidity withdrawal. Together with income, these determine consumption. We then select the optimal pair, yielding the value of contract j:

$$W_i(x;\Gamma^j) + \xi_j + \omega_{ij}.$$

Comparing contracts in the menu to the outside option gives the consumer's take-up and maturity choice.

Firm Profit Expected discounted firm profit during repayment is given by

$$\begin{aligned} V_i^k(v,y,n;\Gamma) =& A^*(v,y,n)\Big(m + \delta\mathbb{E}[V_i^{k-1}(v',y',n-1;\Gamma)|v,y]\Big) \\ &+ (1-A^*(v,y,n))\delta\mathbb{E}[V_i^{k-1}(v',y',n;\Gamma)|v,y], \end{aligned}$$

where $A^*(v,y,n)$ is the consumer's optimal repayment decision. We plug $V_i^k(v,y,n;\Gamma)$ into (10) to obtain the firm's NPV.

C.2 Simulation

We simulate 10^6 consumers over $t = 0$ to $t = 104$ weeks, fixing the random seed for reproducibility. We draw $\bar{y}_i$ and ω_{ij} from their cross-sectional distributions. We draw $y_{i0}/\bar{y}_i$ from its steady-state distribution and income shocks ϵ_{it} so that $y_{it}/\bar{y}_i$ remains stationary.

For each consumer, we interpolate the outside option O_i from a $(y_0/\bar{y}, \bar{y})$ grid and interpolate $W_i(\Gamma^j)$ for each contract. Comparing $\max_j\{W_i(\Gamma^j) + \xi_j + \omega_{ij}\}$ to O_i yields take-up and maturity choice.

Down payments are simulated by interpolating the policy function. Repayment dynamics are simulated by drawing usage value paths v_{it}/v_{i0} and interpolating the repay and no-repay value functions from the $(y_0/\bar{y}, v/v_0, \bar{y}, d, n)$ grid. Comparing these values yields repayment dynamics, simulated sequentially from $t = 1$ to $t = 104$.

C.3 Welfare Calculation

We compute the proportional income increase $\mathcal{W}_i$ that makes consumer i indifferent between access to PAYGo and the no-financing benchmark:

$$\max\left\{\max_{\Gamma^j\in\mathcal{M}_i} W_i(\Gamma^j)+\xi_j+\omega_{ij}, O_i(y_{i0})\right\}=B_i(\hat{y}_{i0}), \tag{29}$$

where $B_i(\hat{y}_{i0})$ is the maximum of buying with cash or contracts with 100% down payment, both under augmented income $\hat{y}_{it}=y_{it}+\mathbb{1}_{\{t\leq 104\}}\mathcal{W}_i y_{it}$:

$$B_i(\hat{y}_{i0})=\max\left\{\max_{\Gamma^j\in\mathcal{M}_i^{\text{down}=100\%}} \hat{W}_i(\Gamma^j)+\xi_j+\omega_{ij}, \hat{O}_i(\hat{y}_{i0})\right\}. \tag{30}$$

We compute $\hat{O}_i(\hat{y}_{it},t)$ by backward induction. For $t>104$, $\hat{O}_i(\hat{y}_{it},t)=O_i(y_{it})$. For $t\leq 104$,

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

If the consumer buys with cash at t,

$$\hat{G}_i(\hat{y}_{it},t)=\max_{c,L} v_0+u(c)-\mu L+\beta\mathbb{E}[\hat{\Pi}_i(v_{i,t+1},\hat{y}_{it+1},t+1)|v_{i,t}=v_0,\hat{y}_{it}],$$

subject to $c+p\leq\hat{y}_{it}+L,\ c,L\geq 0$. $\hat{\Pi}_i$ is computed via backward induction. We write $\hat{O}_i(y)=\hat{O}_i(y,0)$.

Accepting a contract with 100% down payment is equivalent to buying with cash, so $\hat{W}_i(\Gamma^j)=\hat{G}_i(\hat{y}_{i0},0)$ for any $\Gamma^j\in\mathcal{M}_i^{\text{down}=100\%}$. We compute B_i accordingly. To economize on computation, we define a grid for the proportional income increase ($\mathit{GridSizeExtraInc}=200$ points from 0% to 100%) and compute values for each grid point. We obtain $\mathcal{W}$ on the consumer-type grid and then interpolate $\mathcal{W}_i$ for each simulated consumer.

C.4 The TikTak Algorithm

Our SMM uses the TikTak algorithm, which performs well in high-dimensional optimization (Guvenen, 2011; Arnoud et al., 2019). We first set bounds for all parameters. We then generate $N_S=50{,}000$ Sobol' points, evaluate the SMM error $(m(\Theta)-m)'W(m(\Theta)-m)$ at each, and keep the $N^*=100$ with the lowest error. Denote them $\mathbf{s}=\{s_1,\ldots,s_{N^*}\}$. We then run N^* local searches using Nelder–Mead, starting from

$$s_i^{\text{start}}=\theta_i p_{i-1}^{\text{low}}+(1-\theta_i)s_i,$$

where p_{i-1} is the best estimate after the $(i-1)$th minimization ($p_1 = s_1$). Weights are $\theta_i = \min[\max(0.1, (i/N^*)^{1/2}), 0.995]$. We take p_{N^*} as the starting point for a final minimization.

C.5 Standard Errors

The variance–covariance matrix of parameter estimates is $(J' K_{\mathbf{mm}}^{-1} J)^{-1}$, where J is the Jacobian at the estimates and $K_{\mathbf{mm}}$ is the diagonal matrix with the sample variances of data moments. We obtain $K_{\mathbf{mm}}$ via bootstrapping. Standard errors are the square roots of the diagonal elements of $(J' K_{\mathbf{mm}}^{-1} J)^{-1}$.

C.6 Competitive Terms

Competitive terms are the multiple and minimum down payment that maximize welfare $\mathcal{W}_{pop}$ while delivering zero firm profit. We use a penalty method with multiple starts. Define

$$\Lambda(M|\eta) = \mathcal{W}_{pop}(M) - \eta\, \mathbb{E}[\text{NPV}|M]^2,$$

where M are contract terms. Starting from $N = 1{,}000$ random Sobol' draws with $\eta = 0.1$, we pick the $N_\star = 10$ best. For $\boldsymbol{\eta} = \{0.1, 1, 10, 100\}$, we maximize $\Lambda(M|\eta)$ sequentially, updating starting points. This yields 10 candidate contracts; the zero-profit, welfare-maximizing contract is the best of these.

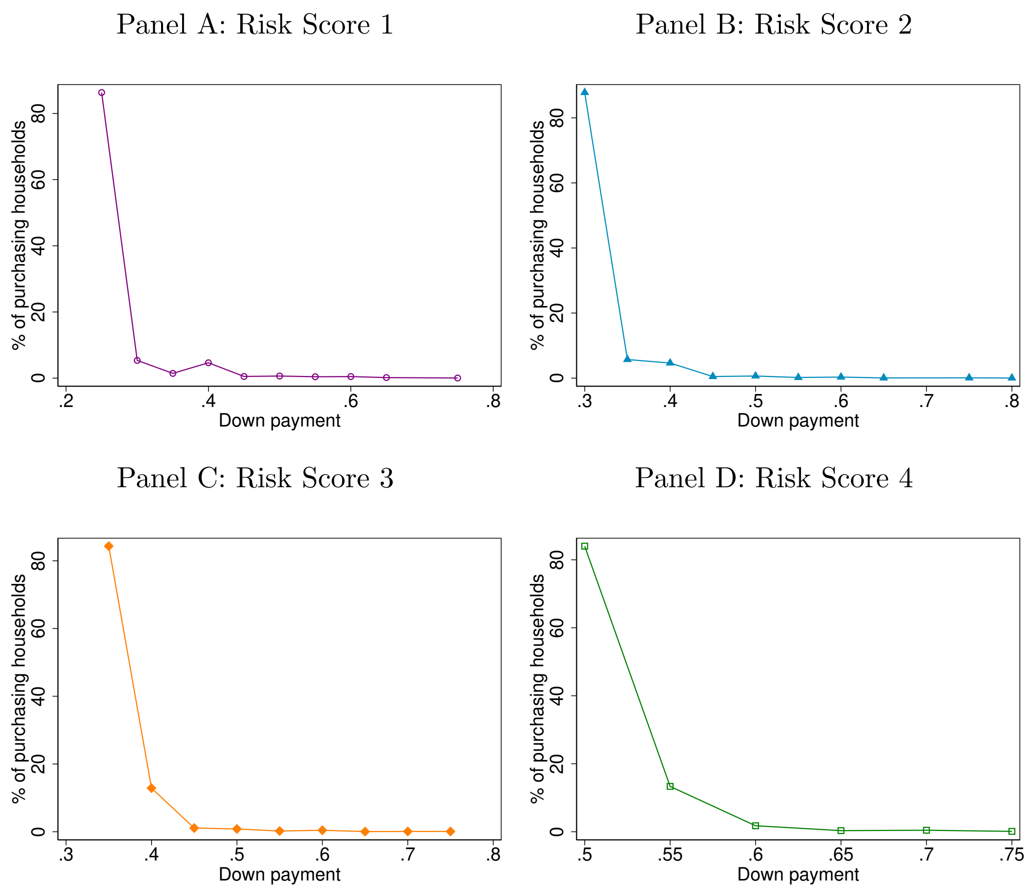
We verify with a brute-force method: for each down payment in a grid of 200 points from 0 to 1, we solve for the multiple that yields zero profit. The zero-profit line in the (multiple, down payment) plane is downward sloping. We then compute $\mathcal{W}_{pop}$ along this line. The contract with the highest welfare matches the optimization result, though brute force is more computationally intensive.

C.7 Parallelization

Solving the model requires value and policy functions for 4 maturities in each of 4 treatment arms. We estimate the model separately for each of 4 risk scores. In total, this involves 64 independent problems, solved in parallel. Simulations are also run in parallel across treatment arms and risk scores. Due to dimensionality, each process in the parallel pool employs a separate GPU. This parallelization greatly reduces computation time.

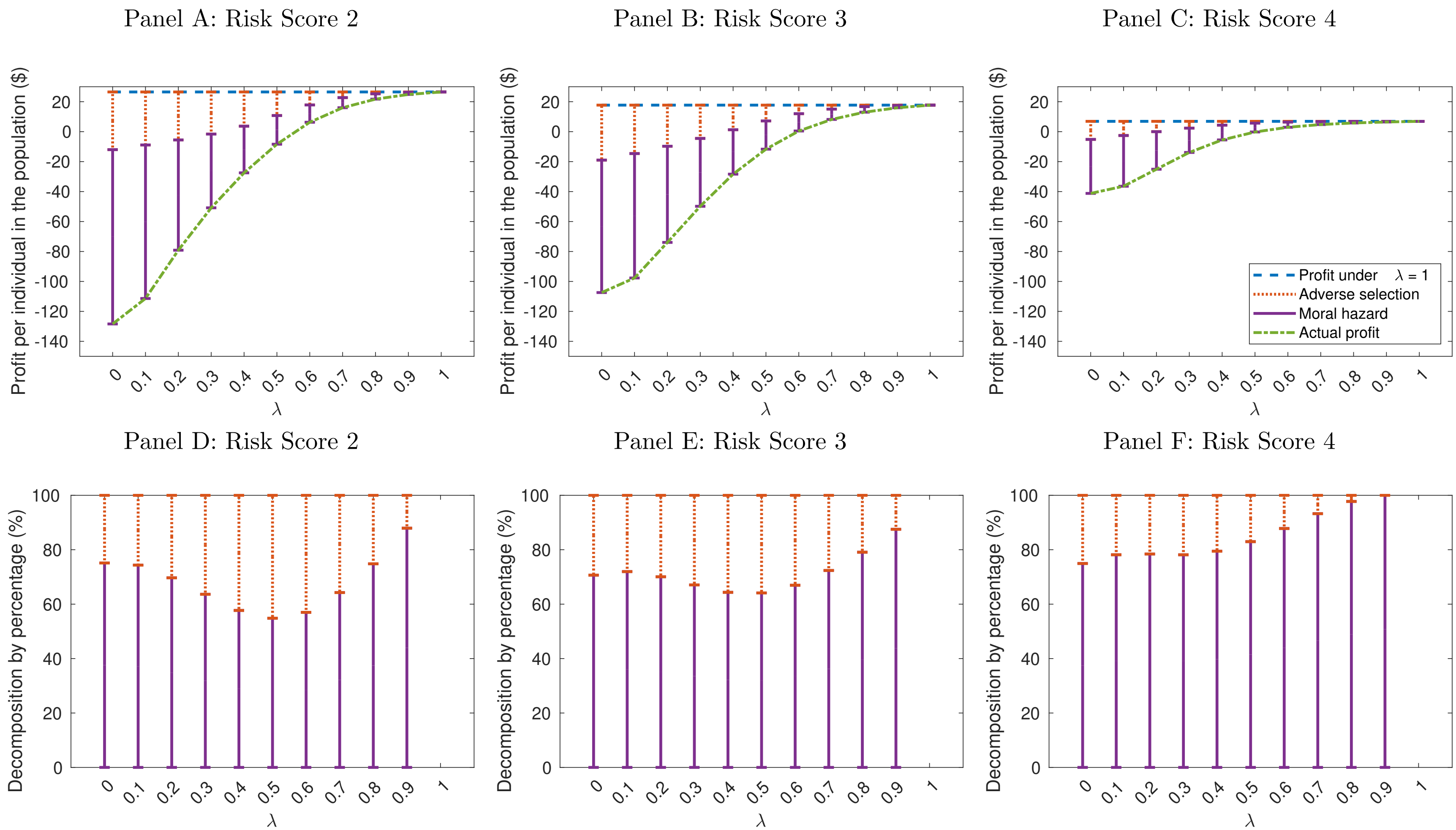
D Additional Figures

Figure A1: Histogram of Down Payments by Risk Score



Note: This figure shows histograms of selected down payments in the control multiple / control down payment arm of the experiment, separately by risk score. The minimum required down payments are 25%, 30%, 35%, and 50% for risk scores 1–4, respectively.

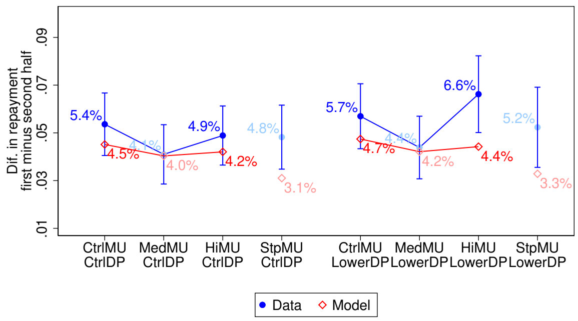
FIGURE A2: Effect of λ on Moral Hazard and Adverse Selection (Risk Scores 2–4)



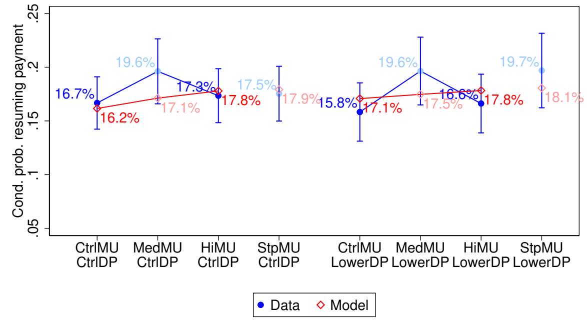
Note: This figure replicates the profit decomposition shown in Figure 6 for risk scores 2–4. Panels A–C show absolute decompositions; Panels D–F show percentage decompositions into adverse selection and moral hazard.

Figure A3: Model Fit – Other Moments (Risk Score 1)

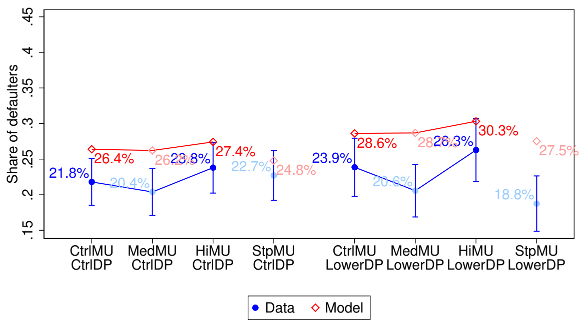
Panel A: Difference in First vs. Second Half Repayment



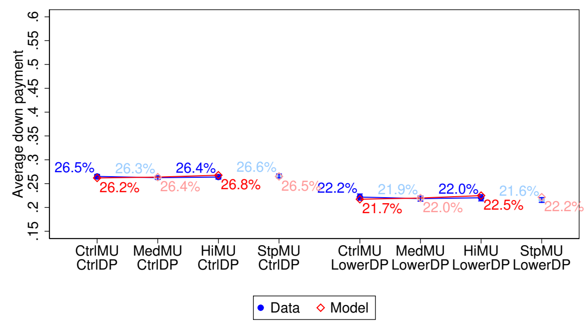
Panel B: Conditional Probability of Resuming Payment



Panel C: Share Not Fully Repaid in Two Years

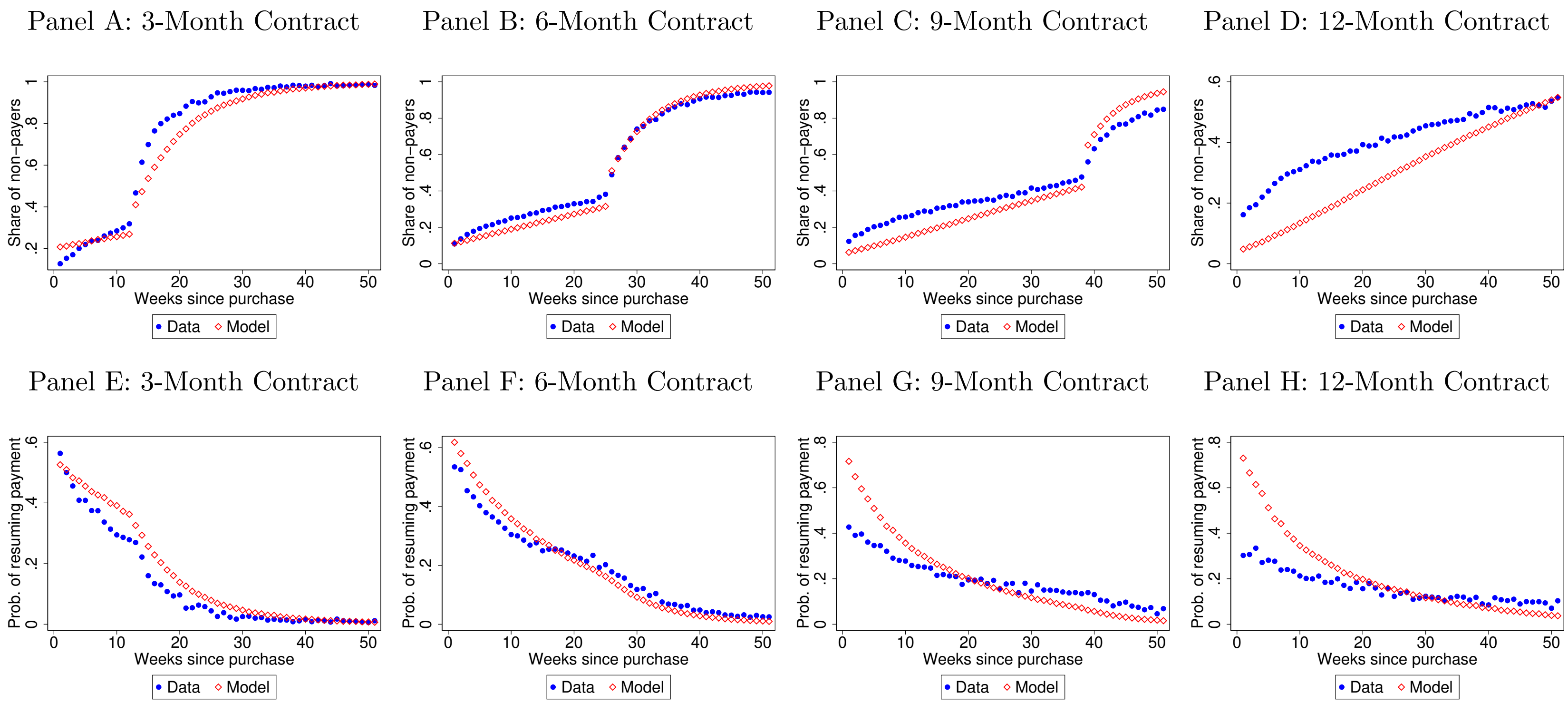


Panel D: Average Down Payment



Note: This figure compares actual (blue) and simulated (red) moments for risk score 1. Panel A shows the difference between repayment in the first and second half of the contract. Panel B shows the probability of resuming payment conditional on missing the previous payment. Panel C shows the share of consumers who did not fully repay within two years. Panel D shows the average down payment as a share of the phone price. 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 down payment arm. Estimation groups are in solid color; validation groups in transparent. Vertical bars show 95% confidence intervals.

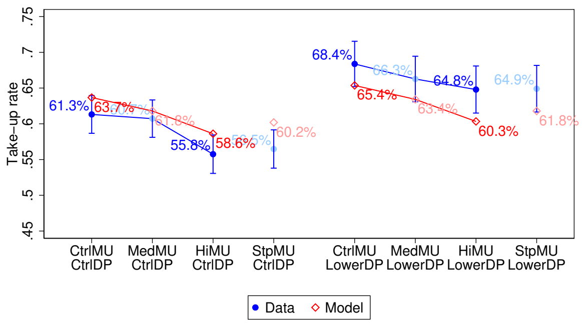
Figure A4: Model Fit – Repayment Dynamics



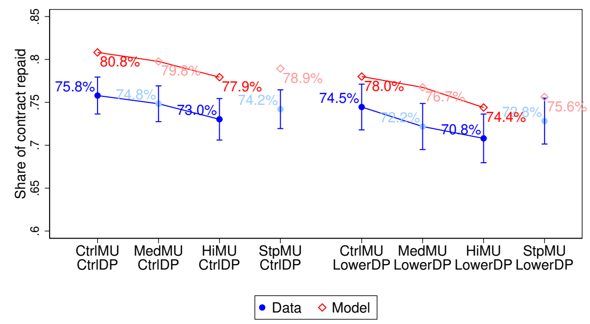
Note: Panels A–D plot the dynamics of the share of non-payers each week since purchase for the 3-, 6-, 9-, and 12-month contracts. Panels E–H plot the probability of resuming payment conditional on not paying in the previous week. All panels average across risk scores and treatment arms.

Figure A5: Summary of Model Fit for Risk Scores 2–4

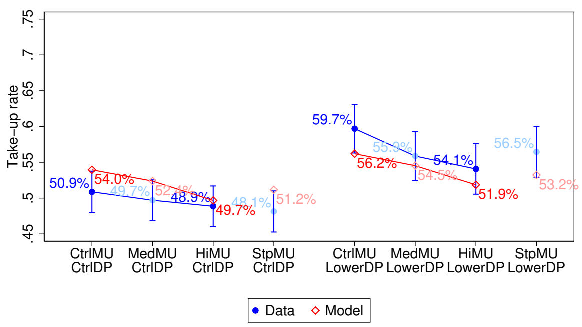
Panel A: Take-up Rates, Risk Score 2



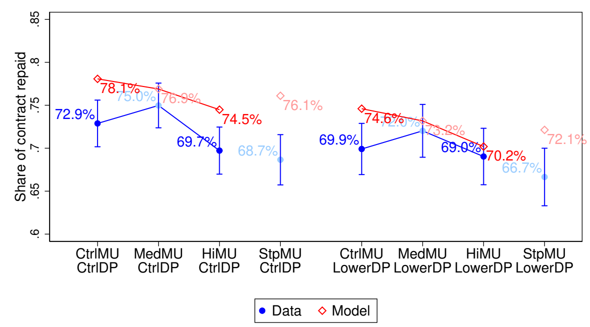
Panel B: Repayment Rates, Risk Score 2



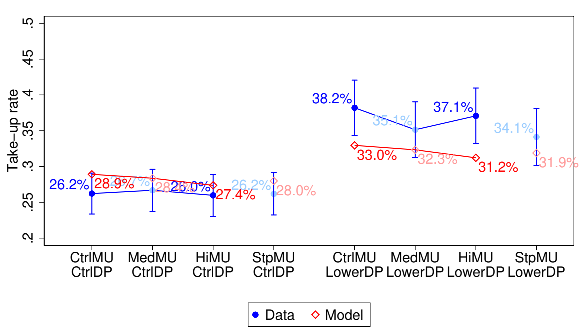
Panel C: Take-up Rates, Risk Score 3



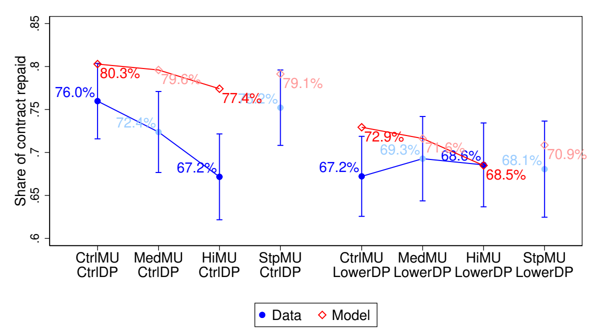
Panel D: Repayment Rates, Risk Score 3



Panel E: Take-up Rates, Risk Score 4

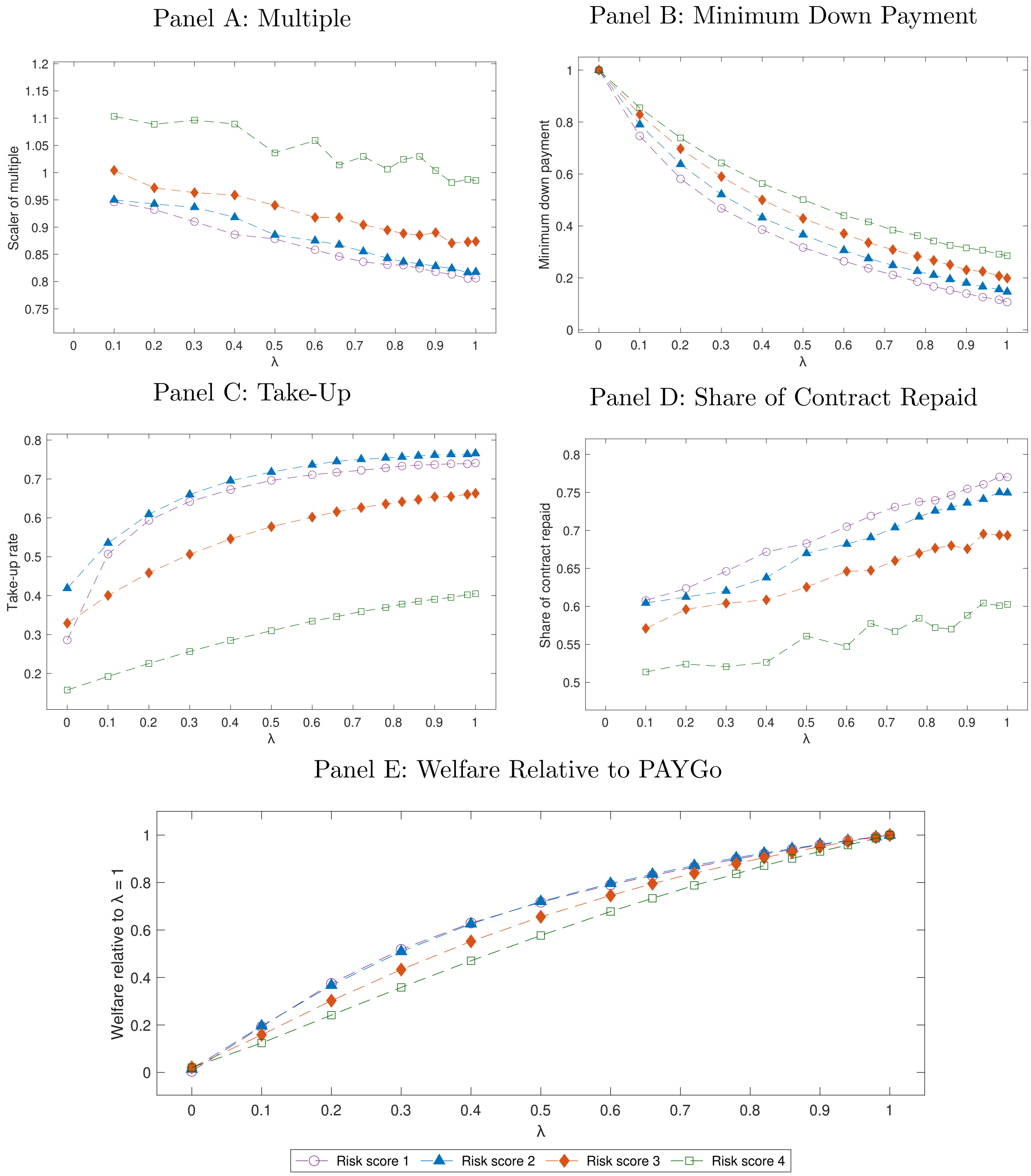


Panel F: Repayment Rates, Risk Score 4



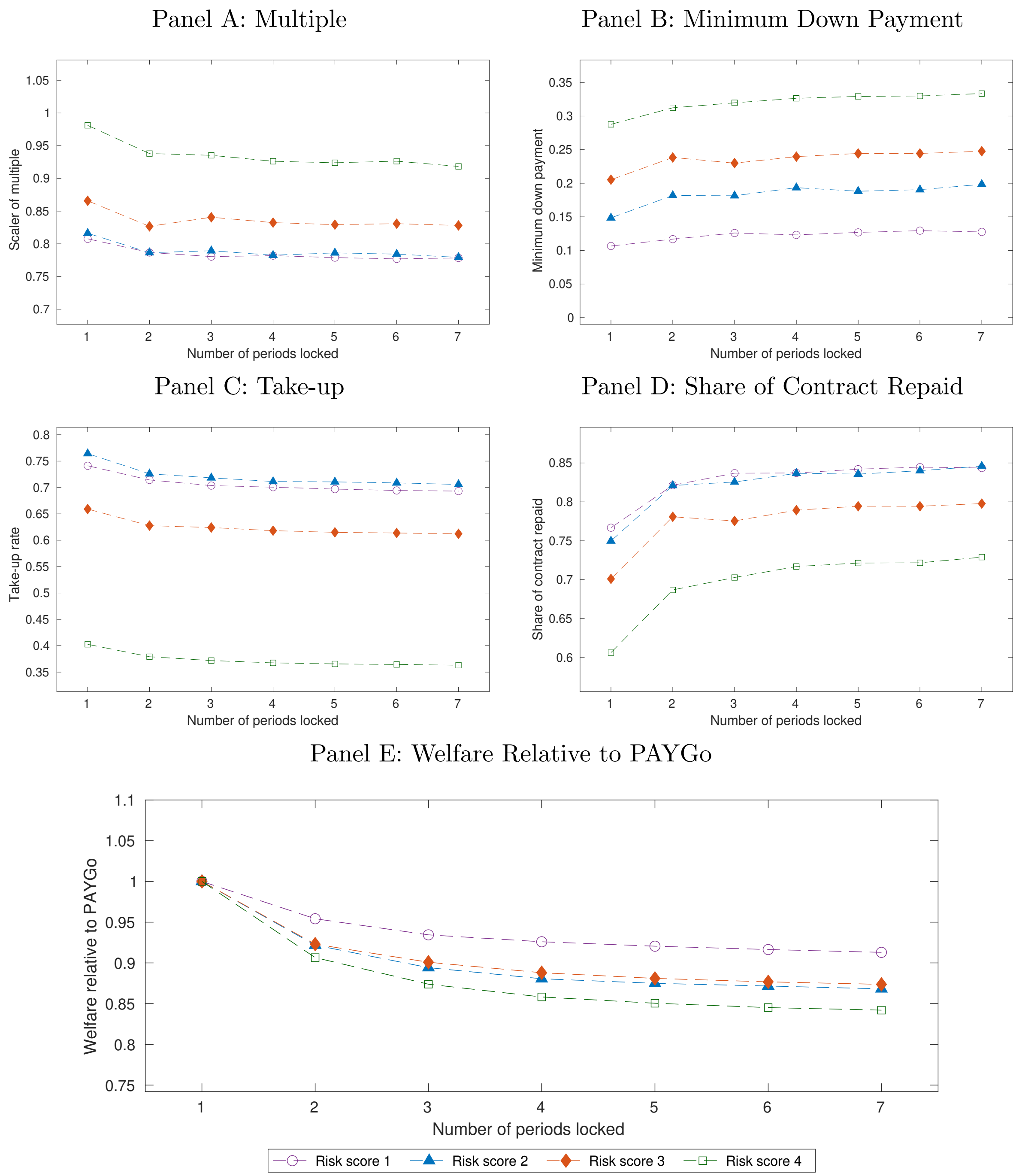
Note: This figure shows take-up rates and the average share repaid at maturity in both actual (blue) and simulated (red) data for risk scores 2–4. The x-axis shows the 8 experimental arms. CtrlMU, MedMU, HiMU, and StpMU are the multiple arms; CtrlDP and LowerDP are the down payment arms. Estimation groups are in solid color; validation groups in transparent. Vertical bars show 95% confidence intervals.

Figure A6: PAYGo Variation: Less Stringent Lockout



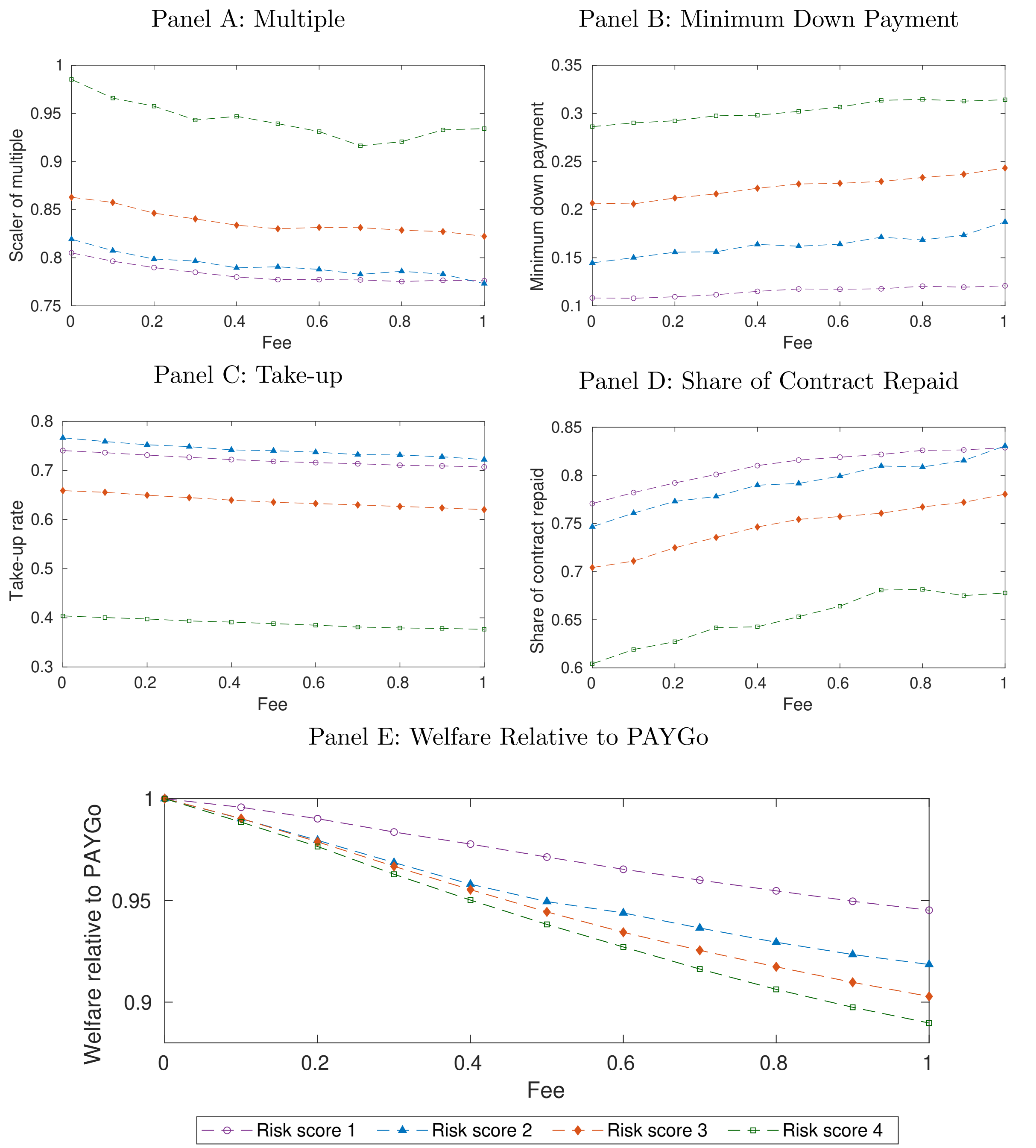
Note: This figure shows competitive terms when lockout efficiency λ varies from 0 to 1. Panel A reports multiples (relative to the control arm), Panel B minimum down payments, Panel C take-up, Panel D repayment, and Panel E welfare gains $\mathcal{W}_{pop}$ relative to PAYGo with $\lambda = 1$. Competitive terms are computed using baseline parameter estimates and multiples proportional to those in the control arm.

Figure A7: PAYGo Variation: Additional Periods Locked After Missed Payments



Note: This figure shows competitive terms when the device remains locked for multiple periods after a missed payment. Panel A reports multiples (relative to the control arm), Panel B minimum down payments, Panel C take-up, Panel D repayment, and Panel E welfare gains $\mathcal{W}_{pop}$ relative to PAYGo. Competitive terms are computed holding multiples proportional to those in the control arm.

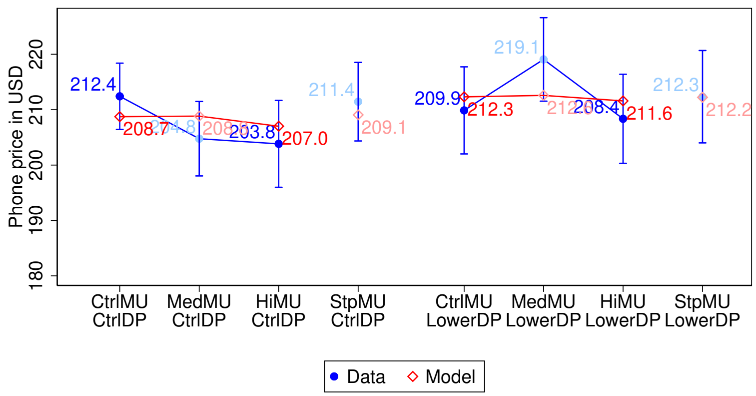
Figure A8: PAYGo Variation: Fees for Missed Payments



Note: This figure shows competitive terms when borrowers must pay a fee after missing a payment. Panel A reports multiples (relative to the control arm), Panel B minimum down payments, Panel C take-up, Panel D repayment, and Panel E welfare gains $\mathcal{W}_{pop}$ relative to PAYGo. Competitive terms are computed holding multiples proportional to those in the control arm.

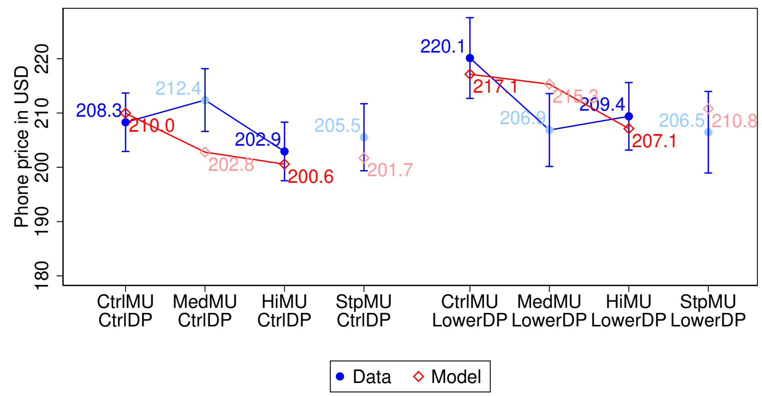
Figure A9: Model Fit for a Phone Choice Model

Panel A: Average Phone Price, Risk Score 1



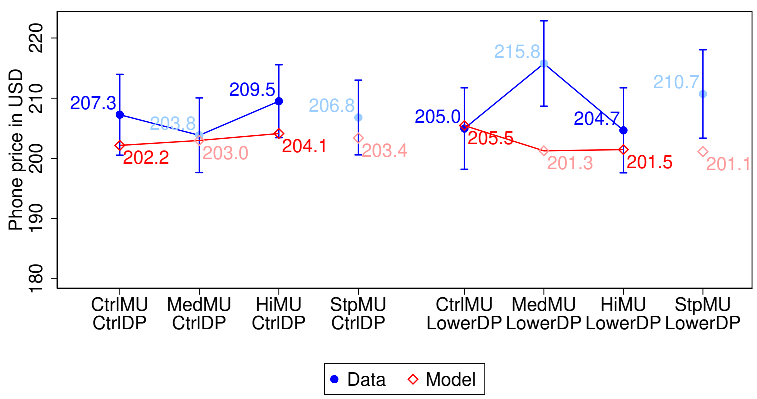
Partial SMM error = 130.3. Full SMM error = 133.3.

Panel B: Average Phone Price, Risk Score 2



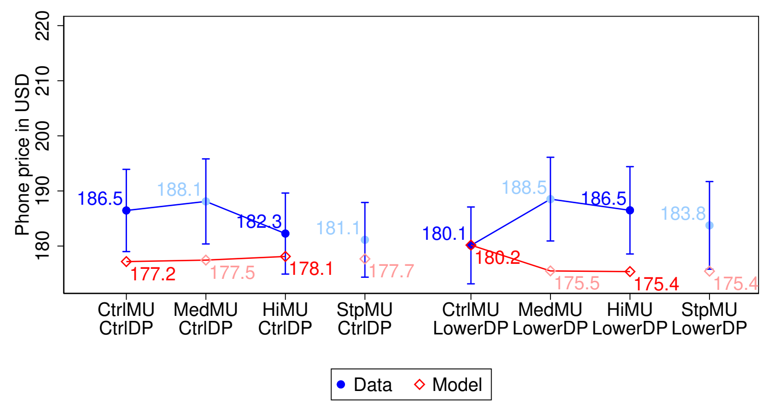
Partial SMM error = 184.7. Full SMM error = 186.9.

Panel C: Average Phone Price, Risk Score 3



Partial SMM error = 151.6. Full SMM error = 157.6.

Panel D: Average Phone Price, Risk Score 4



Partial SMM error = 128.0. Full SMM error = 142.5.

Note: This figure compares average phone prices in actual (blue) and simulated (red) data under the phone choice model. Panels A–D show risk scores 1–4. The x-axis shows the 8 experimental arms; estimation groups are solid, validation groups transparent. Vertical bars show 95% confidence intervals. We report both a partial SMM error (using only estimation moments) and a full SMM error (including phone price moments).

E Additional Tables

Table A1: Balance Across Treatment Groups, Controlling for Risk Score

	Pricing arms							Down payment arms		
	Mean				T-stat			Mean		T-stat
	Control	Medium	High	Steep	Medium-Control	High-Control	Steep-Control	Ctrl	Lower	Lower-Ctrl
Age	32.4	32.4	32.3	32.4	0.80	1.20	0.59	32.4	32.4	–0.31
Gender available	0.85	0.85	0.86	0.85	–1.08	1.76*	–0.95	0.86	0.85	–0.71
Is male	0.44	0.43	0.43	0.43	–1.46	–1.06	–1.36	0.43	0.43	0.00
Has bank account	0.57	0.56	0.57	0.56	–0.81	0.38	–1.89*	0.57	0.56	–1.24
Has credit card	0.21	0.21	0.21	0.21	0.19	–0.33	–0.16	0.21	0.20	–2.43**
Occupation										
- Private sector worker	0.52	0.53	0.53	0.52	1.18	1.16	–0.36	0.53	0.53	0.53
- Public sector worker	0.24	0.24	0.24	0.24	–0.90	–0.21	0.47	0.24	0.23	–1.99**
- Independent entreprenuer	0.16	0.15	0.16	0.16	–1.69*	–1.46	–0.38	0.16	0.16	0.81
- Other (informal economy)	0.07	0.07	0.07	0.07	0.97	0.04	0.52	0.07	0.07	1.14
- Retired	0.00	0.01	0.00	0.00	2.26**	0.54	–0.21	0.00	0.00	0.03
Risk score										
- 1	0.23	0.24	0.23	0.23	.	.	.	0.23	0.24	.
- 2	0.29	0.29	0.29	0.30	.	.	.	0.30	0.29	.
- 3	0.27	0.27	0.27	0.27	.	.	.	0.27	0.27	.
- 4	0.21	0.19	0.20	0.20	.	.	.	0.20	0.20	.
Continuous risk score	0.25	0.25	0.24	0.24	1.24	–1.47	–0.83	0.24	0.25	1.97**
N	7,208	7,358	7,154	7,066				17,417	11,369	

Note: This table examines the balance of consumer characteristics across treatment arms, controlling for risk score fixed effects. We report average characteristics in each arm and t-statistics from regressions comparing other treatment arms to the control. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: 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 entrepreneur	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 entrepreneur	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 A2: 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 ($)	206.1	77.9	193.2	115.9	345.1	210.1	208.8	207.8	184.6
Transaction Characteristics									
Minimum down payment ratio	0.30	0.07	0.30	0.20	0.50	0.23	0.28	0.33	0.45
Minimum down payment amount ($)	61.8	26.0	57.2	29.0	110.1	49.0	59.0	68.8	83.4
Actual down payment ratio	0.31	0.08	0.30	0.20	0.50	0.25	0.29	0.34	0.45
Actual down payment 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: This table reports summary statistics of the sample. The first five columns show statistics pooled across all risk scores; the last four columns show averages within each risk score. Buyer, phone, and transaction characteristics are conditional on being a purchasing consumer; loan outcomes are conditional on the contract being for a Samsung phone. Prices, down payments, financed amounts, weekly payments, and total amounts paid are in U.S. dollars at the exchange rate during the sample period.

Table A3: Sample and Simulated Moments

	(1) Risk Score 1	(2) Risk Score 2	(3) Risk Score 3	(4) Risk Score 4
	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP	CtrlMU/HighMU/CtrlMU/HighMU CtrlDP/CtrlDP/LowerDP/LowerDP
Take-up				
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	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
first minus second half (%)	*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	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
perfect repayers (%)	*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	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
resuming payment (%)	*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	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
defaulters (%)	*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)
Down payment				
Average down payment (%)	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 sample moments alongside simulated moments for each risk score. Within each column, sample moments are reported above and simulated moments below in *italics*. Parentheses show t-statistics from a two-sample equality test.

Table A4: Jacobian and Sensitivity Matrices, 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

Note: This table reports the scaled Jacobian and Sensitivity matrices for risk score 1. Panel A shows J scaled by multiplying parameter estimates, dividing by the standard deviation of moments, and dividing by 100. For example, the first entry, 0.12, means a 1% change in $\bar{y}$ leads to 0.12 $\times$ the standard deviation change in $Takeup_3$. Panel B shows Λ scaled by multiplying by the standard deviations of moments, dividing by parameter estimates, and multiplying by 100. The first entry, 0.35, means a one standard deviation change in $Takeup_3$ leads to 0.35 % change in $\bar{y}$.

Table A5: Parameter Estimates Phone Choice Model

	(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 \$)	49.2	50.4	46.0	39.8
	(2.8)	(2.9)	(3.1)	(3.0)
$\sigma_{\bar{y}}$ (dispersion of mean income)	1.00	0.90	1.05	1.29
	(0.08)	(0.07)	(0.08)	(0.16)
σ (income volatility)	0.37	0.35	0.38	0.46
	(0.03)	(0.02)	(0.02)	(0.02)
Device value parameters:				
ν (normalized initial usage value)	0.098	0.076	0.074	0.058
	(0.015)	(0.007)	(0.008)	(0.006)
ϕ (prob. of depreciation, weekly)	0.029	0.028	0.033	0.040
	(0.001)	(0.001)	(0.001)	(0.002)
Other customer preference parameters:				
β (discount factor, weekly)	0.997	0.998	0.998	0.992
	(0.005)	(0.002)	(0.002)	(0.002)
μ (liquidity cost)	14.90	7.83	5.48	5.05
	(2.47)	(0.71)	(0.52)	(0.60)
σ_ω (std. dev. of random utility shock)	219.4	237.5	262.8	184.0
	(100.3)	(70.7)	(61.9)	(48.3)
ξ_3 (fixed effect for 3 month)	-50.8	-63.3	-59.7	15.0
	(27.0)	(19.2)	(16.7)	(10.6)
ξ_9 (fixed effect for 9 month)	-87.2	-86.7	-118.5	-108.3
	(37.0)	(25.5)	(29.5)	(30.3)
ξ_{12} (fixed effect for 12 month)	-153.6	-161.8	-215.7	-172.9
	(72.7)	(50.3)	(52.3)	(46.9)

Note: This table reports parameter estimates from a model with phone choice. To ease interpretation, ν, σ_ω, ξ_3, ξ_9, and ξ_{12} are scaled by marginal utility evaluated at the population average mean income ($u'(\bar{y})$). For instance, the true value for ν in risk score 1 is $0.098 \times u'(49.2)$. Since $\bar{v} = \nu p$, the initial usage value is $0.098 \times u'(49.2) \times p$, where p is the phone price in U.S. dollars. As discussed in Section 3, μ_i is proportional to marginal utility at mean income: $\mu_i = \mu \times u'(\bar{y}_i)$. Standard errors are calculated using the delta method (Section C.5 in the Online Appendix) and reported in parentheses.

Table A6: Welfare and Profitability from Phone Choice Model

Treatment Group	(1) Take-Up (%)	(2) $\mathcal{W}_{taker}$ (%)	(3) $\mathcal{W}_{pop}$ (%)	(4) NPV ($)	(5) IRR (%)
Risk score 1					
CtrlMultipleCtrlDown	62.8	7.4	4.3	37.3	201
HighMultipleCtrlDown	55.3	6.7	3.8	64.5	444
CtrlMultipleLowerDown	67.5	8.2	5.3	36.3	176
Competitive Pricing	91.5	13.0	11.9	0.0	25
Risk score 2					
CtrlMultipleCtrlDown	61.3	5.4	3.3	34.8	181
HighMultipleCtrlDown	55.8	4.9	2.9	59.7	391
CtrlMultipleLowerDown	68.4	5.9	3.9	35.5	164
Competitive Pricing	93.9	10.0	9.4	0.0	25
Risk score 3					
CtrlMultipleCtrlDown	50.9	4.5	2.3	26.8	143
HighMultipleCtrlDown	48.9	4.1	1.9	53.7	326
CtrlMultipleLowerDown	59.7	4.9	2.7	22.8	109
Competitive Pricing	77.5	6.8	5.3	0.0	25
Risk score 4					
CtrlMultipleCtrlDown	26.2	3.2	0.8	28.3	196
HighMultipleCtrlDown	26.0	2.9	0.7	37.0	239
CtrlMultipleLowerDown	38.2	3.7	1.1	14.4	82
Competitive Pricing	35.9	4.0	1.4	0.0	25

Note: This table reports welfare gains and profitability for each experimental arm based on a model with phone choice. Column (1) reports the take-up rate. Column (2) reports $\mathcal{W}_{taker}$, welfare gains conditional on buying a phone. Column (3) reports $\mathcal{W}_{pop}$, unconditional welfare gains. Column (4) reports the NPV per contract over two years. Column (5) reports the annualized IRR for a portfolio of all contracts in each experimental arm over two years.